Unemployment fluctuations and currency returns in the United Kingdom: Evidence from over one and a half century of data

Deven Bathia*, Riza Demirer†, Rangan Gupta‡ and Kevin Kotzé§

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Abstract

This paper provides a long-term perspective to the causal linkages between currency dynamics and macroeconomic conditions by utilising a long span data set for the United Kingdom that extends back to 1856 and a time-varying causality testing methodology that accounts for the nonlinearity and structural breaks. Using unemployment fluctuations as a proxy for macroeconomic conditions and wavelet decompositions to obtain the fundamental factor that drives excess returns for the British pound, time varying causality tests based on alternative model specifications yield significant evidence of causal linkages and information spillovers across the labour and currency markets over the majority of the sample. Causal effects seem to strengthen during the Great Depression and later following the collapse of the Bretton Woods system, highlighting the role of economic crises in the predictive linkages between the two markets. While the predictive role of currency market dynamics over unemployment fluctuations reflects the effect of exchange rate volatility on corporate investment decisions, which in turn, drives subsequent labour market dynamics (e.g. Belke & Gros (2001); Belke & Kaas (2004); Feldman (2011); among others), we argue that causality in the direction of exchange rates from unemployment possibly reflects the signals regarding monetary policy actions, which in turn, spills over to financial markets. Overall, the findings indicate significant information spillovers across the labour and currency markets in both directions with significant policy making implications.

JEL Classifications: C10.

Keywords: Time-varying Granger Causality, GARCH, DCC-MGARCH, Unemployment, Exchange rates.

*Queen Mary University of London, School of Business and Management, Mile End Road, London, E1 4NS, United Kingdom. Email: d.bathia@qmul.ac.uk.

†Department of Economics & Finance, Southern Illinois University Edwardsville, Edwardsville, IL 62026-1102, USA. Email: rdemire@siue.edu.

‡Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. Email: rangan.gupta@up.ac.za.

§*Corresponding author*: School of Economics, Faculty of Commerce, University of Cape Town, Private Bag, Rondebosch 7701, South Africa. Email: kevin.kotze@uct.ac.za.

1 Introduction

In an informationally efficient setting, financial market fluctuations reflect changes in economic fundamentals and risk preferences. In the case of currencies, the present value models suggest that currency values should reflect investors' expectations about the current and future macroeconomic conditions (Frenkel & Mussa, 1985; Cochrane, 2005). However, a long-standing puzzle exists regarding the linkage between exchange rate movements and macroeconomic fundamentals. Pioneered by the seminal work of Meese & Rogoff (1983) who find that macro-economic fundamentals fail in predicting exchange rate movements, the so-called 'disconnect puzzle' presents a challenge to the present value models in their ability to explain short-run exchange rate fluctuations.[1] In addition, Berkowitz & Giorgianni (2001) and Faust *et al.* (2003) have also cast doubt over the ability of macroeconomic fundamentals to predict variations in exchange rates over the long-run. However, in contrast with these findings, Engel & West (2005), observe that the current economic conditions, as well as expected macroeconomic fundamentals, influence exchange rates. This finding is largely supported by the results in Baxter (1994), Engel *et al.* (2008), Sarno & Schmeling (2014), and Yin & Li (2014), while several other studies have also shown that macroeconomic factors may influence the future behaviour of exchange rates over longer horizons (e.g. Mark, 1995; Abhyankar *et al.*, 2005).[2] Given the mixed findings in the literature and the limitation in the sample periods that largely correspond to the floating exchange-rate regime settings, this study presents a long term perspective to the linkage between exchange rates and unemployment fluctuations by utilising a data set that extends back to 1856 to examine the dynamic causal interactions between currency excess returns and unemployment growth for the United Kingdom (UK).

Although unemployment is an important indicator of economic activity as businesses and policymakers keep a close eye on the changes in the unemployment rate, the role of unemployment fluctuations has received relatively less attention in the international finance literature.[3] In a recent study, however, Nucera (2017) establishes a predictive relationship between unemployment growth rate and currency returns such that currencies of countries with lower (higher) growth in the unemployment rate appreciate (depreciate) in subsequent periods, suggesting the presence of an idiosyncratic unemployment risk factor that is driving currency market performance.[4] In this paper we seek to explore the time-varying nature of this relationship in greater detail over an extended period of time, where we make use of long-span data for the UK and various forms of wavelet decompositions that are used to generate a measure for excess returns. This implies that contrary to most of the previous studies in the literature, we are not constrained to a relatively limited sample length by the use of futures market data, which starts in 1983. The use of long-span data in our context provides an interesting perspective to the currency-macroeconomy relationship as we are able to consider how the use of different exchange rate mechanisms may have influenced this relationship. In addition, as the UK has experienced a rather volatile unemployment pattern over the last century (see Figure 1) with notable highs in the mid-1920s and 1930s in double-digits and episodes of rising and declining unemployment rates. These patterns are accompanied with notable events that influenced economic activity, which start with the first

[1] Obstfeld & Rogoff (2001) coined the term 'exchange rate disconnect puzzle' to refer the exceedingly weak relationship between exchange rates and macroeconomic aggregates.

[2] Furthermore, Engel & West (2006) explore the link between an interest rate rule for monetary policy and the behaviour of the real exchange rate, and find that the deviations of the real exchange rates from steady-state values forecast inflation and output gaps. Also see Chen *et al.* (2010) who find that the 'commodity currencies' have remarkably robust power in predicting future global commodity prices.

[3] Since the great financial crisis of 2008, Federal Reserve kept on citing 'a weak labour market' to be the reason for not changing the federal funds rate.

[4] Nucera (2017) suggests that unemployment fluctuations generate predictable currency excess returns in a study that makes use of a cross-section of 33 OECD member countries and a model that is based on the idiosyncratic consumption risk of Sarkissian (2003). Although the UK is included in the analysis, the sample period is restricted to 32 years (January 1984 - December 2015) and it employs an approach where currencies are allocated into a portfolio of either 'good' or 'bad' currencies according to the past unemployment growth rates.

Commercial Crisis in 1857 and include the Great Depression of 1929, the two world wars, the nationalisation of the coal industry in 1947, post-war immigration from Commonwealth in 1948, the borrowing from the International Monetary Fund in 1976 due to the sterling crisis, the economic recession of 1982, financial deregulation in the mid-1980s and the great financial crisis of 2007-08.

