Time-Varying Causal Relationship between Stock Market and Unemployment in the United Kingdom: Historical Evidence from 1855 to 2017

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Abstract

The influence of financial markets on the real economy, including that of stock market returns on unemployment, is a key focus in the literature. Using DCC-MGARCH Hong tests we analyses time-varying causality between stock market returns and unemployment in the UK using data from 1855 to 2017. The tests reveal that there is significant evidence of information spillover between the stock market and the labour market. This information spillover was found to be significant in the direction of stock market returns to unemployment, insignificant in the opposite direction, and significant bi-directionally. The results were also found to be congruent to the macroeconomic history of the UK.

Keywords: Time-varying Granger causality, stock market returns, unemployment
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1   Introduction

The 2007-08 financial crisis has brought a renewed focus on the link between financial markets and the real economy. For example, Reinhart & Rogoff (2009) examined the aftermath of the 2007-08 financial crisis, and concluded that the 2007-08 financial crisis had lasting effects not only on asset prices but also on output and employment. Others such as Reinhart & Rogoff (2013), Jordà et al. (2015), and Pagano (1993) have demonstrated how financial market imbalances such as asset price bubbles can pose a risk to macroeconomic stability. Similar to Pan (2018), Feldmann (2011), and others this paper specifically focuses on the link between the stock market and unemployment.

It follows that there are several ways in which the stock market can affect unemployment. Feldmann (2011) proposed four channels through which stock markets can have an effect on unemployment. First, the stock markets can improve the efficiency of resource allocation by allowing a large number of savers to invest in a large number firms which facilitates long term economic growth (similar to Levine (1991) and Bencivenga et al. (1995)). This allocative efficiency also applies to the labour market, thereby reducing unemployment. Second, through initial public offerings and the venture capital industry, stock markets improve business formation which is also likely to reduce unemployment. Third, Grossman & Stiglitz (1980) showed that in a liquid stock market investors have the incentive to research firms that show the most promise, and this improves resource allocation and reduces unemployment. Fourth, liquid stock markets can facilitate takeovers which can act as a monitoring device for firm performance (see Stein (1988), and Holmström & Tirole (1993)). Effective monitoring of firms allows for the allocation of resources to the best managed and innovative firms, which leads to reduced unemployment.

Another line of thought focuses on the relationship between expectations of future events on stock market prices and unemployment. Using US data Farmer (2012) argues that household beliefs about US stock market wealth rather than the liquidity crisis drove the shift from a high employment to a low employment equilibrium, after the 2007-08 financial crisis. Indeed, through this channel, Farmer (2013) and Farmer (2015) confirm that the stock market crash of 2008 provides a plausible causal relationship for the Great Recession.

As advanced by Lilien (1982) the sectoral shift hypotheses suggests that unemployment is in part as a result of resource reallocation from contracting to expanding sectors, thereby causing structural unemployment. This implies that the dispersion of stock market prices amongst different industries can be linked to structural unemployment. Loungani et al. (1990), amongst others, confirm this using US data. However, Abraham & Katz (1986) criticised the sectoral shift hypotheses by highlighting the importance of pure aggregate demand shocks in explaining structural unemployment. Mixed evidence of the sectoral shift hypotheses has emerged with, for example, Döpke & Pierdzioch (2000) finding a negligible relationship between sectoral dispersion in the stock market and structural unemployment, and Chen et al. (2017) finding a strong positive relationship.

Mollick & Faria (2010) pursued another channel and found a negative long run relationship between unemployment and Tobin's Q, suggesting that in the long run capital and labour are complements. Tobin (1969) defined Tobin's Q as the ratio between a firms stock market valuation of its existing capital assets and its replacement cost. Therefore the firm invests in capital when its Tobin's Q is above its par value. Depending on the nature of relationship between capital and labour (complements or substitutes) an increase in capital investment leads to an increase in employment. Since firms borrow from financial markets in order to make real investments, the relationship between the financial market and employment is indirect, via Tobin's Q (Tobin & Golub (1998)).

