# On the Direction of Causality Between Business and Financial Cycles*

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September 15, 2018

**Abstract**

This paper investigates the direction of Granger causality between business and financial cycles. Our analysis is based on a vector autoregression model for five industrialized countries. We use mixed frequency data, such as monthly industrial production and quarterly aggregate credit, in order to avoid the effects of data aggregation. We find that there is strong bidirectional causality between business and financial cycles: business cycles cause financial cycles and vice versa. Furthermore, the US business cycle significantly causes other countries' business cycles, especially during recessions. However, the US financial cycle has a less pronounced effect on other countries' cycles.

*Keywords:* Business Cycle; Financial Cycle; Granger Causality Test; Mixed Data Sampling; Vector Autoregression.

*Classification*: C12; E32; E44.

*Acknowledgements:** The authors are grateful for useful comments to Nikola Gradojevic, Delong Li, Alex Maynard, Thanasis Stengos and seminar participants at the University of Guelph and the 2018 Doctoral Workshop in Applied Econometrics at Ryerson University. *Corresponding author*: Haibin Zhang, Department of Economics and Finance, University of Guelph, Guelph, Ontario N1G 2W1, Canada. Tel: 647-607-8188. Email: haibin@uoguelph.ca.

# 1 Introduction

Is Main Street the cause of what happens on Wall Street or vice versa? This is a central question in academic research, policy analysis and financial practice. It is well known that business cycles are closely interlinked with financial cycles (e.g., Claessens, Kose, and Terrones (2012); Borio (2014)). For example, recessions are bad for both Main Street and Wall Street. Conversely, expansions are good for both Main Street and Wall Street. When both business and financial cycles are close to their trough, business and financial conditions are especially tough. When both business and financial cycles close to their peak, business and financial conditions are especially good.[1] These stylized facts establish a correlation but not a causal relation between business and financial cycles. The extent, significance and direction of causality remains an important and yet unanswered question in the literature: do business cycles cause financial cycles or vice versa?

The main objective of this paper is to answer this question and, therefore, fill a gap in the literature. Our analysis of the extent, significance and direction of Granger causality between business and financial cycles is based on a vector autoregression (VAR) model with one important innovation: data on business cycles, which are based on monthly industrial production, are at a higher frequency than data on financial cycles, which are based on quarterly aggregate credit. For this reason, we implement the mixed frequency vector autoregression (MF-VAR) approach of Ghysels, Hill, and Motegi (2016, 2018), which has several econometric advantages that we discuss later.[2]

Our empirical investigation focuses on five industrialized countries: USA, Canada, UK, Germany and Japan. For each separate country, we first examine whether the monthly in-

[1]For example, Claessens, Kose, and Terrones (2012) find that recessions accompanied with financial disruption, such as house and equity price busts, tend to be longer and deeper. On the other hand, recoveries combined with rapid growth in credit and house prices tend to be stronger. Similarly, Borio (2014) finds that recessions that coincide with the contraction phase of a financial cycle are especially severe. These findings are consistent with Romer and Romer (2017), who find that in the aftermath of financial crises, real output falls significantly and persistently.

[2]On a related issue, Borio (2014) finds that the financial cycle has a much lower frequency than the business cycle. While the average length of a business cycle is about eight years, for a financial cycle it is about 16 years.

dustrial production index causes quarterly aggregate credit or vice versa. We also determine the timing of when causality is statistically significant. We then assess the role of the US as a global leader in causing the domestic cycles of other countries. We do so by examining whether US industrial production (or credit) causes the industrial production (or credit) of each of the four other countries.[3]

In addition, we assess whether causality is related to the phase of the cycles, e.g., whether the causal relation between the two cycles is stronger in recessions or expansions. We then evaluate whether causality is related to the nominal interest rate, which is perhaps the most relevant economic fundamental for the two cycles. Next, we further our understanding of financial cycles by exploring whether housing prices and equity prices have a causal relation with aggregate credit. Although aggregate credit is widely considered to be the primary determinant of financial cycles, housing and equity prices are also thought of as determinants of the financial cycle. Finally, we employ the Max causality test, which is a new test statistic recently proposed by Ghysels, Hill, and Motegi (2018), which provides additional statistical evidence on causality over and above the standard Wald test statistic used in our core analysis.

Our main finding is that there is a strong causality between business and financial cycles and it goes in both directions. For the majority of countries, industrial production causes aggregate credit and aggregate credit causes industrial production. The timing of causality varies across countries but for all countries bidirectional causality is strong around the 2007-2008 financial crisis. Furthermore, the US business cycle strongly causes the business cycle of Canada, the UK and Germany. This causal relation is strong at all times but is stronger during bad times. Having said that, there is little evidence that the US financial cycle is causing other countries' business or financial cycles. We also find that the causal relation between housing prices and aggregate credit is stronger than that between equity prices and aggregate credit. Finally, the additional Max test for causality confirms our main results

[3]For example, Rapach, Strauss, and Zhou (2013) perform a similar analysis for equity markets and find that the US is a global leader because it causes the movements of other international equity markets.

based on the standard Wald test.