Previous studies that have attempted to explore the dynamic causal relationships between currency returns and other macro-economic variables have largely focused on the relationship between the exchange rate and a countries' external imbalances (Della Corte *et al.*, 2012, 2016), sovereign risk (Della Corte *et al.*, 2014), and global macroeconomic uncertainty shocks (Berg *&* Mark, 2018; Della Corte *&* Krecetovs, 2016). In addition, several studies have also investigated the significance of exchange rate volatility on the level of unemployment, after taking into consideration the characteristics of the labour market. For instance, Andersen *&* Sørensen (1988) address the importance of exchange rate variability for wage formation in open economies with strong trade unions. They argue that in the case of economies with stronger trade unions, increased exchange rate variability may increase real- and product wages and lower employment. Similarly, Belke *&* Gros (2001) show that an increase in exchange rate variability can induce firms to postpone their investments (which is associated with less employment) as it raises uncertainty of future earnings. Similar findings are provided in Belke *&* Kaas (2004), where it is suggested that higher exchange rate volatility will provoke firms in countries with significant labour market rigidities and wage bargaining power to delay job creation.[5] Similarly, Stirböck *&* Buscher (2000) and Feldman (2011) also find that higher exchange rate volatility increases the unemployment rate. Hence, although the existing literature provides a number of economic arguments that can be used to establish a causal relationship between exchange rate volatility and unemployment dynamics, it has not considered how this relationship has evolved over an extended period of time.

This study contributes to this literature in multiple aspects. First, we propose new time-varying causality tests to investigate the predictive relationship between unemployment fluctuations and currency excess returns. As is noted in Cogley *&* Sargent (2005) and Primiceri (2005), although the widely used time-varying parameter vector autoregressive (VAR) models can detect time-varying causal relationships, these models are not able to show the overall causal effects of the individual variables. In our case, we not only assess time-varying causal relationships, but also estimate their overall (bi-directional) causal effects, which makes it applicable to the time-varying market integration and financial contagion context. Second, ours is the first study that assesses the predictive causation between the unemployment fluctuations in the UK and currency excess returns using long range data extending back to 1856. Finally, our study also presents a technical novelty via the use of the wavelet decomposition approach in order to generate an underlying fundamental value for the exchange rate that is then used to compute the excess currency returns as futures data (traditionally used to compute excess currency returns) is only available after the mid-1980s, thus largely restricting the sample period.

Our findings suggest that there are significant information spillovers in both directions over the majority of the sample, suggesting that currency excess returns and unemployment dynamics capture valuable predictive information over the subsequent state of the other variable. This result is in stark contrast to the standard linear Granger causality test which finds no evidence of bi-directional causality, possibly due to the presence of structural breaks and nonlinearity in the relationship between the two variables and hence indicative of misspecification in the linear model. We also present evidence of instantaneous causation, particularly when we consider the transmission from the more readily available exchange rate data. While the predictive role of currency market dynamics over unemployment fluctuations reflects the effect of exchange rate volatility on corporate investment decisions, which in turn, drives subsequent labour market dynamics (e.g. Belke *&* Gros (2001); Belke *&* Kaas (2004); Feldman (2011); among others), we argue that causality in the direction of

[5]Also see Belke *&* Gros (2002*b*,*a*); Belke (2005) that empirically analyse the effect of exchange rate volatility on unemployment. In each of these studies, the author(s) find that exchange rate adversely affects unemployment.

exchange rates from unemployment possibly reflects the signals regarding monetary policy actions, which in turn, spills over to financial markets. Overall, the findings indicate significant information spillovers across the labour and currency markets in both directions with signification implications for policy makers.

The rest of the paper is structured as follows. Section 2 provides details relating to the construction of the test statistics and section 3 describes the essential characteristics of the data. Section 4 reports the empirical findings for time-varying causality and section 5 concludes.

2 Time-varying Granger causality tests

Despite the significant economic volatility experienced by Britain in the 20th century, resulting in recessions, the business cycle was relatively shorter after World War II than in the 19th century (e.g. Matthews *et al.*, 1982; Dimsdale, 1990). Against this backdrop, Keynes (1931) claimed in 'The Economic Consequences of Mr. Churchill', that the sterling was overvalued by about 10% when Britain reinstated the gold standard in April 1925. The sterling, therefore, became less competitive under the restored gold standard which eventually contributed to the high level of unemployment including industrial unrest over wage cuts during 1925-1931. Although subsequent studies, including Johnson (1975) and Moggridge (1969), agreed to the overvaluation of the sterling, Matthews (1986), however, questioned the overvaluation argument since the UK economy was already close to the 'natural rate of unemployment' in the mid-1920s.[6] The argument that the overvaluation of the sterling possibly leads to a rise in unemployment brings about an important research question that involves a predictive causation between unemployment fluctuations and currency returns. This study enlarges our understanding of such a causal relationship by (i) employing a long span of data dating back to 1859; (ii) utilising wavelet decompositions in order to capture the fundamental factor that drives exchange rate fluctuations; and (iii) examining time varying causal interactions between unemployment fluctuations and currency returns.

Granger causality tests in various forms have been widely applied in a number of fields after Granger (1969) adapted the definition of causality proposed by Wiener (1956) into a practical form.[7] According to this axiom, "the past and present may cause the future, but the future cannot cause the past". This statement lends itself to tests that have been constructed in the time domain, where the most widely used methods are based on VAR models that were introduced by Sims (1972). More recent examples of studies that employ this methodology include Aaltonen *&* Östermark (1997), Cogley *&* Sargent (2001), Cogley *&* Sargent (2005), Primiceri (2005) and Christopoulos *&* León-Ledesma (2008), which have incorporated various time-varying features to observe changes in the degree of Granger causality over time. In addition, Geweke (1982, 1984) has also presented an additive spectral decomposition to test for Granger causality, which utilises techniques from the frequency domain of time series analysis. Breitung *&* Candelon (2006) extend this methodology after imposing a set of linear hypotheses on the autoregressive parameters, to test for predictability at some pre-specified frequency. This methodology may be implemented to identify whether there is either short-run or long-run causality and it may also be applied to cointegrated systems. In addition, Park *&* Hahn (1999) extend the framework of Engle *&* Granger (1987), where if two time series are cointegrated there must be some evidence of Granger causality in either or both directions, to construct a time-varying cointegrating regression that allows for the parameters in the model to vary with time. This framework has been extended further in Bierens *&* Martins (2010), where they introduce the cointegrating vectors that are smooth functions of time in a vector error correction model (VECM) that is reminiscent of the maximum-likelihood approach that has been adopted in Johansen (1995). Such a methodology would be of particular interest when considering the potential presence of

[6]Friedman (1977) introduced a term, 'natural rate of unemployment' that depends on 'real' factors including effectiveness of the labour market, the extent of competition or monopoly, the barriers or encouragements to working in various occupations, and so on.

[7]See, Geweke (1984) for an insightful review of the application of Granger causality methods.

long-run causality.

In what follows, we focus our attention on relatively short-run Granger causality, between stationary representations of the respective variables, where the continued development of methods that are based on cross correlation functions (CCF) incorporate useful properties, especially when used to measure time-varying Granger causality.[8] These tests largely build on Haugh (1976) who proposed an asymptotically χ^2 test that is based on the residual cross correlations. Cheung *&* Ng (1996) extended these tests to investigate causality in variance, while Hong (2001) proposed a more general test statistic for this problem, which is also suited to investigations that consider time-varying Granger causality. In addition, the Granger (1969) test statistic could be regarded as a special case of the Hong (2001) test, when a uniform kernel weight is applied to the test statistic. Hong (2001) showed that the use of non-uniform kernel weighting can significantly improve the power of his test statistic. To investigate time-varying Granger causality with the aid of these CCF tests, Lu *et al.* (2014) showed how the test statistic of Hong (2001) and Haugh (1976) may be applied to rolling regressions and multivariate models. In this study, we make use of the time-varying Granger causality tests that implement the methodology of Hong (2001) and Haugh (1976) to assess the degree to which the causal relationship between the exchange rate and macroeconomic conditions may have changed over an extended period of time. The main motivation for using these statistics is that they have desirable properties (particularly when compared to traditional Granger causality test statistics). In addition, the methodology is relatively intuitive and the test produces results that are easy to interpret, particularly when examining the time-varying causal interactions between variables over the short-run.