Empirically, various techniques have been applied in understanding the relationship between stock markets and unemployment, that have revealed contrasting results. Amongst others, Phelps (1999) found a positive relationship between employment growth and the price earnings ratio (and the profit rate) in the US context. Pan (2018) applied panel Granger causality tests in 30 developed countries and 11 emerging and developing countries and found strong causality of the stock market to the unemployment rate in developed countries. However, in emerging and developing countries the direction of causality reversed. In addition, using German data Fritsche & Pierdzioch (2016) confirmed this causality between stork market and unemployment aswell. However, others such as Farsio & Fazel (2013), using quarterly data over the period 1970 to 2011 in the US, China and Japan, applied cointegration and Granger causality tests and found no stable long run relationship between the stock market and unemployment.

Given this context, this paper seeks to investigate for the first time the relationship between the stock market and unemployment in the United Kingdom over a monthly period of 1855 and 2017. This study departs from previous studies by using time-varying Granger causality as outlined in Hong (2001) and extended by Lu et al. (2014). This has the advantage of estimating changes in the causality across time, that is, causality is estimated at each time period and therefore changes across time. Specifically, we utilise Dynamic Conditional Correlation Multivariate Generalised Autoregressive Conditional Heteroskedasticity (DCC-MGARCH) Hong tests to investigate whether and to what extend the nature of information spillover between the stock market and labour market in the UK changes across time. The usage of the longest possible data involving the two variables of concern, allows us to avoid sample-selection bias, while simultaneously tracking the historical evolution of the stock and labor markets.

The rest of the paper is organised as follows: Section 2 presents methodology, while Section 3 presents the results, and Section 4 draws some conclusions.

2 Methodology

Following Lu et al. (2014), we consider two stationary time series Y_t and X_t. Given $Z_t(j) = \begin{pmatrix} X_t \\ Y_t \end{pmatrix}$ where j represents the lag order used in the dynamic correlation coefficient, the DCC-MGARCH model is defined as follows inline with Engle (2002):

$$
\begin{aligned}
Z_t(j)|I_{t-1} &\sim N(0, D_{t,j} R_{t,j} D_{t,j}) \\
D_{t,j}^2 &= \mathrm{diag}\{\omega_{i,j}\} + \mathrm{diag}\{\kappa_{i,j}\} \ \mathrm{o} \ Z_t(j) Z_t'(j) + \mathrm{diag}\{\lambda_{i,j}\} \ \mathrm{o} \ D_{t-1,j}^2 \\
u_{t,j} &= D_{t-1,j}^{-1} Z_t(j) \\
Q_{t,j} &= S \ \mathrm{o} \ (u u' - A - B) + A u_{t-1,j} u_{t-1,j}' + B Q_{t-1,j} \\
R_{t,j} &= \mathrm{diag}\{Q_{t,j}\}^{-1} Q_{t,j} \mathrm{diag}\{Q_{t,j}\}^{-1}
\end{aligned}
\tag{1}
$$

For the widely used DCC-MGARCH(1,1) model, the dynamic correlation estimator with lag j is:

$$
\begin{aligned}
\rho_{pq,t}(j) &= \overline{\rho_{pq}}(j) + \alpha_j(u_{p,t-1} u_{q,t-1-j} - \overline{\rho_{pq}}(j)) + \beta_j(\rho_{pq,t-1}(j) - \overline{\rho_{pq}}(j)) \\
&\qquad r_{pq,t}(j) \frac{\rho_{pq}(j)}{\sqrt{\rho_{11,t}\rho_{22,t}(j)}}
\end{aligned}
\tag{2}
$$

where $p,q =1,2$.

