South African Stock Returns Predictability using Domestic and Global Economic Policy Uncertainty: Evidence from a Nonparametric Causality-in-Quantiles Approach

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Abstract

This paper analyses whether we can predict South African stock returns based on a measure of economic policy uncertainty (EPU) of South Africa and twenty other developed and emerging markets. While, linear Granger causality tests fail to find evidence of predictability, barring couple of cases, strong evidence of causality is detected from all the EPUs using a nonparametric causality-in-quantiles test. In addition, predictability is found to hold over the entire conditional distribution of stock returns, with the same being strongest around the median, i.e., when the stock market is in a normal mode. Given the existence of nonlinearity and regime changes in our data set, we consider the results from the nonparametric test as more robust relative to the standard causality test.

Keywords : Economic Policy Uncertainty; Stock Prices; Linear Causality; Nonparametric Quantile Causality; South Africa
JEL Classification : C32; C53; E60; G12; G17

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1 - Introduction

While, predictability of stock returns is important for practitioners in finance for asset allocation, academics in finance are interested in stock return predictability, since it has important implications for tests of market efficiency, which in turn, helps to produce more realistic asset pricing models [Rapach *et al.* (2013), Rapach and Zhou (2013), Neely *et al.* (2014)]. However, stock return prediction is highly challenging, since it inherently contains a sizable unpredictable component [Rapach and Zhou (2013)]. Understandably, the international literature on stock returns prediction is huge, with wide array of models (univariate and multivariate; linear and nonlinear) and predictors (such as, domestic and international financial and macroeconomic variables, institutional and behavioural factors, and technical indicators) used [see Aye *et al.* (forthcoming)] and references cited therein for further details). Not surprisingly, the evidence is mixed, with results contingent on models, variables, sample period and countries under consideration. Not surprisingly, the story is the same for an emerging market economy like South Africa – our case study in this paper.

The evidence in favour of stock return predictability for South Africa, based on domestic and international macroeconomic and financial variables, is, at best, weak. Studies like, [Gupta and Modise (2012a, b, 2013)], [Aye, Gupta and Modise (2013)], and [Sousa *et al.* (forthcoming)] finds very limited evidence of stock returns predictability, to the extent, that these papers thus conclude that the South African stock market is possibly efficient. Note that, all these studies use bivariate predictive regression models (with stock returns being the dependent variable) - the standard framework used for predicting stock returns [Goyal and Welch (2008), Rapach and Zhou (2013)]. However, as Gupta *et al.* (forthcoming) finds that stock return predictability increases dramatically for South Africa, when either forecast combination (and or bagging) approaches (i.e., combining forecasts from individual bivariate predictive regressions) or Bayesian predictive regressions (which uses many predictors simultaneously in the predictive regression model) are employed – a result in line with the study of [Rapach *et al.* (2013)] for US stock returns.

Related to stock returns predictability, there exists a recent (but growing) literature, which analyses the role of economic policy uncertainty (EPU). In this regard, some mixed, primarily in-sample, empirical evidence can be found in [Antonakakis *et al.* (2013), Kang and Ratti (2013), Gupta *et al.* (2014), Bekiros, Gupta and Kyei (2015), Bekiros, Gupta and Majumdar

(2015), Brogaard and Detzel (2015), Chang *et al*. (2015), Jurado *et al*. (2015), Kang and Ratti (2015), Redl (2015), Li *et al.* (forthcoming), and Sum (forthcoming)]. All these above studies have related the own-country EPU with own-country stock returns, with [Redl (2015)] doing it for South Africa based on quarterly data. The two exceptions in this regard are: [Sum (2012), and Mensi *et al.* (2014)]. While, [Sum (2012)] relates US EPU with stock returns in the BRIC (Brazil, Russia, India and China) countries, [Mensi *et al.* (2014)] adds South Africa to the BRIC countries, while analysing the impact of US EPU, besides other global shocks. Mensi *et al.* (2014), however, finds no evidence of the role of contemporaneous values of US EPU in explaining daily South African stock returns, based on a quantile regression framework.

Against this backdrop, the objective of our paper is to analyse whether the EPU of South Africa, as well as, the EPUs of twenty other developed and emerging markets (Australia, Brazil, Canada, China, France, Germany, Hong Kong, India, Italy, Japan, Malaysia, Mexico, The Netherlands, South Korea, Spain, Sweden, Switzerland, UK and US), can predict South African stock returns, based on a quantile causality approach (developed recently by [Jeong *et al.* (2012)]), over the monthly period of 1990:01-2012:03. The causality-in-quantile approach employed in our study has two important novelties: First, the test is robust to functional misspecification errors and can detect general dependence between time series. This is particularly important in our application, since it is well known (and as we show) that financial data display nonlinear dynamics and structural breaks (as emphasized in [Aye *et al.* (2013)]). And second, the test statistic does not only test for causality in the mean, but also tests for causality that may exist in the tail area of the joint distribution of the series. This is again important, given that stock returns generally tend to have (and as we show) non-normal distribution. To the best of our knowledge, this is the first attempt to provide an extensive predictive analysis of South African stock returns based on global EPUs, over and above the same for South Africa. At this stage, it is important to highlight two facts: First, given the weak evidence of South African stock returns predictability in bivariate predictive regressions, our paper aims to revisit the issue of predictability in a bivariate context again, but using a nonlinear causality-in-quantile approach, but now using EPUs as possible predictors. As part of future research, it would be interesting to reconsider the predictability of the macroeconomic and financial variables used in the South African stock returns literature, using the causality-in-quantile approach used here. And second, it is important to emphasize the departure of our work from that of

[Mensi *et al.* (2014), and Redl (2015)]. Unlike the two above-mentioned studies, we consider EPUs of not only the US, but twenty other countries, including South Africa. But, more importantly, we perform a predictive analysis, based on a causality-in-quantile approach, and not a contemporaneous analysis as in [Mensi *et al.* (2014)], and the conditional mean-based vector autoregressive (VAR) approach of Redl (2015).

A relevant question, which we have been silent so far, but needs to be asked is: What is the theoretical background that causes one to believe that EPU (both domestic and global) can predict stock returns? Asset returns are functions of the state variables of the real economy, and the real economy itself displays significant fluctuations. Besides standard theoretical justifications of such fluctuations based on productivity and/or policy shocks, a recent strand of literature relates the impact of various forms of policy-generated uncertainty, to movements in macroeconomic variables [Bloom (2009), Aastviet *et al.* (2014), Colombo (2013), Jones and Olson (2013), Mumtaz and Zanetti (2013), Karnizova and Li (2014), Alessandri and Mumtaz (2014), Mumtaz and Surico (2013), Balcilar *et al.* (2014, 2015), Mumtaz and Theodoridis (2014, 2015), Jurado *et al.* (2015), Redl (2015), Carriero *et al.* (forthcoming)], which in turn, is expected to affect stock returns. While, this explanation relates to the role a South Africa's EPU can play in affecting its stock returns, as depicted by [Redl (2015)], we also need to understand why EPU of other countries might predict South African stock returns? The explanation in this regard, emanates from the following lines of thinking: South Africa, along with the other BRIC countries, is the major recipient of global investment flows. As changes in the EPU of a specific foreign country would affect that economy's domestic and global investment potential, it is likely to feed into South Africa's growth process and its stock markets [Sum (2012), Mensi *et al.* (2014)]. Moreover, international investors are interested in South African stock market (besides the BRICs) for risk diversification opportunities, which in turn, provides a direct channel through which a change in the EPU of a foreign nation, can affect South African stock returns [Sum (2012), Mensi *et al.* (2014)]. In other words, foreign EPUs are expected to affect South African stock returns, given the increased economic integration of South Africa with the world economy. The remainder of the paper is organized as follows: Section 2 presents the methodology, while Section 3 discusses the data and the results. Finally Section 4 concludes.