In order to test the cross-dependence patterns between two time-varying processes, $y_{1,t}$ and $y_{2,t}$, Hong (2001) makes use of a one-sided test that is asymptotically normal and is based on the results of a cross correlation function (CCF) that may be applied to the standardised residuals. This test may be used to derive Granger causalities given the information set, I_t, from the two time series available in period t and the information sets attributable to the individual variables $I_{1,t}$ and $I_{2,t}$.[9] Following Granger *et al.* (1986) and Hong (2001), one can formulate the null hypotheses as:

$$H_0 \quad : \quad \mathbb{E}\left\{(y_{1,t}|I_{t-1})\,|I_{1,t-1}\right\} = (y_{1,t}|I_{t-1})\,, \tag{1}$$

$$H_1 \quad : \quad \mathbb{E}\left\{(y_{1,t}|I_{t-1})\,|I_{1,t-1}\right\} \neq (y_{1,t}|I_{t-1})\,. \tag{2}$$

Accordingly, test results supporting H_0 would imply that $y_{2,t}$ does not Granger-cause $y_{1,t}$ with respect to I_{t-1}, suggesting that information from $I_{2,t-1}$ does not influence the expected value of $y_{1,t}$. Similarly, if H_1 holds, one can suggest that $y_{2,t}$ Granger-causes $y_{1,t}$ with respect to I_{t-1}. Rearranging the two yields a similar hypothesis that can be used to test if $y_{1,t}$ Granger-causes $y_{2,t}$ with respect to the information set I_{t-1}. Furthermore, instantaneous causality between the two time series could be examined via the following condition,

$$\mathbb{E}\left\{(y_{1,t}|I_{t-1})\,|I_{t-1}\right\} \neq (y_{1,t}|I_{1,t-1}, I_{2,t})\,, \tag{3}$$

in which we examine the informational value of the current information about $y_{2,t}$ on the current value of $y_{1,t}$. Such testing of instantaneous causality may be of particular interest to analysts who work with real-time higher-frequency data that is provided by the foreign exchange market, which may influence data that is sampled at a relatively low frequency and where such data is provided after a period of time has elapsed, such as in the case of unemployment data. For example, since data on the rate of unemployment is usually reported with a lag, while data from the foreign exchange market is provided in real-time, we could potentially make use of current data from the foreign exchange market to predict

[8]The study of Nucera (2017) is also largely focused on the relative short-run dynamic relationships between these variables.

[9]See, Granger (1969, 1980) for the original derivation of Granger causality.

what would be reported for unemployment once this data for the current period is released at some point in the future.

2.1 Rolling Hong tests

To obtain standardised residuals one could make use of the popular generalised autoregressive conditional heteroscedasticity (GARCH) framework, since most financial time series would often incorporate a certain degree of heteroscedasticity. In our case we employ the GARCH(1,1) model that may be formulated as:

$$
\begin{aligned}
y_{i,t} &= b_i + \epsilon_{i,t}, && (4)\\
\epsilon_{i,t} &= \xi_{i,t}\sqrt{h_{i,t}}, && (5)\\
h_{i,t} &= \alpha_i \epsilon_{i,t-1} + \beta_i h_{i,t-1}. && (6)
\end{aligned}
$$

In this model the residuals $\epsilon_{i,t} = \xi_{i,t}\sqrt{h_{i,t}}$ may be heteroscedastic, where $\xi_{i,t}$ is a vector that incorporates the standardised residuals and $h_{i,t}$ contains the estimated conditional variance of $\epsilon_{i,t}$. These estimates can be used to derive values for the centred squared standardised residuals,

$$
\hat{\mu}_{i,t} \equiv \epsilon^2_{i,t}/\hat{h}_{i,t} - 1. \tag{7}
$$

This framework can then be used to compute the sample cross-correlation function $\hat{\rho}_\mu(j,s)$ over different sub-samples of the data to obtain rolling estimates for this statistic. In our case, s denotes the different sub-samples in $[t-s+1,\ldots,t]$ and j is used to denote the lag in the cross-correlation function. Therefore,

$$
\hat{\rho}_\mu(j,s) = \frac{C_{12,t}(j,s)}{\sqrt{C_{11,t}(0,s)\,C_{22,t}(0,s)}}, \tag{8}
$$

where $C_{11,t}(0,s)$ and $C_{22,t}(0,s)$ are the variances in each sub-sample for $\mu_{i,t}$, while $C_{12,t}(j,s)$ is the lag j cross-covariance between $\mu_{1,t}$ and $\mu_{2,t}$, which is calculated as follows,

$$
C_{12,t}(j,s) = \begin{cases} \frac{\sum_{i=0}^{s-j-1} \mu_{1,t-i}\mu_{2,t-i-j}}{s}, & j = 0,1,\ldots,s-1 \\ \frac{\sum_{i=0}^{s-j-1} \mu_{1,t-i+j}\mu_{2,t-i}}{s}, & j = -1,-2,\ldots,1-s \end{cases}. \tag{9}
$$

Using the methodology of Hong (2001) and Cheung & Ng (1996), Lu *et al.* (2014) note that $\hat{\rho}_\mu(j,s)$ would be approximately normally distributed for a fixed lag j. This allows for the convenient construction of test statistics that are used to assess unidirectional Granger causality, which may be derived from,

$$
H^{\rho}_{1,t}(s) = \frac{s\sum_{j=1}^{s-1} k^2\left(\frac{j}{M}\right)\rho^2_{\mu\upsilon,t}(j,s) - C_{1s}(k)}{\sqrt{2D_{1s}(k)}}, \tag{10}
$$

where,

$$
\begin{aligned}
C_{1s}(k) &= \sum_{j=1}^{s-1}\left(1-\frac{j}{s}\right)k^2\left(\frac{j}{M}\right),\\
D_{1s}(k) &= \sum_{j=1}^{s-1}\left(1-\frac{j}{s}\right)\left(1-\frac{j+1}{s}\right)k^4\left(\frac{j}{M}\right).
\end{aligned}
$$