Based on the choice of a positve interger M, and a kernel function $k(x)$, the unidirectional DCC-MGARCH Hong test for Y_t to X_t is denoted as $H_{1,t}(k)$:

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

where

$$
C_{1T}(k) = \sum_{j=1}^{T-1} \left(1 - \frac{j}{T}\right) k^2\left(\frac{j}{M}\right)
$$

$$
D_{1T}(k) = \sum_{j=1}^{T-1} \left(1 - \frac{j}{T}\right)\left(1 - \frac{j+1}{T}\right) k^4\left(\frac{j}{M}\right)
$$

The bidirectional DCC-MGARCH Hong test from Y_t to X_t is denoted as $H_{2,t}(k)$:

$$H_{2,t}(k) = \frac{T \sum_{j=2-T}^{T-2} k^2 \left(\frac{j}{M}\right) r_{12,t}^2(j) \ - \ C_{2T}(k)}{\sqrt{2D_{2T}(k)}} \tag{4}$$

where

$$C_{2T}(k) = \sum_{j=1-T}^{T-1} \left(1 - \frac{|j|}{T}\right) k^2 \left(\frac{j}{M}\right)$$

$$D_{2T}(k) = \sum_{j=1-T}^{T-1} \left(1 - \frac{|j|}{T}\right) \left(1 - \frac{|j|+1}{T}\right) k^4 \left(\frac{j}{M}\right)$$

The instantaneous DCC-MGARCH Hong test from Y_t to X_t is denoted as $H_{3,t}(k)$:

$$H_{3,t}(k) = \frac{T \sum_{j=0}^{T-2} k^2 \left(\frac{j+1}{M}\right) r_{12,t}^2(j) \ - \ C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \tag{5}$$

where $C_{1T}(k)$ and $D_{1T}(k)$ are estimated in $H_{1,t}(k)$.

It is not feasible to estimate all lagged dynamic correlations in DCC-MGARCH. As shown in Hong (2001) it is possible to deal with this by choosing a suitable kernel function. The choice of non-uniform kernels and M has little impact on the size of the DCC-MGARCH Hong tests. The Bartlett[1] kernel is typically used in empirical studies (Lu et al. (2014)).

2.1 Data

Monthly data was used for the UK FTSE All Share Stock Index (ALSI) and unemployment. The data was obtained from the A Millenium of Macroeconomic Data for the UK maintained by the Bank of England[2], who recently expanded this data to 2017. Therefore, the sample size for both variables is from January 1855 to December 2017.

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[1] The Bartlett kernel is defined as follows:

$$k(z) = \begin{cases} 1 - |z|, & \text{if } |z| < 1 \\ 0, & \text{if } |z| > 1 \end{cases}$$

when $j \geq M$, the Bartlett kernel $k\left(\frac{j}{M}\right) = 0$.

[2] The data is available for download from: https://www.bankofengland.co.uk/statistics/research-datasets.

The real monthly stock return was computed as the natural logarithm difference $sr_t = log(r_t) - log(r_{t-1})$, where r_t is the real ALSI level and is calculated as $r_t = \frac{p_t}{wpi_t}$. This is when p_t is the nominal ALSI level, and wpi_t is the wholesale price index. Furthermore, the monthly unemployment variable of concern was calculated as the natural logarithm $u_t = log\left(100 * \left(\frac{un_t}{1-un_t}\right)\right)$ where un_t is the unemployment rate. Figure 1 shows plots of sr_t and u_t which through visual inspection reveals outliers and volatility clustering in the data.

Table 1 reports the descriptive statistics of u and sr. Both variables exhibit negative skewness which suggests that losses in stock returns may be coupled with declines in unemployment. The Kurtosis statistics for both variables suggest that both variables are not normally distributed (exceeding 3 for a normal distribution), and this is confirmed by the Jarque-Bera statistics. Lastly, both variables were found to be stationary using the Augmented Dickey Fuller test.

3   Results

3.1   Linear Granger causality test

As a starting point we test for linear Granger causality (Granger (1969)) between sr and u using a VAR(5)[3], and these are presented in Table 2. The test confirmed linear causality in the direction of u to sr, and rejected the opposite direction. That is, the test indicates that past information about u is significant in explaining sr.