2 - Methodology

We study the predictability of domestic and global EPUs by turn on stock returns of South Africa using the method of nonlinear causality proposed by [Jeong *et al.* (2012)]. We denote stock returns as (y_t) and EPU as (x_t).

Following [Jeong *et al.* (2012)], the quantile-based causality is defined as follows:[1]

x_t does not cause y_t in the θ-quantile with respect to the lag-vector of $\{y_{t-1},...,y_{t-p},x_{t-1},...,x_{t-p}\}$ if

$$Q_\theta\{y_t \mid y_{t-1},...,y_{t-p},x_{t-1},...,x_{t-p}\} = Q_\theta\{y_t \mid y_{t-1},...,y_{t-p}\} \quad (1)$$

x_t is a prima facie cause of y_t in the θth quantile with respect to $\{y_{t-1},...,y_{t-p},x_{t-1},...,x_{t-p}\}$ if

$$Q_\theta\{y_t \mid y_{t-1},...,y_{t-p},x_{t-1},...,x_{t-p}\} \neq Q_\theta\{y_t \mid y_{t-1},...,y_{t-p}\} \quad (2)$$

where $Q_\theta\{y_t \mid \cdot\}$ is the θth quantile of y_t depending on *t* and $0<\theta<1$.

Let $Y_{t-1} \equiv (y_{t-1},...,y_{t-p})$, $X_{t-1} \equiv (x_{t-1},...,x_{t-p})$, $Z_t = (X_t, Y_t)$ and $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ 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. The conditional distribution $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ is assumed to be absolutely continuous in y_t for almost all Z_{t-1}. If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t \mid Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t \mid Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_q(Z_{t-1}) \mid Z_{t-1}\} = q$ with probability one. Consequently, the hypotheses to be tested based on definitions (1) and (2) are:

$$H_0 = P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) \mid Z_{t-1}\} = q\} = 1 \quad (3)$$

$$H_1 = P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) \mid Z_{t-1}\} = q\} < 1 \quad (4)$$

[1] The exposition in this section closely follows [Jeong *et al.* (2012)].

Jeong *et al.* (2012) employs the distance measure $J = \{\varepsilon_t E(\varepsilon_t \mid Z_{t-1}) f_Z(Z_{t-1})\}$ where ε_t is the regression error term and $f_Z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_t emerges based on the null in (3), which can only be true if and only if $E[\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1}) \mid Z_{t-1}\}] = \theta$ or equivalently $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Jeong *et al.* (2012) specify the distance function as follows:

$$J = E[\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} - \theta\}^2 f_Z(Z_{t-1})] \qquad (5)$$

In Eq. (5), it is important to note that $J \geq 0$ i.e., the equality holds if and only if H_0 in (3) is true, while $J > 0$ holds under the alternative H_1 in Eq. (4). Jeong *et al.* (2012) show that the feasible kernel-based test statistic for J has the following form:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right)\hat{\varepsilon}_t \hat{\varepsilon}_s \qquad (6)$$

where $K(\cdot)$ is the kernel function with bandwidth h while $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is estimated as follows:

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq Q_\theta(Y_{t-1}) - \theta\}$$

$\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θth conditional quantile of y_t given Y_{t-1}. Below, we estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as:

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(\theta \mid Y_{t-1})$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1})$ is the *Nadarya-Watson* kernel estimator given by:

$$\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left((Y_{t-1} - Y_{s-1})/h\right) 1(y_s \leq y_t)}{\sum_{s=p+1, s\neq t}^{T} L\left((Y_{t-1} - Y_{s-1})/h\right)} \tag{7}$$

with $L(\cdot)$ denoting the kernel function and h the bandwidth.

The empirical implementation of causality testing via quantiles entails specifying three important choices: the bandwidth h, the lag order p, and the kernel type for $K(\cdot)$ and $L(\cdot)$ in Eq. (6) and (7) respectively. In our study, the lag order of one is determined using the Schwarz Information Criterion (SIC) under an autoregressive (AR) model for South African stock returns, as well as, VARs comprising of the South African stock returns and the various EPUs by turn.[2] Note that, using a lag-length of one makes our analysis consistent with the predictive regression-based studies on the South African stock returns, discussed in the introduction. The bandwidth value is selected using the least squares cross-validation method. Lastly, for $K(\cdot)$ and $L(\cdot)$ we employ Gaussian-type kernels.

3 - Data and results

Our analysis is based on monthly South African stock prices and EPUs of 21 countries including that of South Africa. The Johannesburg All Share Index (ALSI) is used as the measure of stock prices in South Africa (in line with the stock market literature of South Africa), and is obtained from the International financial statistics database of the International Monetary Fund. Since stock prices were non-stationary, based on standard unit root tests,[3] we work with stock returns, which are in turn, obtained as the first-differences of the natural logarithmic values of the ALSI expressed in percentages. The data on EPU for the 21 countries is derived from [Brogaard and Detzel (2015)].[4] The authors construct the EPU indexes based on data from an internet search

[2] Complete details of the lag-length tests are available upon request from the authors.
[3] Complete details of the unit root tests are available upon request from the authors.
[4] We thank Jonathan Brogaard for providing us with the EPU data. Note that, though Brogaard and Detzel (2015) created the EPU for 21 countries in an earlier version of the paper, they only concentrated on the US stock market in the published version.

and count of articles that use key words associated with economic policy uncertainty in these countries. The source for their data is the Access World News database. The data, in general, starts from 1990:01 and stretches till 2012:03.[5] The exceptions are that of Brazil, China, India, Mexico and Russia, with the respective countries starting, respectively, from 1993:08, 1994:08, 1990:02, 1990:02 and 1998:02. We work with natural logarithmic levels of the EPU indexes, which, in turn are found to be stationary, based on standard unit root tests.[6] Hence, the basic condition of stationarity of the variables required for our causality-in-quantiles approach holds with stock returns and the various EPU indexes. Note that, since the ALSI is available from 1957:01, we can start our analysis from 1990:01, and do not lose an observation (1990:01) when computing stock returns. The distribution of the stock returns was found to be negatively skewed (-3.1961), and have excess kurtosis (26.5269), yielding a Jarque-Bera statistics of 6612.4120, whereby the null of normality was overwhelmingly rejected at 1 percent level of significance. This, in turn, is indicative of a heavy left-tail for the stock returns, and provides an initial motivation to look at the effect of the EPUs over its entire distribution, rather than just in the conditional-mean.[7]

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[5] Note that, an alternative source of monthly EPU is the news-based index constructed by [Baker et al. (2013)], and available for download from: www.policyuncertainty.com. However, these indexes, though available until more recent months of 2015, do not include South Africa, and are only available for Canada, France, Germany, India, Italy, Japan, Russia, South Korea, Spain, The Netherlands, UK and US. Also, these indexes do not stretch back to 1990 for many of these countries. Further, for the sake of comparability of the effect of the EPUs of various country on South African stock returns, we felt it was wise to use data from the same source with the same methodology, i.e., of [Brogaard and Detzel (2015)], for a wider number of countries, even if it meant compromising on data for some recent months for certain countries. In addition, given that our sample covers 1990:01-2012:03, it includes all the major episodes following South Africa's integration into the world economy in 1994. Redl's (2015) quarterly data on South African EPU could not be accessed upon writing to the author, and hence, was not considered.