The calculated test statistic for bidirectional Granger causality test would then be assessed with,

$$H_{2,t}^{\rho}(s) = \frac{s\sum_{j=2-s}^{s-2} k^2\left(\frac{j}{M}\right)\rho_{\mu\upsilon,t}^2(j,s) - C_{2s}(k)}{\sqrt{2D_{2s}(k)}}, \tag{11}$$

where,

$$\begin{aligned} C_{2s}(k) &= \sum_{j=1-s}^{s-1}\left(1-\frac{|j|}{s}\right)k^2\left(\frac{j}{M}\right), \\ D_{2s}(k) &= \sum_{j=1-s}^{s-1}\left(1-\frac{|j|}{s}\right)\left(1-\frac{|j|+1}{s}\right)k^4\left(\frac{j}{M}\right). \end{aligned}$$

To allow for the fact that data relating to the exchanges rate is provided in real time, while the unemployment data is reported after a significant lag, we also consider the use of instantaneous rolling Hong tests, which take the form,

$$H_{3,t}^{\rho}(s) = \frac{s\sum_{j=0}^{s-2} k^2\left(\frac{j+1}{M}\right)\rho_{\mu\upsilon,t}^2(j,s) - C_{1s}(k)}{\sqrt{2D_{1s}(k)}}, \tag{12}$$

where M is a positive integer and $k(\cdot)$ is the kernel function that is calibrated to values that are discussed in Hong (2001). The test statistics from equation (10) to (12) are then compared to the upper-tail critical values of the $\mathcal{N}(0,1)$ distribution at an appropriate level of significance. If the test statistic is larger than the critical value, then the null hypothesis, H_0, is rejected and we conclude that there is Granger causality at time t. However, if the test statistic is relatively small, then the null hypothesis is not rejected.[10]

2.2 DCC-MGARCH Hong tests

In order to use the available data more efficiently, Lu *et al.* (2014) suggest that the dynamic conditional correlation multivariate generalised autoregressive conditional heteroscedasticity (DCC-MGARCH) model that was discussed in Engle (2002) and Engle *&* Sheppard (2001) may be used to derive appropriate time-varying standardised residuals. In this case, we stack the variables in a vector, $y_t(j) = \binom{y_{1,t}}{y_{2,t-j}}$ with lag j and construct DCC-MGARCH models for $y_t(j)$:

$$\begin{aligned} y_t(j)|I_{t-1} &\sim \mathcal{N}(0, D_{t,j}R_{t,j}D_{t,j}), \\ D_{t,j}^2 &= \operatorname{diag}\{\omega_{i,j}\} + \operatorname{diag}\{\kappa_{i,j}\}\, y_{t-1}(j)y_{t-1}'(j) + \operatorname{diag}\{\lambda_{i,j}\}\, D_{t-1,j}^2, \\ u_{t,j} &= D_{t,j}^{-1}y_t(j), \\ Q_{t,j} &= S(\iota\iota' - A - B) + Au_{t-1,j}u_{t-1,j}' + BQ_{t-1,j}, \\ R_{t,j} &= \operatorname{diag}\{Q_{i,j}\}^{-1}Q_{t,j}\operatorname{diag}\{Q_{i,j}\}^{-1}. \end{aligned} \tag{13}$$

In the widely used DCC-MGARCH(1,1) model, the dynamic correlation estimator with lag j would be derived as,

$$\begin{aligned} \rho_{pq,t}(j) = \hat{\rho}_{pq,t}(j) &+ \alpha_j\left(u_{p,t-1}u_{q,t-1-j} - \hat{\rho}_{pq,t}(j)\right) + \\ &\ldots \beta_j\left(\rho_{p,t-1} - \hat{\rho}_{pq,t}(j)\right) r_{pq,t}(j)\frac{\rho_{pq,t}(j)}{\sqrt{\rho_{11,t}\rho_{22,t}(j)}}, \end{aligned} \tag{14}$$

[10]In this case, the upper-tailed asymptotic critical values are 1.65 and 2.33 at the 5% and 1% levels, respectively.

where p, $q = 1, 2$.

Based on the dynamic correlation estimators, the unidirectional DCC-MGARCH Hong test from $y_{2,t}$ to $y_{1,t}$ is denoted as $H_{1,t}(k)$:

$$H_{1,t}(k) = \frac{T \sum_{j=1}^{T-1} k^2 \left(\frac{j}{M}\right) r_{12,t}^2(j) - C_{1T}(k)}{\sqrt{2D_{1T}(k)}}, \tag{15}$$

where,

$$\begin{aligned} C_{1T}(k) &= \sum_{j=1}^{T-1} \left(1 - \frac{j}{T}\right) k^2 \left(\frac{j}{M}\right), \\ D_{1T}(k) &= \sum_{j=1}^{T-1} \left(1 - \frac{j}{T}\right) \left(1 - \frac{j+1}{T}\right) k^4 \left(\frac{j}{M}\right). \end{aligned}$$

Similarly, the bidirectional DCC-MGARCH Hong test would then be denoted as $H_{2,t}(k)$:

$$H_{2,t}(k) = \frac{T \sum_{j=2-T}^{T-2} k^2 \left(\frac{j}{M}\right) r_{12,t}^2(j) - C_{2T}(k)}{\sqrt{2D_{2T}(k)}}, \tag{16}$$

where,

$$\begin{aligned} C_{2T}(k) &= \sum_{j=1}^{T-1} \left(1 - \frac{|j|}{T}\right) k^2 \left(\frac{j}{M}\right), \\ D_{2T}(k) &= \sum_{j=1}^{T-1} \left(1 - \frac{|j|}{T}\right) \left(1 - \frac{|j|+1}{T}\right) k^4 \left(\frac{j}{M}\right). \end{aligned}$$

The instantaneous DCC-MGARCH Hong test from y_2 to y_1 is proposed to facilitate consideration of unidirectional spillover of instantaneous information. This test is denoted as $H_{3,t}(k)$:

$$H_{3,t}(k) = \frac{T \sum_{j=0}^{T-2} k^2 \left(\frac{j+1}{M}\right) r_{12,t}^2(j) - C_{1T}(k)}{\sqrt{2D_{1T}(k)}}, \tag{17}$$

where $k(\cdot)$ and M are calibrated parameters that relate to the kernel function and a positive integer. Since we expect that the dynamic correlations tend to zero as the number of lags increase, we follow the literature and make use of the Bartlett kernel, which may be defined as,

$$k(z) = \begin{cases} 1 - |z|, & |z| < 1 \\ 0, & |z| \geq 1 \end{cases}. \tag{18}$$

Hence, if $j \geq M$ then $k(j/M) = 0$ and we only need to calculate the correlations where $M > j > -M$. Equations (15) to (16) are then used to perform the DCC-MGARCH Hong tests, where the critical values that were provided for the rolling Hong tests apply in this case as well. Hence, if the test statistic is larger than the 2.33, then the null hypothesis, H_0, is rejected and we conclude that there is Granger causality at the 1% level of significance. Following Lu *et al.* (2014), we set $M = 10$ for the proposed time-varying causality tests.