Literature on the reverse causality between sr and u such as Blanchard (1981), Orphanides (1992), Farsio & Fazel (2013), and Phiri (2017) reveals uncertainty about the validity of this reverse causality as, amongst other factors, this reverse causality depends of the state of the economy. Therefore, these studies have highlighted concerns about the stability of this causality in the long run.

3.2   Structural break and non-linearity tests

Observation of u (see Figure 1) indicates possible breaks points in the series, as such we consider the presence of structural breaks in how variables relate, given the long time span of the data. In this regard we implement the Bai & Perron (2003)[4] test for multiple structural break points of a VAR(5) model of u and sr. The results in Table 3 reveal that there is evidence of multiple structural breaks in the relationship between sr and the u. This makes the linear Granger causality test unreliable.

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[3] Using the minimum Akaike Information Criterion and Schwarz Criterion a VAR(5) model was found to be the optimal model between sr and u.

[4] Bai & Perron (2003) tests for 1 to M global breaks with a trimming of 15 per cent, maximum breaks of 5, at significance level of 5 per cent.

Next, we test for residual serial dependence using Brock et al. (1996)[5], using the same VAR(5) model of sr and u. Table 4 confirms that the nature of the relationship between sr and u is non-linear, which a clear rejection of the null at a 1 per cent level of significance. Both tests motivate for time-varying tests such as the DCC-MGARCH Hong tests.

3.3 Time-varying Granger causality tests

In Figures 2 to 4 we show the unidirectional, instantaneous, and bi-directional DCC-MGARCH Hong tests[6]. The top panels depict the DCC-MGARCH Hong test value. The bottom panels show the p values at a 5 per cent level of significance.

Overall, the tests show significant evidence of time-varying causality in the direction of sr to u ($sr \rightarrow u$), indicating that there is causality between sr and u. However, time remains a key variable as there are periods when causality is not observed. In the main, evidence of time-varying causality in the opposite direction ($u \rightarrow sr$) was insignificant. This was confirmed by both the unidirectional and the instantaneous tests. The instantaneous test accounts for the fact that causality may occur contemporaneously due to non-synchronous trading. The bi-directional ($sr \leftrightarrow u$) test also revealed significant two way time-varying causality, indicating instantaneous two way causality between sr and u.

Are these results congruent to the macroeconomic history of the UK? Hills et al. (2010) summarise three key drivers of the UK business cycle, and splits them into three periods (1700-1830, 1830-1913, 1913-2007). The first period is characterised as the industrialising period with relatively volatile output. This output volatility originated from uncertain harvests, intermittent wars, and financial crises. As a result the investment cycle was dominated by waves of optimism and waves of pessimism. The private sector, in particular, speculated on business activity using network credit during upturns or during periods when expectations of growth were positive. Essentially, this was a boom and bust cycle which contributed to the volatility of output. Hills et al. (2010) note that this is an essential feature of the UK economy through out history, which has subsided with the introduction of stable fiscal and monetary policy.

Indeed in the next period, the Victorian Age, output stabilised and the impact of industrialisation and technological progress became more apparent. This period saw fluctuations in investment driven by massive expansion of infrastructure and uncertainty in caused by the threat of war. In addition, exports to the rest of the world became a key source of growth for the UK economy during this period. However, financial crises continued to be a feature of the business cycle, with the collapse of the Glasgow Bank in 1878 being a case in point. As such the boom and bust cycle continued during this period, although to a

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[5] In this regard, we used fraction pairs equal to 0.7 and maximum correlation dimension of 6.

[6] M was set to 5 in the Hong tests inline with the lags in the static Granger causality test. $M = 12$ and $M = 24$ tests were also conducted with consistent results, which are available upon request from the authors.

lesser extent as result of the introduction of the monetary system based on the gold standard.

The 20th century presented significant challenges to the UK economy. The Great Depression resulted in a significant rise in unemployment, and investment and exports collapsed in response to the downturn. Post world-war two, the recovery was underpinned by significant fiscal expansion, with mild intermittent down-swings. The 1980s introduced money supply targets and monetary policy was significant in stabilising the business cycle and preventing financial crisis. The financial crisis of 2007-08 in comparison was relatively milder as compared to previous recessions, as a result of stable fiscal and monetary policy. However, feature of the boom and bust cycle remained.