[6] Theoretically, measures of uncertainty should be stationary. However, statistically, it could deviate from this due to the sample period considered. But, the unit root tests revealed that the natural logarithm of the EPUs did not contain unit roots, and hence, could be used in levels in our analysis. Complete details of the unit root tests are available upon request from the authors.

[7] The Jarque-Bera test rejected the null of normality of the EPUs at 1 percent level of significance for France, Germany, Hong Kong, India, Italy, Japan, Mexico, Russia, South Africa, Spain, The Netherlands and Sweden. The null was rejected at 10 percent level for Canada and Switzerland. Complete details of the summary statistics of the South African stock returns and the 21 EPUs are available upon request from the authors.

Though our objective is to analyse the causality-in-quantiles running from EPU to the stock returns, for the sake of completeness and comparability, we also conducted the standard linear Granger causality test based on a VAR(1). The results have been reported in Table 1. As can be seen, barring Japan and Russia, there is no evidence of predictability originating from the EPU for South African stock returns at the conventional 5 percent level of significance. If the cut-off limit is weakened to 10 percent, we can add China and South Africa, with Germany being on the borderline (given a *p*-value of 0.1020). Overall, the evidence is weak in terms of the ability of domestic and global EPU to predict South African stock returns.

Next, to motivate the use of the nonparametric quantile-in-causality approach, we investigate two features of the relationship between the stock returns and the EPUs, namely, nonlinearity and structural breaks. To check for nonlinearity, we apply the [Brock *et al.* (1996, BDS)] test on the residuals of an AR(1) model for stock returns, and the stock returns equation in the VAR(1) model involving the various EPUs by turn. The BDS test, reported in Table 2, rejected the null of serial dependence at various dimensions, at the highest levels of significance, for the residuals of stock returns from the AR(1) model, and for the VAR(1) model involving the EPUs of Brazil, Canada, France, Italy, Malaysia, Mexico, South Africa, South Korea, Spain, Sweden, Switzerland, and The Netherlands. These results provide strong evidence of nonlinearity in the South African stock returns, and its relationship with its own EPU, and the EPU of the above-mentioned countries. This means that, though, the results of the linear Granger causality test between South African stock returns and the EPUs for Japan and Russia (and to some extent China and Germany) can still be relied upon; the weak evidence obtained from the South African EPU, cannot not be considered robust. But recall that, the BDS test does suggest that South African stock returns do have a nonlinear data generating process in the first place. Hence, the null of no Granger causality cannot be based on a linear AR(1) model.

Next, we turn to the Bai and Perron (2003) test of multiple structural breaks, applied again to the AR(1) model for stock returns, and the stock returns equation in the VAR(1) model involving the various EPUs by turn. As can be seen from the results reported in Table 3, there is at least one break in the stock returns equation of the VAR(1) model, with the most common break being 2009:05, i.e., during the recent financial crisis. The South African stock returns too is observed to have a break during the same period, thus driving this break point for all the countries, barring South Korea, Spain and the UK, during this month. However, as under the BDS test, existence of structural breaks in the stock returns, and its relationship with the EPUs, imply that the Granger causality tests based on a linear framework is likely to suffer from misspecification.

Given the strong evidence of either nonlinearity or regime changes or both in all the relationships between South African stock returns and the various EPUs, we now turn our attention to the causality-in-quantiles test. As can be seen from Figures 1 to 21, the null hypothesis of no Granger causality is overwhelmingly rejected in all the cases at 5 percent level of significance and that too, over the entire conditional distribution of the stock returns – a result which starkly contrasts the weak evidence of predictability under the linear framework. While causality does hold for the entire conditional distribution, the predictability is strongest around the median, i.e., when the South African stock market is in a normal mode.

In the same set of Figures, we also report the causality test over a sub-sample that ends in 2006:12, i.e., the pre-financial crisis period. Note that, nonparametric tests are quite data intensive, and hence, could not be performed over the in-crisis and post-crisis sub-sample (2007:01-2012:03, i.e., 75 observations) due to bandwidth issues. As can be seen from the results of the sub-sample, the evidence of causality is weakened relative to the full-sample in all cases, especially around the tails. However, there is still ample evidence of the role of EPU in predicting South African stock returns around the median of the conditional distribution. Though, we could not perform the causality-in-quantiles test for the period of 2007:01-2012:03, the fact that EPU has stronger predictability on stock returns for the full-sample relative to the pre-crisis sample, can be considered or speculated as an evidence, though not conclusive, of the importance of EPU in affecting the South African stock market over and after the crisis period as well. Overall, our results highlight the importance of accounting for nonlinearity when testing for the role of EPUs in predicting South African stock returns, and also that, irrespective of the sample periods, domestic and global EPUs tends to be a strong predictor for the stock returns, especially when the market is performing in a normal fashion.

4 - Conclusion

In an interdependent world economy, it can be hypothesized that uncertainty regarding economic policies of other economies are likely to predict South African stock returns, over and above the domestic uncertainty. Against this backdrop, we use a nonparametric causality-in-quantiles test (proposed by [Jeong *et al.* (2012)]) to verify our null hypothesis based on economic policy uncertainty (EPU) of twenty one countries, including that of South Africa, over a monthly period of 1990:01-2012:03. For the sake of comparability, we started off with the standard linear Granger causality test, which, in turn, revealed that, barring Japan and Russia, there is no evidence of predictability originating from the EPUs for South African stock returns at the conventional 5 percent level of significance. However, the results from the conditional mean-based linear Granger causality test cannot be deemed robust, since the linear model is found to be misspecified due to the strong evidence of nonlinearity and regime changes in our data. But, when we apply the nonparametric causality-in-quantiles test, which is robust to model misspecification due to nonlinearity and structural breaks, we find that the null hypothesis of no Granger causality is overwhelmingly rejected, over the entire conditional distribution of the stock returns, in all the cases at 5 percent level of significance. In addition, the evidence in favour of predictability is strongest when the South African stock market is in a normal mode i.e., around the median of the conditional distribution of the stock returns. So based on the role played by EPUs in predicting stock returns, the South African stock market cannot be considered to be efficient, as concluded by previous studies for this market. In general, our results highlight the importance of accounting for nonlinearity and regime changes when predicting South African stock returns based on EPUs. As part of future analysis, it would be interesting to extend our study to check if our results continue to hold over an out-of-sample, since, in-sample predictability does not guarantee favourable forecasting results [Rapach and Zhou (2013)]. In addition, it would also be worthwhile to revisit in future, the weak evidence of stock returns predictability for South Africa in bivariate predictive regression models based on domestic and international macroeconomic and financial variables, using our causality-in-quantiles approach.

Appendix

Table 1: Linear Granger Causality Test

Causal Variable (EPU)	F-stat	Prob.
Australia	2.55802	0.11094
Brazil	0.33990	0.56052
Canada	0.00038	0.98441
China	3.52618	0.06173
France	0.06552	0.79817
Germany	2.69220	0.10204
Hong Kong	1.00823	0.31625
India	2.53261	0.11272
Italy	0.03051	0.86148
Japan	5.97616	0.01516*
Malaysia	0.30677	0.58014
Mexico	0.53255	0.46619
Russia	5.84412	0.01671*
South Africa	2.90032	0.08975
South Korea	0.36875	0.54421
Spain	1.34567	0.24709
Sweden	0.00352	0.95272
Switzerland	1.23360	0.26773
The Netherlands	0.01827	0.89259
United Kingdom	2.35372	0.12619
United States	1.36851	0.24313

Note: Dependent variable is the stock returns of South Africa. * indicates rejection of the null of no Granger causality at 5 percent level of significance.