3 Data

The monthly data for the unemployment rate in the UK and the exchange rate between the British pound and the United States dollar is obtained from the database, "A Millennium of

Macroeconomic Data", which is maintained by the Bank of England.[11] To ensure that the measure of unemployment is stationary, we make use of the year-on-year growth rate of this variable. This data is displayed for both the unemployment rate and unemployment growth rate is displayed in figures 1b and 1c, respectively. Building on the findings in Nucera (2017) that establish a predictive relationship between unemployment growth and excess currency returns, we compute the excess returns for British pound using futures data sourced from Commodity Systems Inc. (csidata.com) as,

$$\frac{S_{t+1} - F_t}{S_t}, \tag{19}$$

where S_t is the spot exchange rate in period t and F_t is the futures rate that is quoted in period t (to be settled in period $t + 1$). The one limitation of this approach, however, is that the available sample for futures data starts in February 1983, while the historical exchange rate data for the British pound goes back to January 1855. Therefore, in order to extend the sample period further and thus provide insight from a long history of data, we utilise various wavelet decompositions to represent the expected movements in the exchange rate. This decomposition utilises the smoothed orthogonal and compactly supported wavelet functions, which include the Daubechies, Coiflets, and Symlets representations with between one and five scales.[12] We then compare various combinations of the different scales to determine the decomposition that provides the smallest deviation to the futures data over the sub-sample that starts in February 1983 when futures data becomes available.

Based on the comparison of various wavelet functions, the wavelet decomposition that provides the smallest deviation for the same sample period is found to be the Dabauchies 11 wavelet function with 1 scale. This decomposition, along with the excess return series obtained using the futures data starting in 1983, is depicted in Figure 1a. We observe that the wavelet decomposition tracks the futures data very closely over time, suggesting that the use of the wavelet function can successfully be used to extend the sample period in our subsequent analysis. The comparison of the descriptive statistics for these two variables, presented in the last two columns in Table 1, further supports the visual association observed in Figure 1a, indicating that the wavelet decomposition successfully generates the underlying fundamental factor of the excess return series obtained from the futures data.

We observe in Table 1 that unemployment growth has a small positive mean with a positive skew and a large kurtosis value, possibly due to the multitude of armed conflicts and economic crises that occurred during the long sample period that starts in 1855. The Box-Pierce statistics suggest the presence of serial correlation in the first moment after both five and ten lags, while there also appears to be serial correlation in the second moment, after we have taken the square of the variable. This finding is further supported by the Engle (1982) autoregressive conditional heteroscedasticity (ARCH) test statistics, based on the Lagrange multiplier. Although less volatile compared to unemployment growth, the excess returns for the British pound also exhibit positive skewness and excess kurtosis, while the Box-Pierce statistics indicate serial correlation in the second moment only, which is also supported by the Engle (1982) ARCH test. Overall, the preliminary tests provide support for the use of the GARCH framework in our subsequent tests, allowing us to account for serial correlation in the second moment.

To ensure that that the result of the subsequent analysis are not influenced by a few extreme outliers in either the expected exchange rate movements or the unemployment growth rate, we have repeated the analysis after we initially consider the case where there is a single outlier in each variable, before considering the case of several outliers in each variable. The results of this investigation are contained in the online appendix.

[11] See `https://www.bankofengland.co.uk/statistics/research-datasets` for a dataset that contains a broad set of macroeconomic and financial data for the UK stretching back in some cases to the 13^{th} century.

[12] The number of scales could be interpreted as the number of frequency components that are incorporated in the decomposition. We made use of between one and fourteen Daubechies wavelet functions, between one and five Coiflets functions, and between two and fourteen Symlets functions.

4 Empirical findings

Before we begin our discussion of the results from the time varying causality analysis, for the sake of comparability and completeness, we first examine the standard linear Granger causality tests based on VAR models of order 10, with the lag-length chosen by the Akaike Information Criterion (AIC). The null of no-Granger causality running from year-on-year unemployment growth to currency excess returns (and vice versa) yields $\chi^2(10)$ statistics of 0.4915 and 0.6967, with the corresponding p-values of 1.000 in both cases. Thus, the standard linear causality tests indicate no evidence of causality in either direction. However, considering that the sample period includes 164 years of monthly data, over which both the labour and currency markets in the UK have undergone massive evolution (as discussed in the introduction), it is expected that the relationship between the two variables exhibits significant nonlinearity and structural breaks. Accordingly, one can argue that the linear model would be misspecified, rendering the associated causality test results from the linear specification unreliable. Indeed, the results from the BDS test of Broock *et al.* (1996) applied to the residuals obtained from each of the two equations of the VAR(10) model, reported in Table 2, confirm nonlinearity, indicated by the strong rejection of the null of independent and identically distributed residuals. The finding of nonlinearity is further supported by the powerful *UDmax* and *WDmax* tests of Bai *&* Perron (2003) to detect 1 to M structural breaks (allowing for heterogenous error distributions across the breaks), applied to the two equations of the VAR(10) model individually. The *UDmax* and *WDmax* tests yield the following break dates: 1865:01, 1920:03, 1931:08, 1940:10, and 1949:12 for the excess currency return equation and 1913:04, 1921:05, 1938:03, 1946:04, and 1954:05 for the unemployment growth equation. Overall, the evidence of both nonlinearity and regime changes provide strong statistical support for the time-varying approach and the time-varying DCC-MGARCH Hong tests provide a robust testing framework in this regard.

Figures 2–4 present the results of Hong tests based on the estimated DCC-MGARCH model in which at least one of the variables is expressed in the form of lagged values. Figures 2 and 3 present causality results in the direction of unemployment growth and currency excess returns, respectively, while Figure 4 presents the findings for bidirectional causality. In each figure, we show the value for the Hong test statistic, while the grey lines in the background indicate the results for Granger causation, allowing us to consider the relative size of the test statistic when compared to the maximum value at each point in time. The bars below each plot indicate time points during which the test statistic is above the critical values that correspond to the 5% and 1% levels of significance. The findings overall indicate significant spillovers in each direction for the majority of the sample period. For example, examining causality in the direction of unemployment growth from currency excess returns, out of the 1,957 total observations in the sample, 1,819 (1,791) are found to be above the critical value at the 5% (1%) level of significance. The test statistics seem to show local highs during the Great Depression and later following the collapse of the Bretton Woods system, highlighting the role of economic crises in the predictive causality effects. The predictive role of currency market information over unemployment fluctuations is in line with the effect of exchange rate volatility on corporate investment decisions, which in turn, drives subsequent labour market dynamics (e.g. Belke *&* Gros (2001); Belke *&* Kaas (2004); Feldman (2011); among others).

Interestingly, the findings reported in Figure 3 suggest the presence of causality running from unemployment to currency excess returns as well. Although the value of the estimated test statistics is relatively smaller, they are still significant in 1,931 (1,926) out of the 1,957 total observations for the 5% (1%) level of significance. Not surprisingly, the findings in Figure 4 indicate significant bidirectional causality during much of the sample period with relatively large values for the estimated test statistic, significant on 1,950 time points at both the 5% and 1% levels of significance. This finding suggests that unemployment fluctuations also carry predictive information over the direction of exchange rates, possibly due to the signals they capture regarding future macroeconomic conditions and monetary policy actions. These inferences obtained from the DCC-MGARCH models are further supported by the findings from rolling GARCH models, displayed in Figures 5–7. Once again, we observe significant causal linkages in both directions, implied by significant test statistic values during a vast majority of sample points. Overall, the findings indicate significant information spillovers across the labour and currency markets in both directions.