Therefore, Figures 2 to 4 reveal that given this boom and bust cycle, in periods of key macroeconomic shocks which cause volatility in output and financial markets, we do not observe causality. We observe this most significantly during the two world wars when unemployment declined rapidly as a result of the war effort, contrary to increased volatility in output and financial markets. This is observed in the 1870s as a results of the impact of uncertain harvests, intermittent wars, and financial crises. This can also be observed with the dot-com bubble in the period 2001 to 2002. However, ultimately the results attest to the causality between sr and u, with the boom and bust cycle as an essential driver.

4   Conclusion

The DCC-MGARCH Hong tests revealed evidence of information spillover in the direction of the stock market to the the labour market. This is well in-line with the relevant literature which emphasised this direction of causality. However, static Granger causality tests which showed causality in the opposite direction. As highlighted in the literature, causality in the opposite direction has not proved to be reliable in the long run, especially in the presence of structural breaks and non-linearity as shown in this paper. The time-varying nature of the DCC-MGARCH Hong tests proved to be advantageous, showing that causality varied overtime. In addition, the direction of causality reversed in-line with the literature. That is, the DCC-MGARCH Hong tests found that causality in the opposite direction was insignificant. This is a key advantage of time varying Granger causality compared to static Granger causality.

The results were also supported by the macroeconomic history of UK. In essence the boom and bust cycle of the UK economy, which throughout history has been a driver of the UK business cycle, is key to explaining information spillover between the stock market and the labour market. However, in of periods of macroeconomic shock, such as those in the 1940s which cause significant volatility in output, the boom and bust cycle did not explain changes in unemployment as economic conditions mainly responded to such shocks. In recent years the role of policy has been prominent as monetary and fiscal policies have sought to stabilise output which has led to reduced stock market volatility, thereby enhancing the

ability of policy to reduce unemployment. This was apparent in the 2007-08 financial crisis, which historically had less of an impact on output and therefore unemployment.

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Tables

Table 1: Descriptive statistics

Variable	u	sr
Sample	1855:01 - 2017:12	1855:01 - 2017:12
Obs	1956	1956
Mean	1.50	0.0007
Std. Dev	0.81	0.03
Skewness	-1.69	-0.34
Kurtosis	8.30	13.37
ADF	-4.09^a	-35.69^a
JB	3227.42^a	8814.27^a

Notes: ^{a}: $p < 0.01$ significance levels, respectively. u: unemployment variable and sr: stock returns. Obs: observations. Std. Dev: standard deviation. JB: Jarque-Bera. ADF: Augmented Dickey Fuller.

Table 2: Static Granger causality tests

H_0	F-statistic
$u \nrightarrow sr$	2.73^a
$sr \nrightarrow u$	0.89

Notes: ^{a}: $p < 0.01$ significance level. u: unemployment variable and sr: stock returns. $\nrightarrow$: "does not Granger cause". The linear Granger causality was implemented on a VAR(5) model.

Table 3: Estimated break points using Bai & Perron (2003) test

u	sr
1887:12	1879:10
1912:05	1905:3
1945:01	1932:8
1969:05	1961:4
1993:09	1987:12

Notes: Tests on individual VAR(5) equations; Dates are in the format "Year:Month".

Table 4: Residual serial dependence tests using Brock et al. (1996)

Dimension	Test Statistic u residuals	Test Statistic sr residuals
2	0.07^a	0.02^a
3	0.13^a	0.06^a
4	0.18^a	0.07^a
5	0.22^a	0.09^a
6	0.23^a	0.09^a