Table 2: [Brock *et al.* (1996)] BDS Test

	Dimension				
	2	3	4	5	6
South African Stock Returns	0.00	0.00	0.00	0.00	0.00
Australia	1.00	0.98	0.96	0.94	0.93
Brazil	0.00	0.00	0.00	0.00	0.00
Canada	0.00	0.00	0.00	0.00	0.00
China	1.00	0.98	0.96	0.94	0.92
France	0.00	0.00	0.00	0.00	0.00
Germany	1.00	0.98	0.96	0.94	0.93
Hong Kong	1.00	0.98	0.96	0.94	0.93
India	0.95	0.98	1.00	0.98	0.97
Italy	0.00	0.00	0.00	0.00	0.00
Japan	0.95	0.93	0.92	0.91	0.90
Malaysia	0.00	0.00	0.00	0.00	0.00
Mexico	0.00	0.00	0.00	0.00	0.00
Russia	1.00	0.97	0.95	0.93	0.91
South Africa	0.00	0.00	0.00	0.00	0.00
South Korea	0.00	0.00	0.00	0.00	0.00
Spain	0.00	0.00	0.00	0.00	0.00
Sweden	0.00	0.00	0.00	0.00	0.00
Switzerland	0.00	0.00	0.00	0.00	0.00
The Netherlands	0.00	0.00	0.00	0.00	0.00
UK	1.00	0.98	0.96	0.94	0.93
US	1.00	0.98	0.96	0.94	0.93

Note: Values in cell represent *p*-value of the BDS test statistic.

Table 3: [Bai and Perron (2003)] Multiple Break Point Test

	Break Date(s)
South African Stock Returns	2009:05
EPUs	
Australia	2009:05
Brazil	1998:10, 2002:06, 2003:05, 2008:07, 2009:05
Canada	2009:05
China	2009:05
France	2009:05
Ger:any	2009:05
Hong Kong	2009:05
India	2009:05
Italy	2009:05
Japan	2009:05
:alaysia	2009:05
:exico	2009:05
Russia	1998:12, 1999:08, 2004:08, 2008:07, 2009:05
South Africa	2009:05
South Korea	1995:01, 1998:10, 2002:08, 2008:12
Spain	1998:10, 2003:01, 2008:06
Sweden	2009:05
Switzerland	2009:05
The Netherlands	2009:05
UK	2004:08
US	2009:05

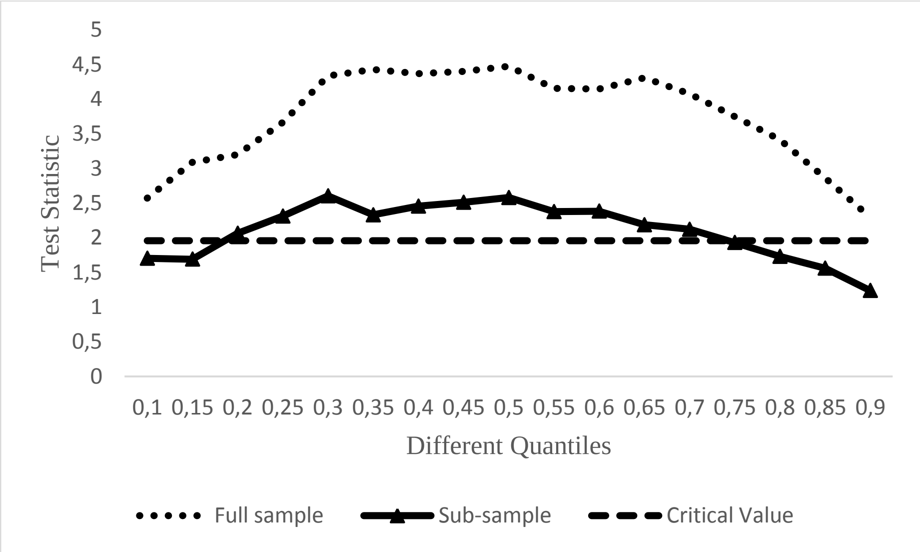

Figure 1: Causality-in-Quantiles: (EPU−Australia)