Finally, we report in Figures 8 and 9 the results for instantaneous causation, which tests for a causal effect of the readily available exchange rate series on unemployment. Note that while traditional Granger causality considers whether the inclusion of *past* information about a particular variable may result in an improved forecast for another variable, instantaneous Granger causality considers whether *current* information about a particular variable may lead to improved forecasts for another variable. In other words, this test allows us to provide evidence of contemporaneous spillovers between the currency and the labour markets. Consistent with the earlier findings, we observe 1,799 and 1,771 significant test statistics, above the 5% and 1% levels of significance respectively, for the DCC-MGARCH model, while the rolling GARCH model yields 1,767 and 1,733 test statistics that are above the 5% and 1% levels of significance, respectively.

5 Conclusion

The relationship between exchange rate movements and unemployment fluctuations has been investigated in numerous studies with mixed evidence of a potential relationship between these key economic and financial variables. Most studies in this strand of the literature, however, have provided limited insight as they are largely restricted to a sample period that corresponds to the post-Bretton Woods era. This paper provides a long-term perspective to the causal linkages between currency and labour market dynamics by utilising a long span data set that extends back to 1856 and a time-varying causality testing methodology that accounts for the nonlinearity and structural breaks experienced over this period. Considering that excess currency returns are traditionally computed using futures market data which is only available after 1983, a novel feature of the study is that we utilise wavelet decompositions to obtain the fundamental factor that drives excess currency returns, which in turn, allows us to extend our causality tests to the pre-1983 sample period. Having obtained an optimal wavelet decomposition, where we minimise the difference between the futures data and the different wavelets decompositions over the common sample period, we are then able to compute time-varying estimates for Granger causality via the cross conditional functions and test statistics of Hong (2001) and Haugh (1976).

While the preliminary analysis based on the linear Granger causality tests indicates no evidence of causality, as the linear specification is misspecified due to uncaptured nonlinearity and structural breaks, we find evidence of significant time-varying Granger causality between excess currency returns and unemployment fluctuations in both directions over the majority of the sample period. The inferences are robust for both the rolling GARCH and DCC-MGARCH models and across the Hong (2001) and Haugh (1976) test statistics. The test statistics seem to show local highs during the Great Depression and later following the collapse of the Bretton Woods system, highlighting the role of economic crises in the predictive causality effects. While the predictive role of currency market dynamics over unemployment fluctuations reflects the effect of exchange rate volatility on corporate investment decisions, which in turn, drives subsequent labour market dynamics (e.g. Belke *&* Gros (2001); Belke *&* Kaas (2004); Feldman (2011); among others), we argue that causality in the direction of exchange rates from unemployment possibly reflects the signals regarding monetary policy actions, which in turn, spills over to financial markets. Finally, our results indicate evidence of instantaneous Granger causality, where changes in the more readily available exchange rate data Granger causes movements in the unemployment growth rate, i.e., allows for contemporaneous spillovers. Overall, the findings indicate significant information spillovers across the labour and currency markets in both directions.

As noted previously, these findings are largely focused on the short-run time-varying Granger causality. Future studies that consider the relationship between these variables at lower frequencies, where the methods that are described in Breitung *&* Candelon (2006) or Bierens *&* Martins (2010) may be employed, could provide results that would be of further interest. In addition, investigations into the potential Granger causality in each of the different moments of these variables could also improve our understanding of the relationship between these variables, where one could make use of the techniques that are discussed in Chen (2016).

Table 1: Descriptive statistics

	Unemployment Growth	Excess Returns [Wavelet: 1855-2019]	Exchange Rate [Futures: 1983-2019]	Exchange Rate [Wavelet: 1983-2019]
Mean	0.264	0	1.588	1.588
Maximum	108.252	0.651	2.079	2.06
Minimum	-0.95	-0.329	1.073	1.1
Stdev	3.861	0.026	0.187	0.186
Skewness	23.331	6.107	0.209	0.182
Kurtosis	604.579	207.628	-0.056	-0.102
JB-stat	30181752	3577965	3.309	2.613
JB-pval	0	0	0.191	0.271
ADF-stat	-10.713	-12.667	-2.338	-2.482
ADF-pval	0.01	0.01	0.435	0.374
Q-stat-5	2290.919	197.288	1766.346	1833.575
Q-pval-5	0	0	0	0
Q-stat-10	2304.784	210.592	2885.545	2997.226
Q-pval-10	0	0	0	0
Q^2-stat-5	1017.351	172.433	1751.532	1819.942
Q^2-pval-5	0	0	0	0
Q^2-stat-10	1017.367	172.783	2853.454	2964.889
Q^2-pval-10	0	0	0	0
Arch-stat-5	730.899	33.261	556.684	2923.937
Arch-pval-5	0	0	0	0
Arch-stat-10	412.301	16.552	274.362	1467.385
Arch-pval-10	0	0	0	0
nobs	1966	1981	445	446

Note: This table presents the descriptive statistics for the unemployment growth series as well as the excess currency returns obtained from the wavelet decomposition along with that obtained from the actual futures data starting in 1983.

Table 2: Broock et al. (1996), BDS nonlinearity tests.

Dependent Variable	Dimension (m) 2	3	4	5	6
Excess Exchange Rate Returns	22.7157***	27.0628***	30.9556***	35.0406***	39.7880***
Unemployment Rate Growth	37.9517***	43.5839***	47.4074***	51.8975***	57.7396***

Note: Entries correspond to the z-statistic of the BDS test for the null of *i.i.d.* residuals obtained from the excess exchange rate returns and unemployment growth rate models including ten lags for each variable. *** indicates rejection of the null hypothesis at 1% level of significance.