Notes: ^{a}: $p < 0.01$ significance level which rejects the null of independence. u: unemployment variable and sr: stock returns. Tests on residuals from a VAR(5) model.
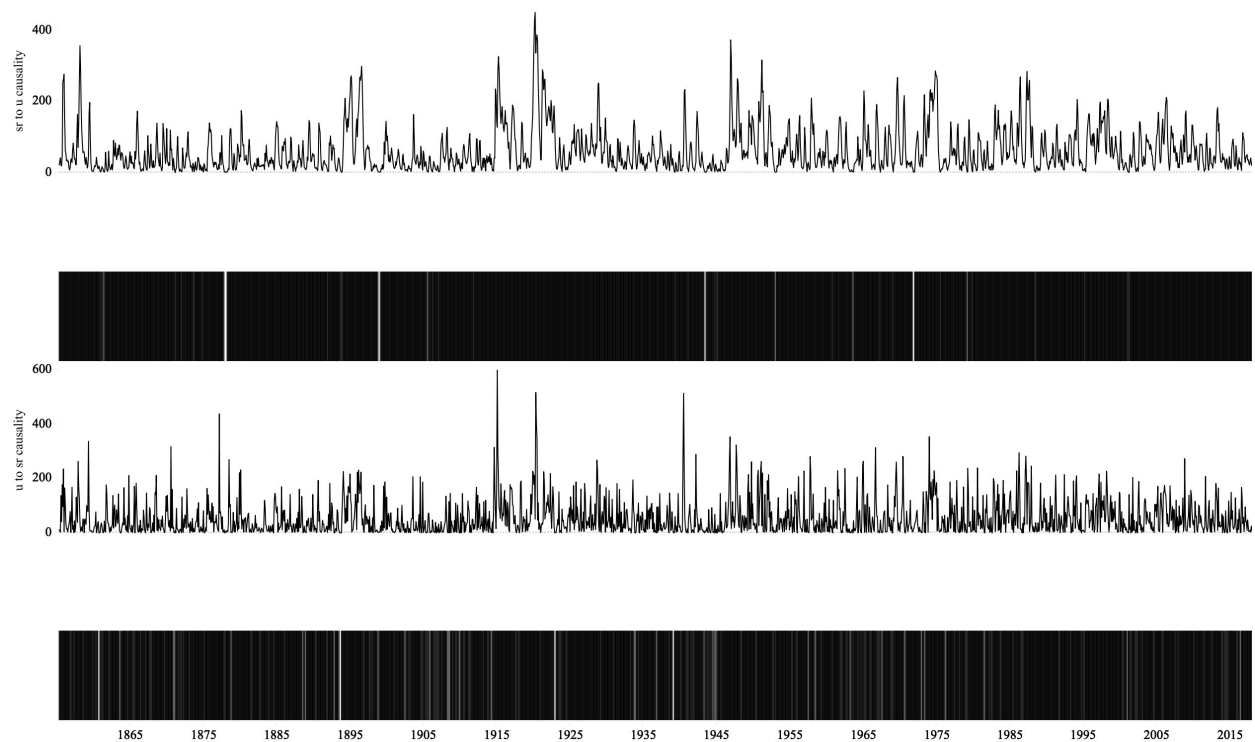
Figures