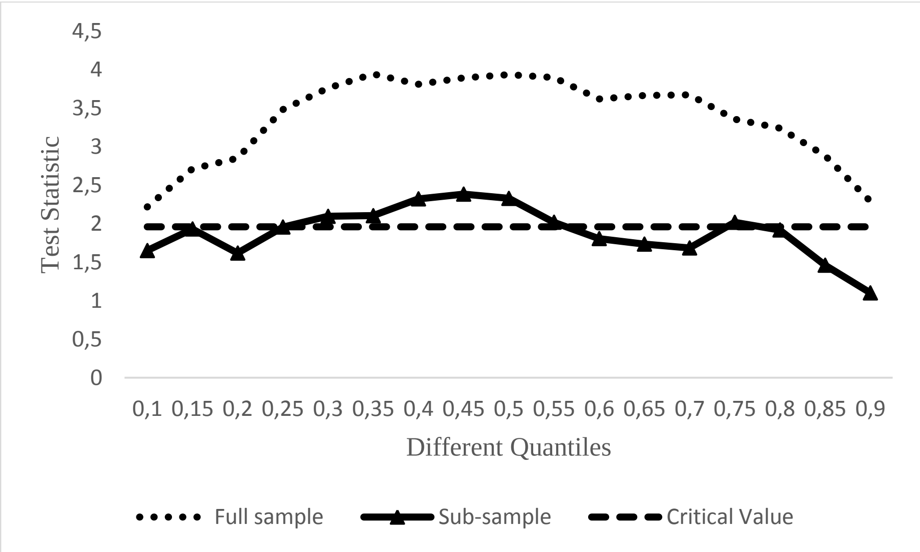

Figure 2: Causality-in-Quantiles: EPU−Brazil

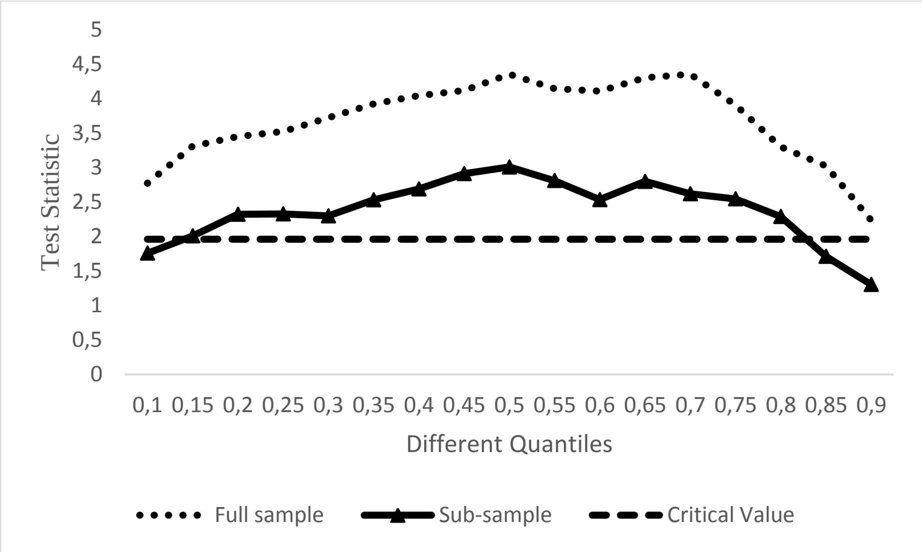

Figure 3: Causality-in-Quantiles: EPU−Canada

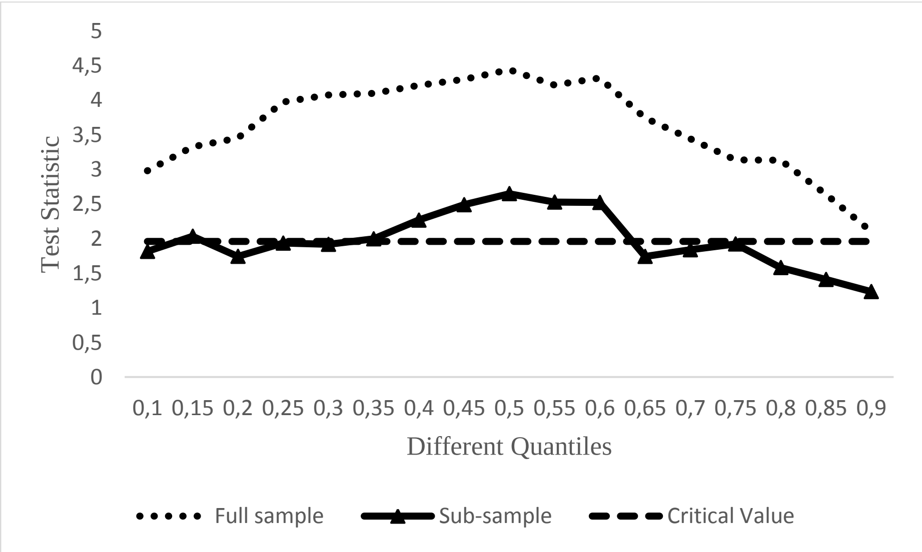

Figure 4: Causality-in-Quantiles: EPU−China

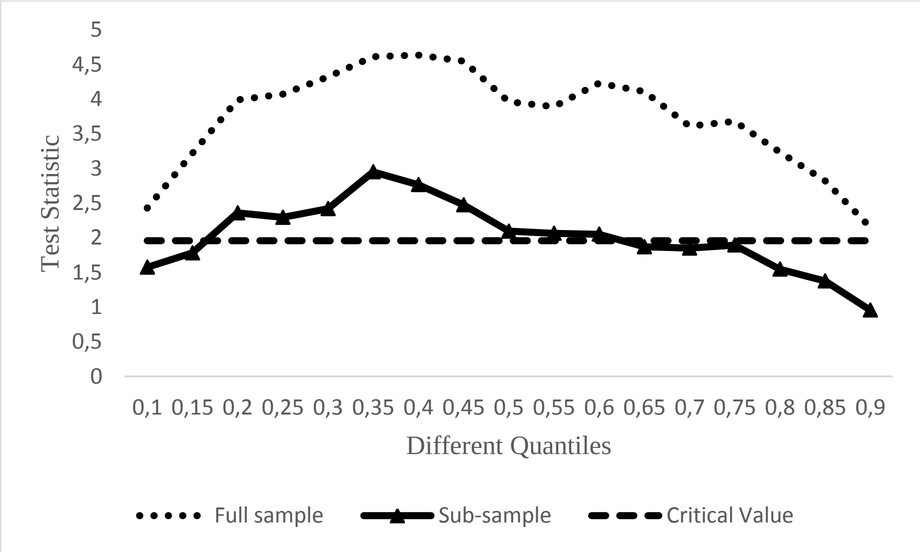

Figure 5: Causality-in-Quantiles: EPU−Germany

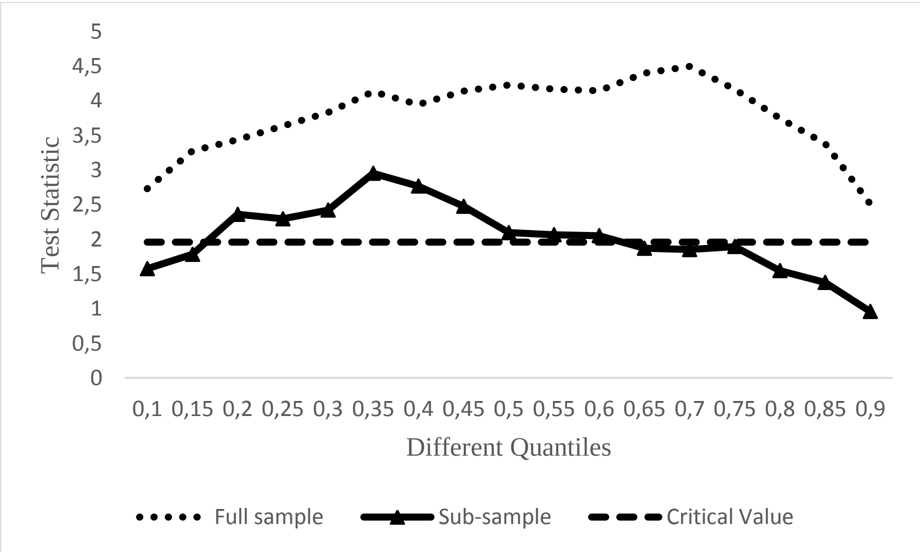

Figure 6: Causality-in-Quantiles: EPU−France