Figure 1: Monthly exchange rate and unemployment series

(a) Expected exchange rate movements

(b) Unemployment rate

(c) Unemployment growth

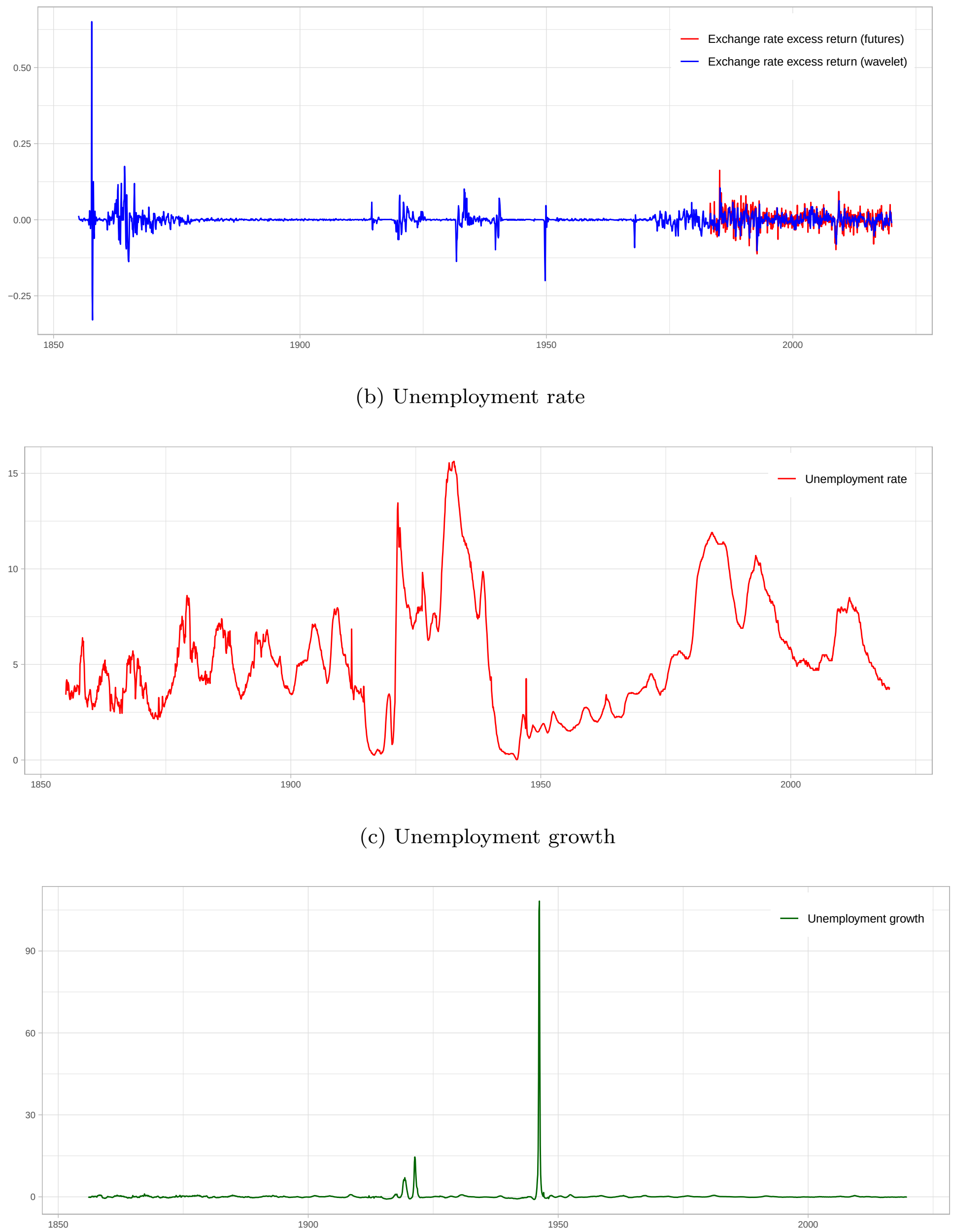
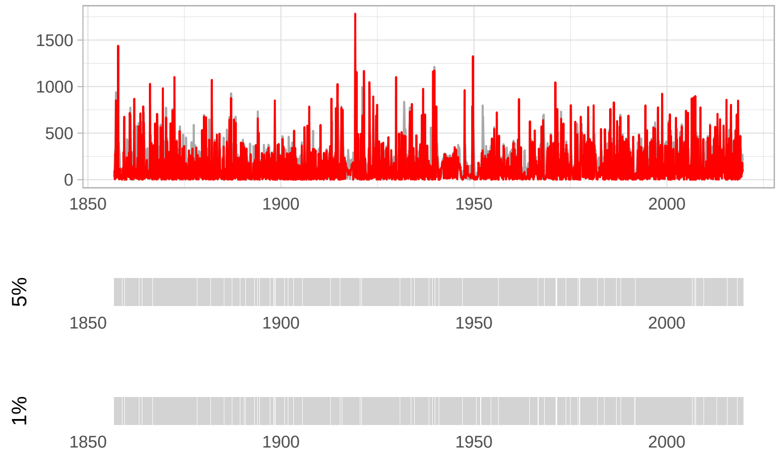
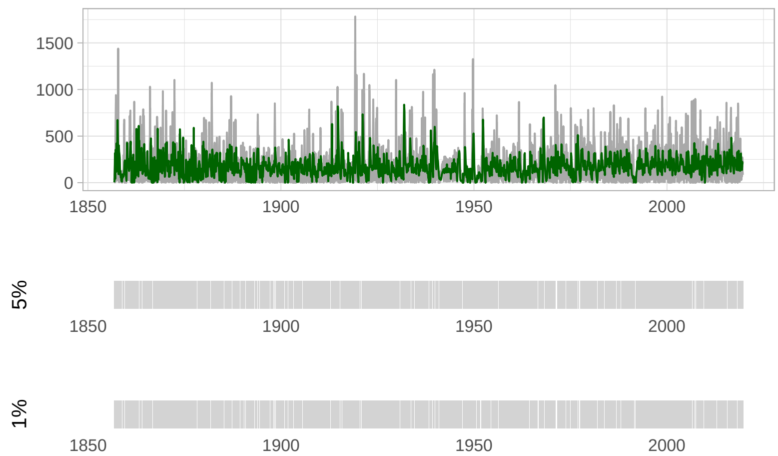


Figure 2: Time varying causality from exchange rate to unemployment–*DCC-MGARCH Hong test*



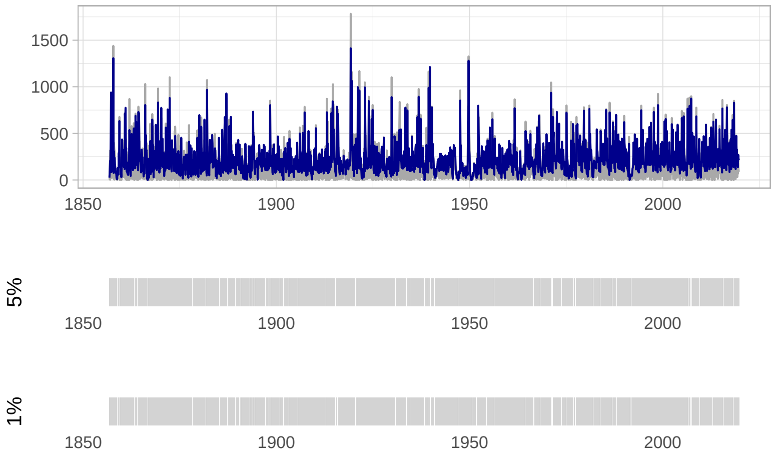
Note: The figure presents the tests statistics for causality in the direction of unemployment growth from exchange rates based on the DCC-MGARCH Hong test.