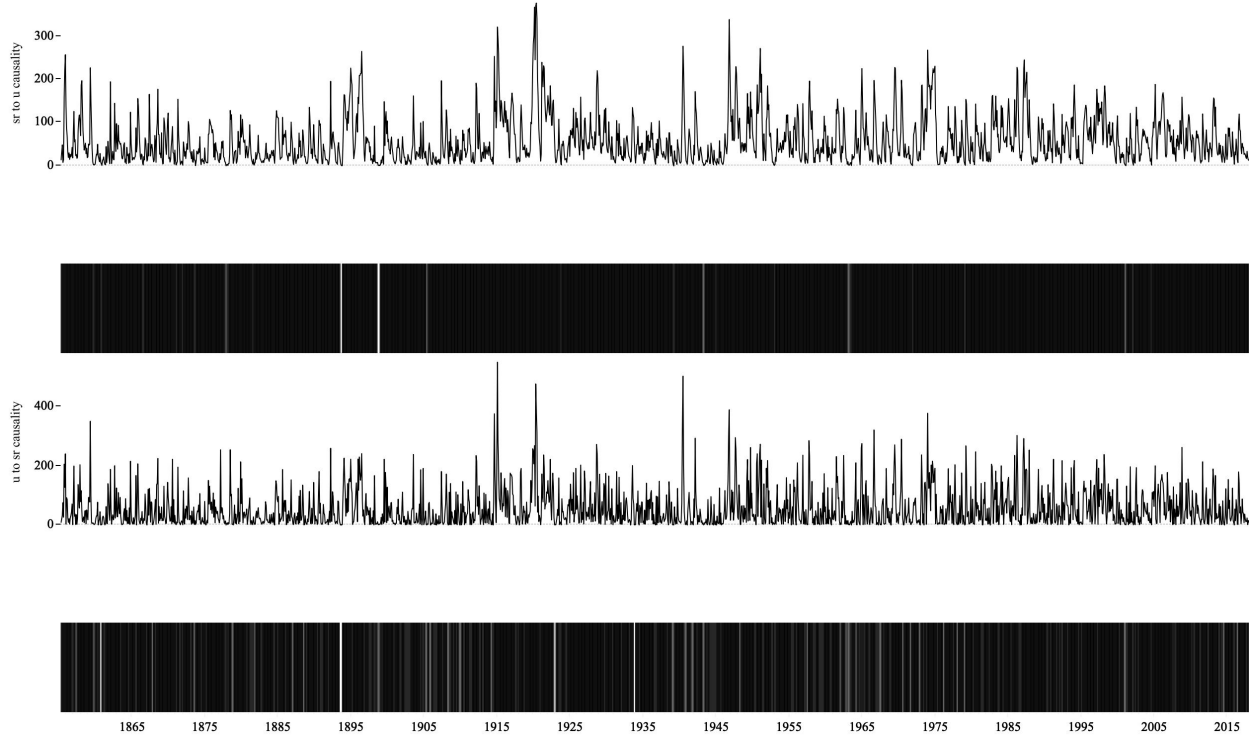Figure 1: Unemployment and stock returns
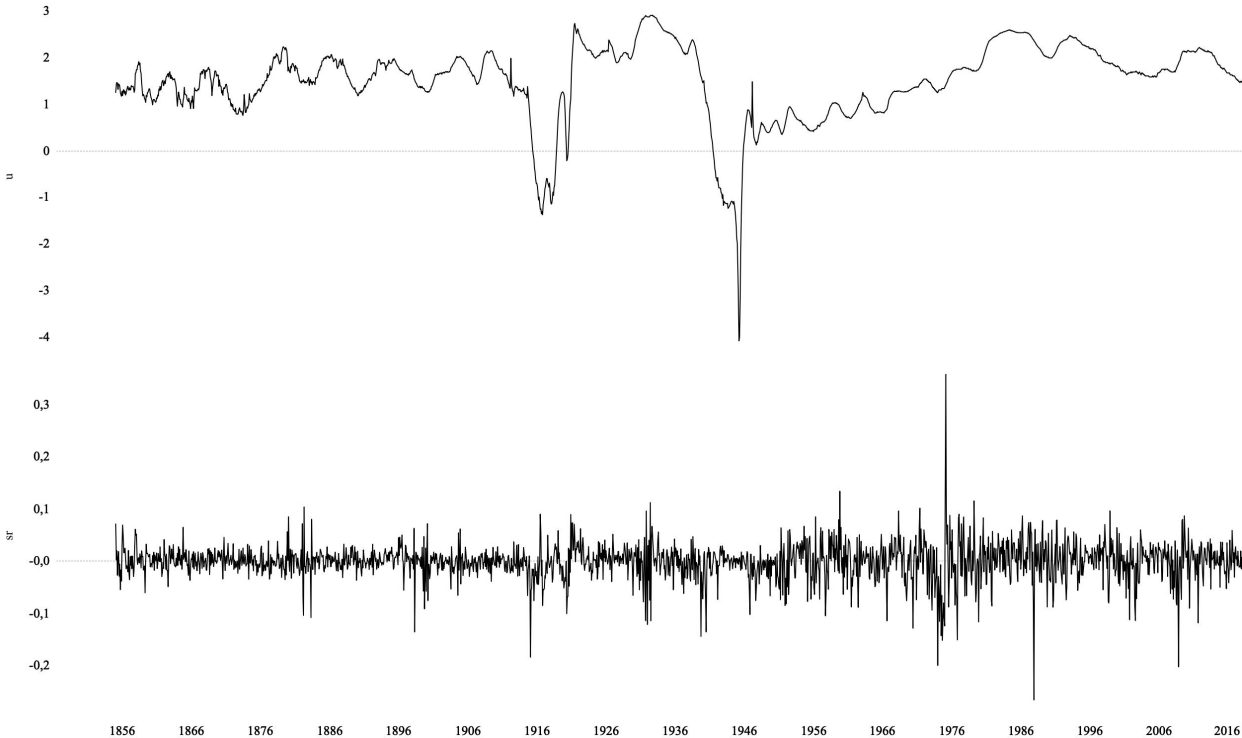
Notes:u: unemployment variable and sr: stock returns
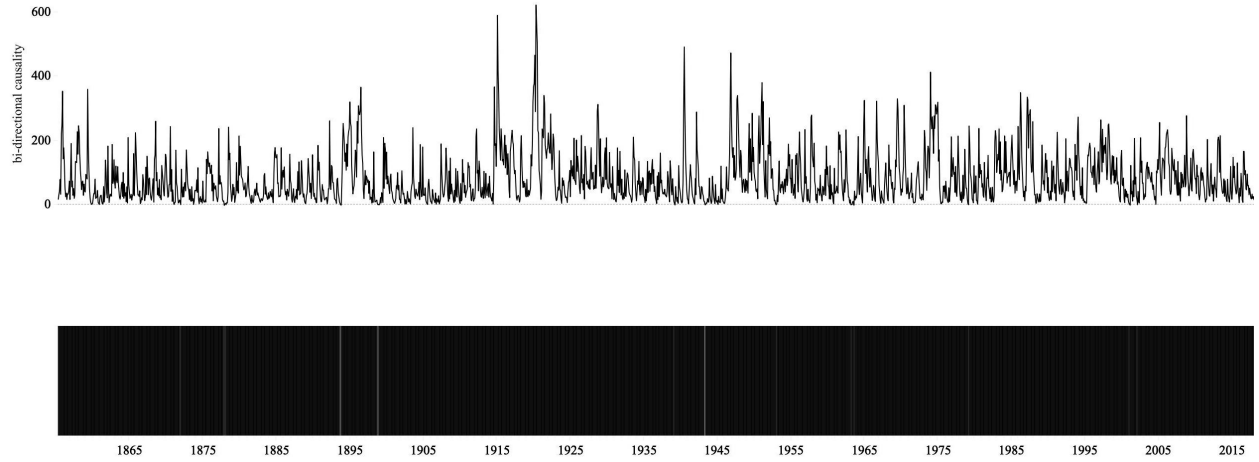
Figure 2: Unidirectional Granger causality test

Notes:*u*: unemployment variable and *sr*: stock returns. The top panels show the time-varying DCC-MGARCH Hong test statistic. The bottom panels show p values associated with the test above. The shaded region shows the month during which the test is statistically significant at the 5 per cent level.

Figure 3: Instantaneous Granger causality test

Notes:u: unemployment variable and sr: stock returns. The top panels show the time-varying DCC-MGARCH Hong test statistic. The bottom panels show p values associated with the test above. The shaded region shows the month during which the test is statistically significant at the 5 per cent level.

Figure 4: Bi-directional Granger causality test

Notes:*u*: unemployment variable and *sr*: stock returns. The top panel shows the time-varying DCC-MGARCH Hong test statistic. The bottom panel shows p values associated with the test above. The shaded region shows the month during which the test is statistically significant at the 5 per cent level.