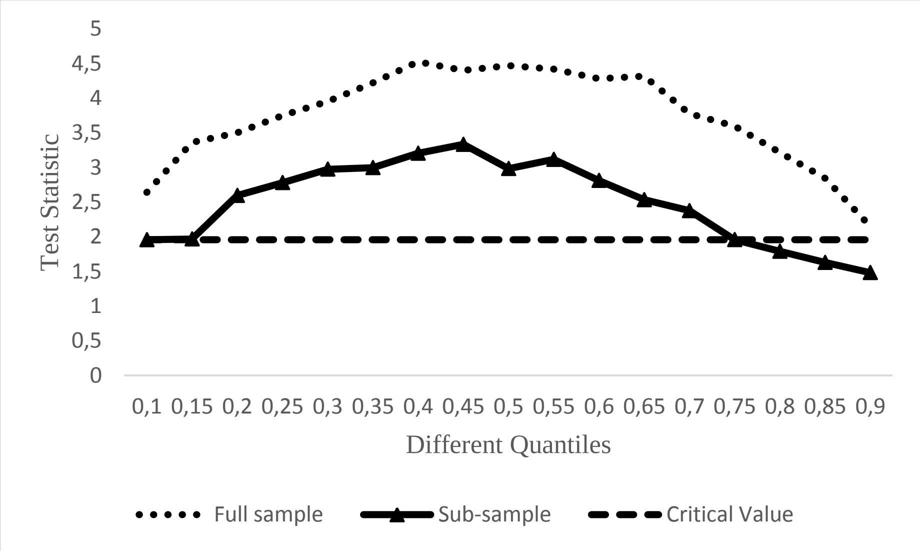

Figure 7: Causality-in-Quantiles: EPU−Hong Kong

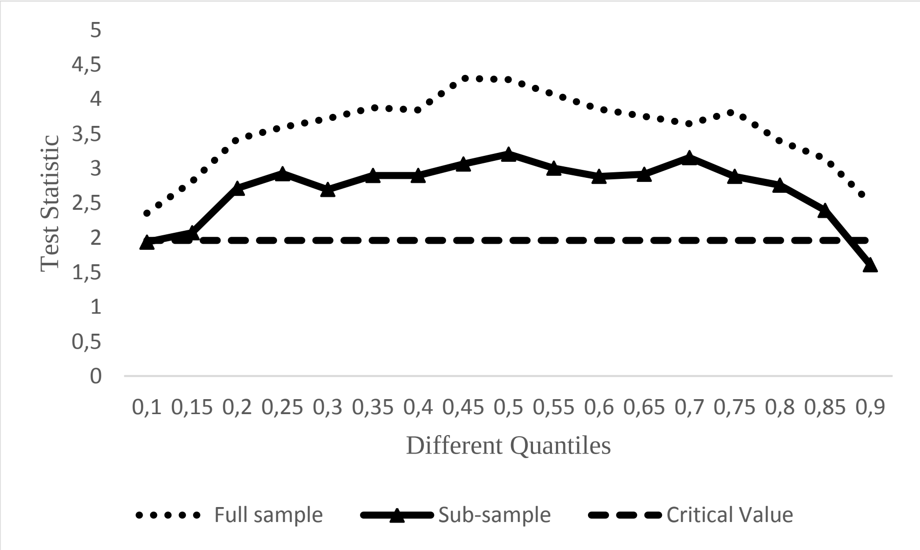

Figure 8: Causality-in-Quantiles: EPU−India

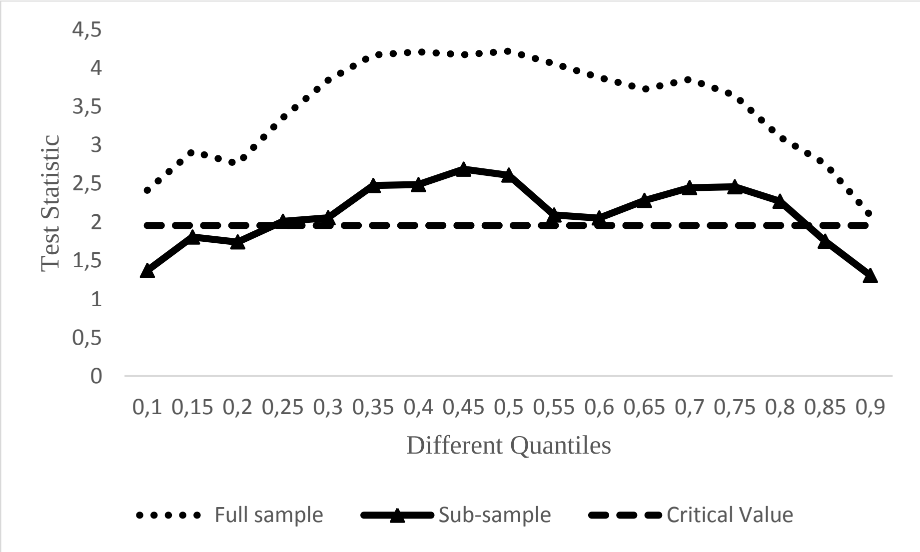

Figure 9: Causality-in-Quantiles: EPU−Italy

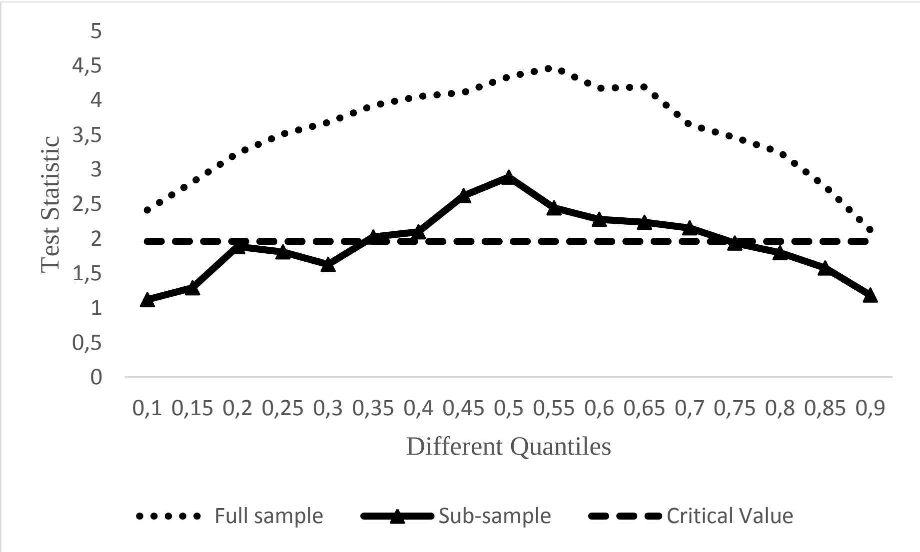

Figure 10: Causality-in-Quantiles: EPU−Japan

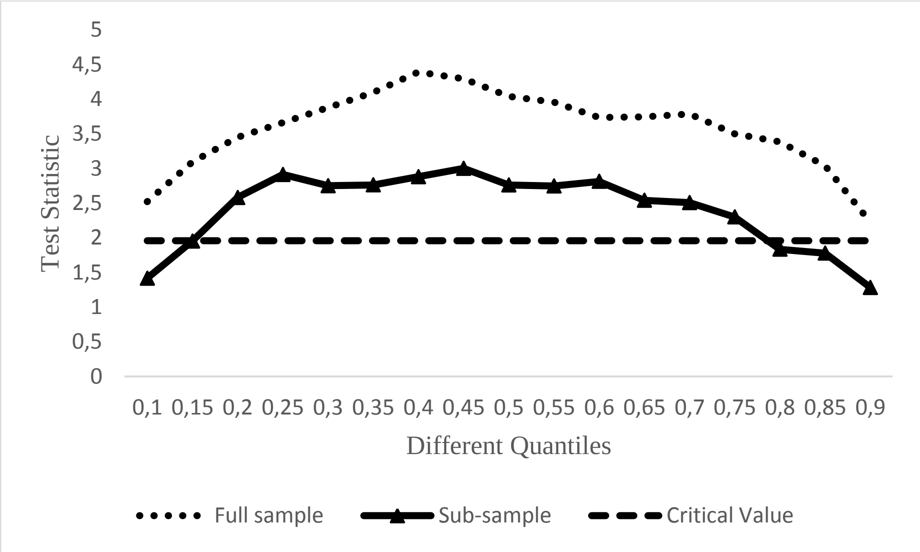

Figure 11: Causality-in-Quantiles: EPU−Malaysia

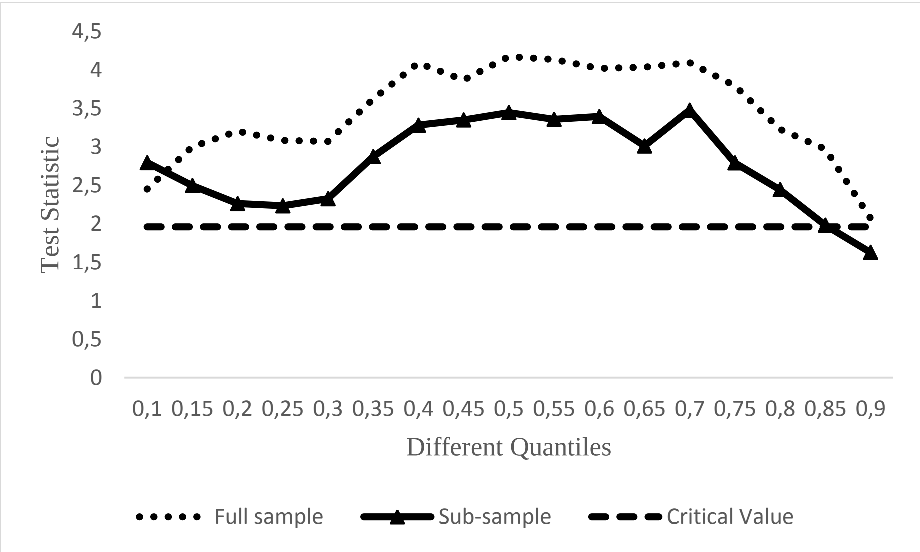