Figure 3: Time varying causality from unemployment to exchange rate–*DCC-MGARCH Hong test*



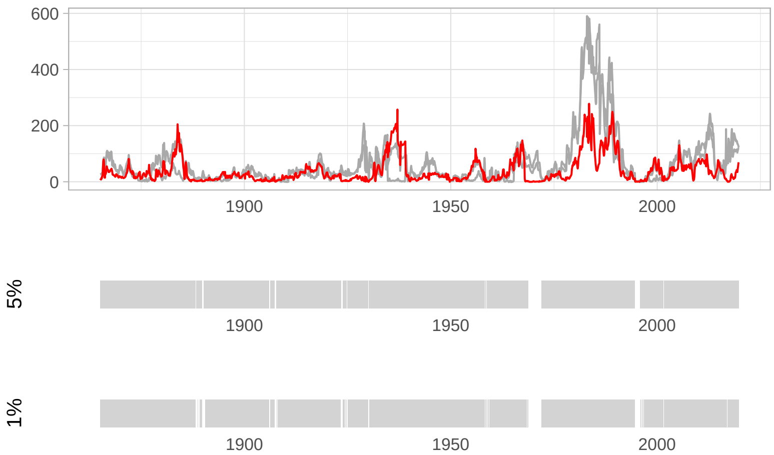
Note: The figure presents the tests statistics for causality in the direction of exchange rates from unemployment growth based on the DCC-MGARCH Hong test.

Figure 4: Time varying bidirectional Granger causality–*DCC-MGARCH Hong test*



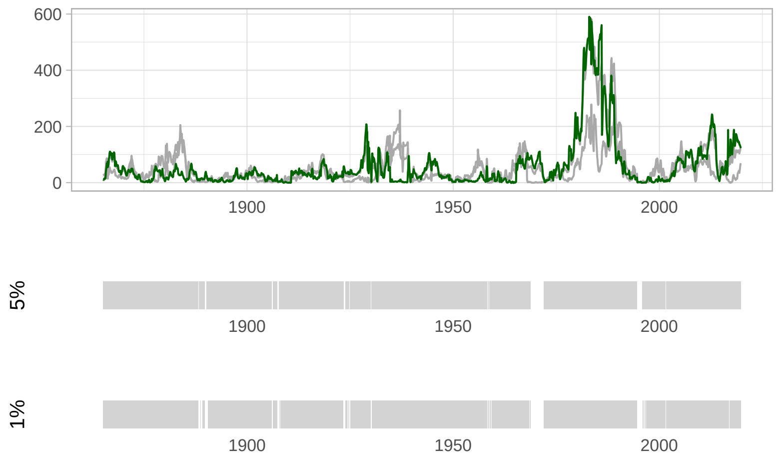
Note: The figure presents the tests statistics for bidirectional causality between exchange rates and unemployment growth based on the DCC-MGARCH Hong test.

Figure 5: Time varying causality from exchange rate to unemployment–*Rolling GARCH Hong test*



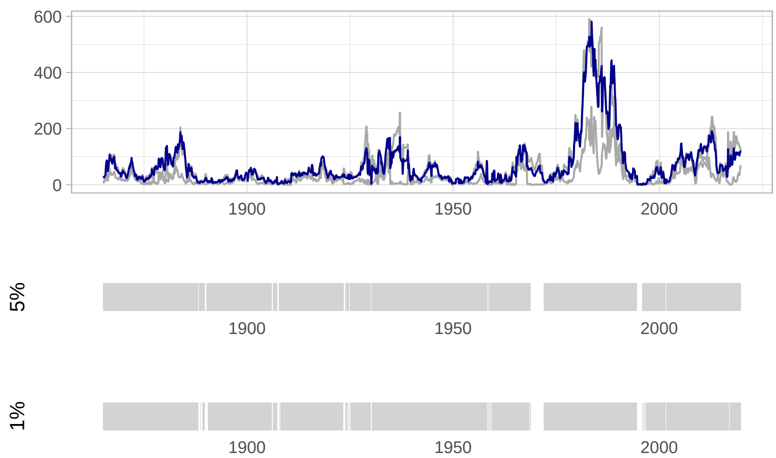
Note: The figure presents the tests statistics for causality in the direction of unemployment growth from exchange rates based on the rolling GARCH Hong test.

Figure 6: Time varying causality from unemployment to exchange rate–*Rolling GARCH Hong test*



Note: The figure presents the tests statistics for causality in the direction of exchange rate from unemployment growth based on the rolling GARCH Hong test.

Figure 7: Time varying bidirectional causality between unemployment and exchange rate–*Rolling GARCH Hong test*



Note: The figure presents the tests statistics for bidirectional causality between exchange rate and unemployment growth based on the rolling GARCH Hong test.

Figure 8: Instantaneous spillovers from exchange rate to unemployment–*DCC-MGARCH Hong test*

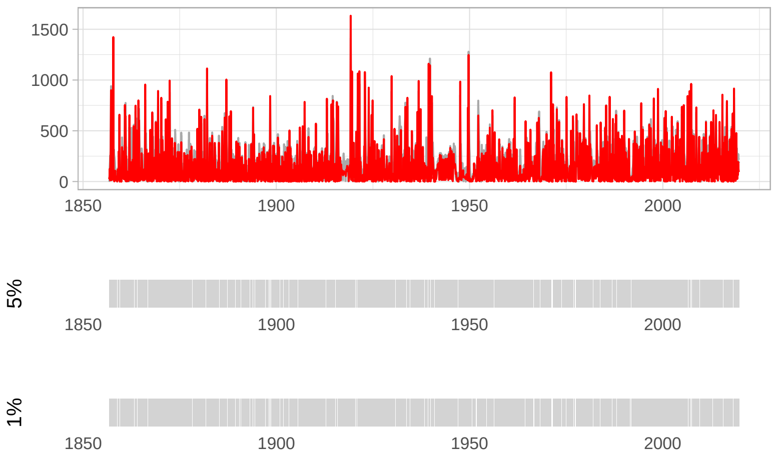
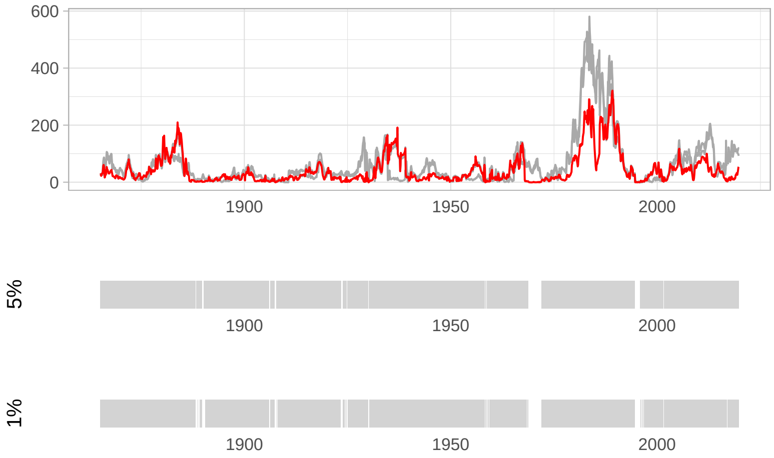


Figure 9: Instantaneous spillovers from exchange rate to unemployment–*Rolling GARCH Hong test*



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