Figure 12: Causality-in-Quantiles: EPU−Mexico

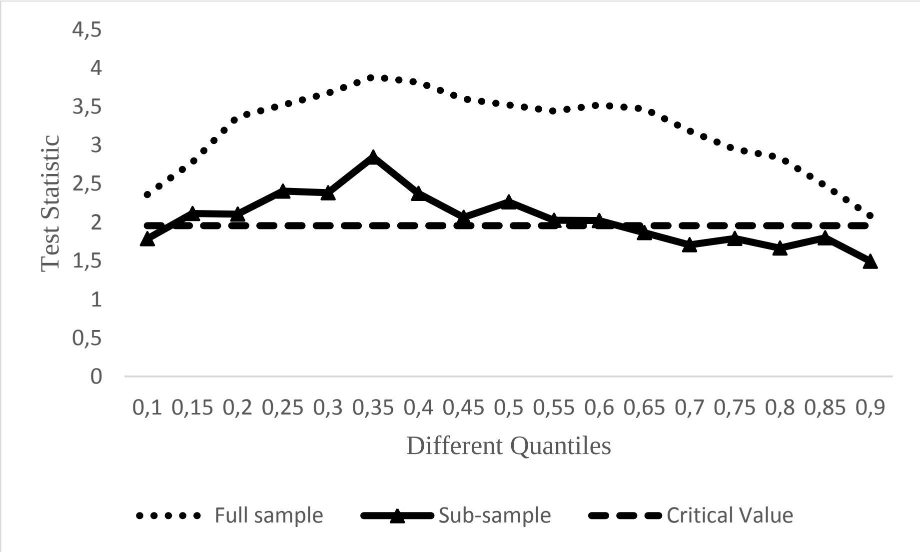

Figure 13: Causality-in-Quantiles: EPU−Russia

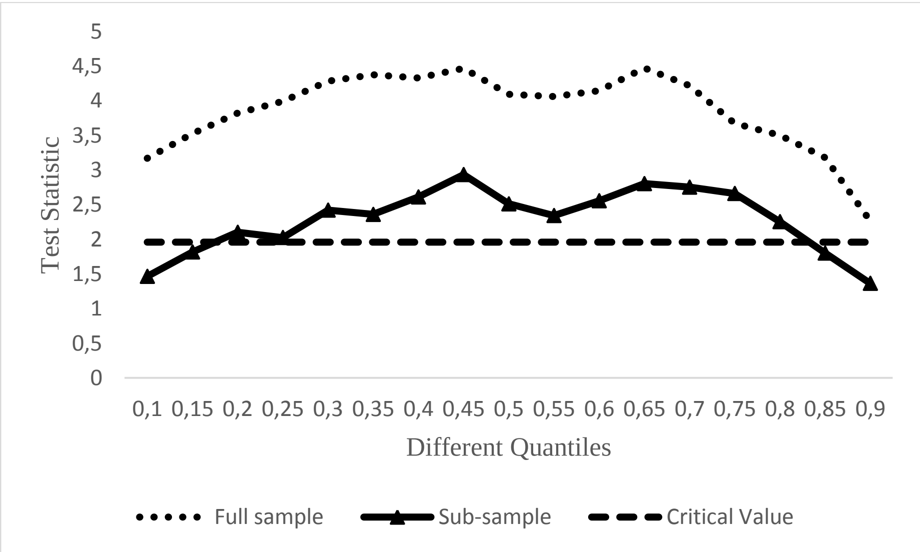

Figure 14: Causality-in-Quantiles: EPU−South Africa

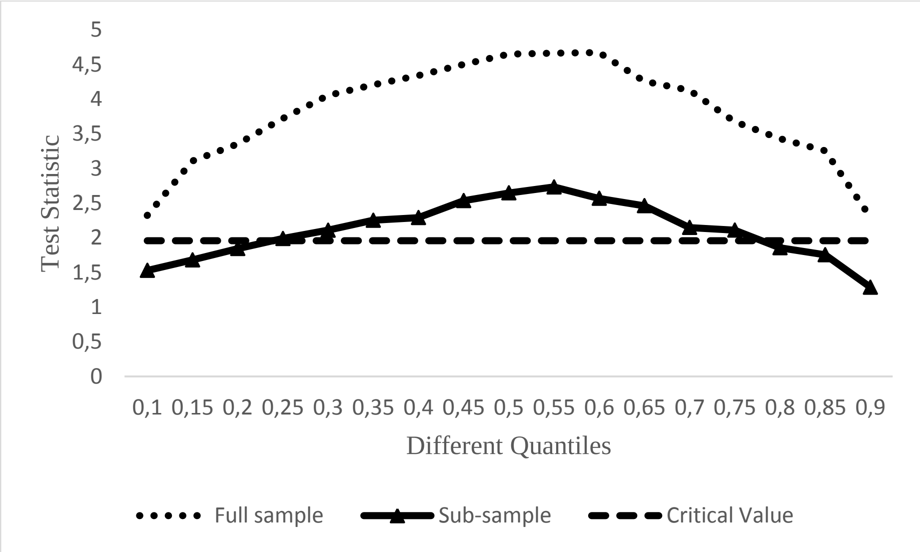

Figure 15: Causality-in-Quantiles: EPU−South Korea

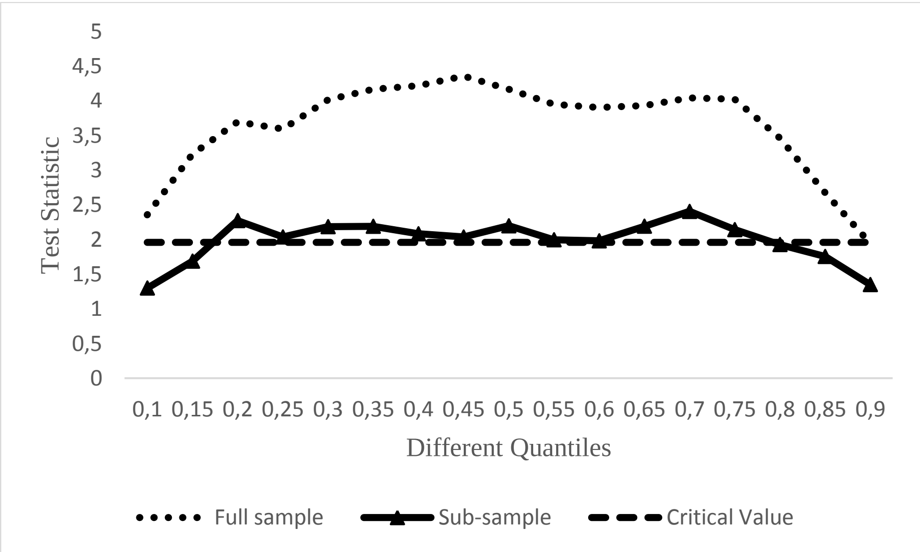

Figure 16: Causality-in-Quantiles: EPU−Spain

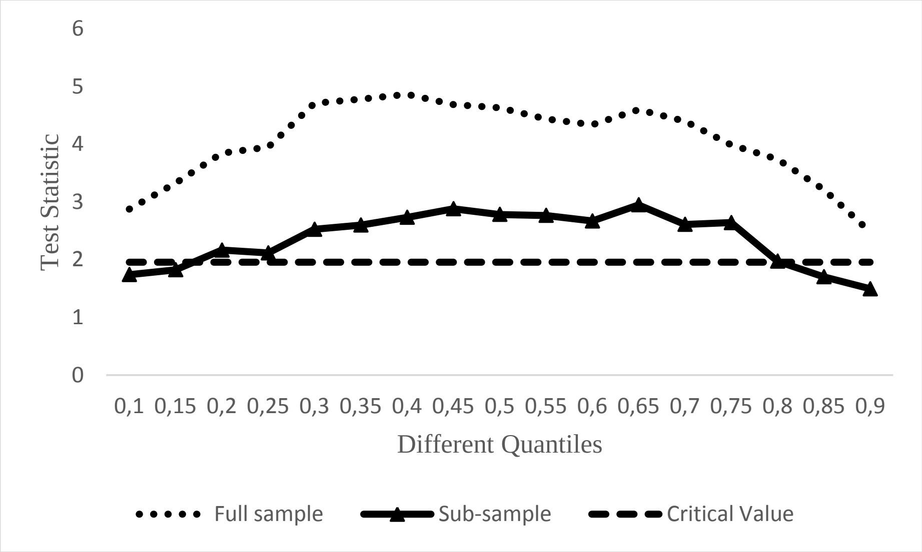

Figure 17: Causality-in-Quantiles: EPU−Sweden

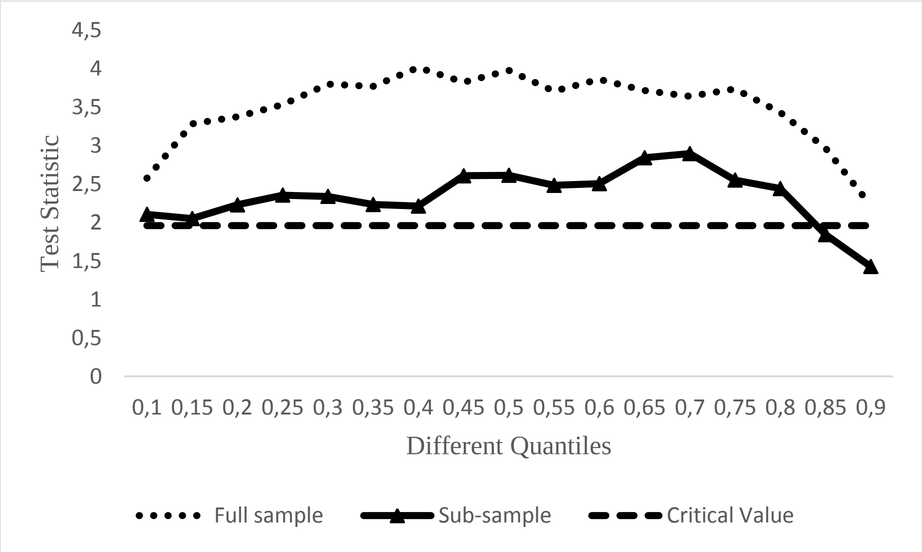

Figure 18: Causality-in-Quantiles: EPU−Switzerland

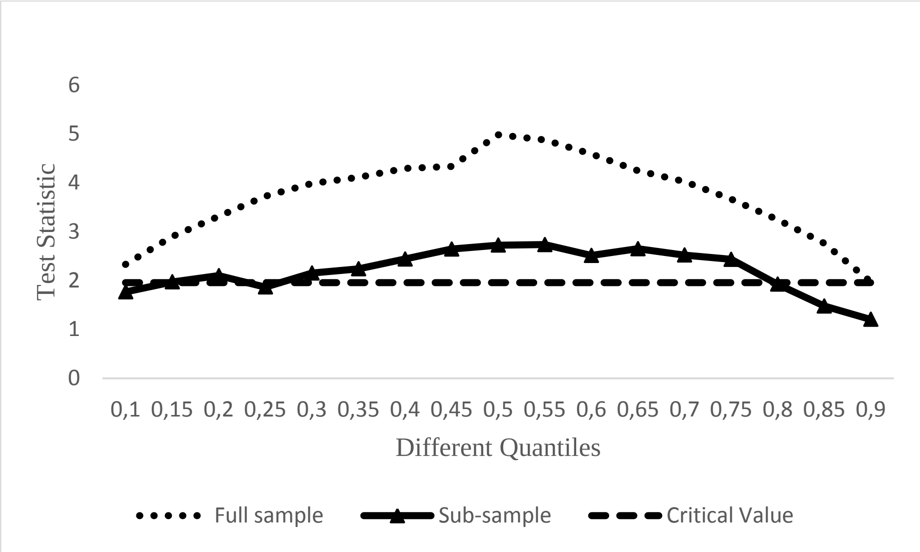

Figure 19: Causality-in-Quantiles: EPU−The Netherlands

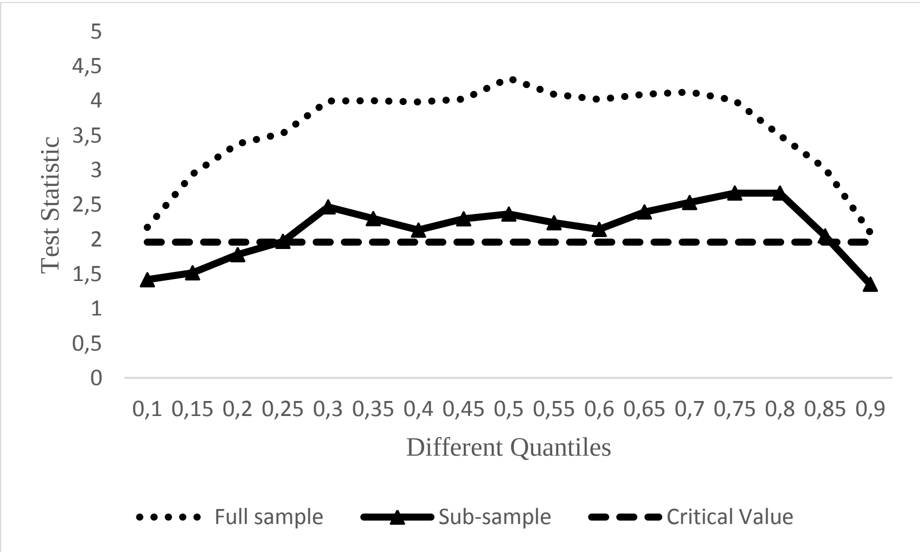

Figure 20: Causality-in-Quantiles: EPU−UK

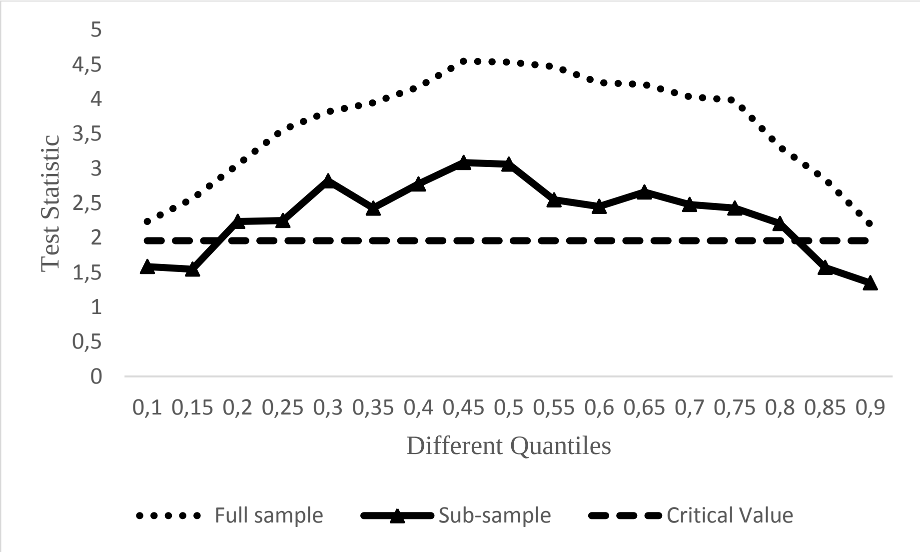

Figure 21: Causality-in-Quantiles: EPU−US

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