An important aspect of our analysis is that, in addition to same frequency (quarterly) data, also use mixed frequency data. This is motivated by data availability: the business cycle is determined by industrial production, which is available monthly, but the financial cycle is determined by aggregate credit, which is available quarterly. Given the mixed frequency of the data, it is natural for our main analysis to be based on mixed frequency causality tests. We compare the mixed frequency causality tests to the benchmark of same (quarterly) frequency causality tests for which we aggregate the higher frequency variable to the lower frequency (i.e., monthly to quarterly). In a nutshell, the advantage of mixed frequency causality tests is that they avoid data aggregation and hence preserve the dynamics of the monthly variable thus lowering the risk of detecting spurious causality.[4]

Our empirical analysis is motivated by the theoretical framework of Bernanke and Gertler (1989) and Kiyotaki and Moore (1997). In this work, a productivity shock in the real economy is amplified and propagated due to credit constraints. For example, consider a firm that is highly levered with secured loans against collateralized fixed assets (e.g., land). Suppose that this firm experiences a temporary productivity shock that lowers its net worth. Due to credit constraints, the firm will be unable to borrow more and, therefore, will have to cut its future investment expenditure in fixed assets against which it borrows. This will hurt the firm in the next period as it earns less revenue, its net worth falls further, and again due to credit constraints it reduces investment. This feedback effect continues so that an initial temporary shock is amplified and propagated over many periods in the future. In short, therefore, credit constraints can reduce real economic activity thus motivating that the credit (financial) cycle has a profound effect on the business cycle.

The Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) argument relates to the effect of primary financial markets on real economic activity. It is also possible that real economic activity is affected by secondary financial markets, in which securities

[4]See Breitung and Swanson (2002) for a detailed discussion of these issues.

are traded among investors (such a the stock market) without any capital flowing back to firms. Bond, Edmans, and Goldstein (2012) discuss three reasons why secondary financial markets not only reflect but can also affect economic fundamentals. First, real decision makers learn new information (e.g., firm value) from secondary market prices and use this information to guide their real decisions, in turn affecting the firm's cash flow and value. For example, credit rating agencies are known to be influenced by stock prices, and their decisions can determine the availability of credit to firms. Second, managers might care about the firm's stock price because their compensation is often tied to the stock price, which in turn affects their incentives in taking real actions. Finally, third, managers may even irrationally follow the stock price and use it as an anchor simply because of their general belief that prices are informative. In all these cases, there will be a feedback effect from secondary financial markets to the real economy thus motivating the causal relation between business and financial cycles.

The remainder of the paper is organized as follows. In the next section, we describe the data and define business and financial cycles. The empirical framework for the causality tests using both same frequency and mixed frequency data is set out in Section 3. In Section 4, we report the empirical results. In Section 5, we investigate the causal relation between housing prices, equity prices and credit. The alternative Max test statistic for testing causality is presented in Section 6. Finally, we conclude in Section 7.

## 2 Business and Financial Cycles

We assess the causal relation between business and financial cycles for five industrialized countries: USA, Canada, UK, Germany and Japan. The business cycle is determined by the monthly industrial production index in each country. Industrial production is a standard measure of real economic activity and is near perfectly correlated with GDP (which is only available quarterly).

The financial cycle is determined by quarterly aggregate credit, which is standard in the literature (e.g., Claessens, Kose, and Terrones (2012); Borio (2014). Credit is a natural aggregate we can use to analyze the financial cycle because it constitutes the most important link between savings and investment.

### 2.1 Data

The seasonally-adjusted monthly industrial production index (IPI) is obtained from the FRED database of the Federal Reserve Bank of St. Louis. The IPI data are all in real terms and begin on the following dates: January 1960 for the US and Germany, January 1961 for Canada, January 1963 for the UK, and October 1964 for Japan. For all countries the IPI data sample ends in June 2016.

Quarterly data on aggregate credit are obtained from the Bank for International Settlements. These data are for nominal aggregate credit in domestic currency offered by domestic banks to the private non-financial sector. The credit data begin on the following dates: Q1 (first quarter) of 1960 for the US and Germany, Q1 of 1961 for Canada, Q1 of 1963 for the UK, and Q4 of 1964 for Japan. For all countries, the credit data sample ends on Q2 of 2016.

We convert the credit data to real terms by dividing nominal credit by the consumer price index (CPI) of each country. The CPI index is obtained from the FRED database of the Federal Reserve Bank of St. Louis. With this conversion, all business and financial cycle variables are expressed in real terms. In order to avoid potential seasonal effects, we follow Ghysels, Hill, and Motegi (2016) in using the annual growth rate of industrial production (month-by-month) and credit (quarter-by-quarter). Table 1 reports descriptive statistics on the real annual growth rates of the two variables.

### 2.2 Defining Business Cycles

We define the business cycle for the US using the peak and trough dates determined by the NBER's business cycle dating committee. For the other four countries, we define the business cycle using the OECD-based Recession Indicators obtained from the FRED database of the Federal Reserve Bank of St. Louis. In all cases, the recession phase is defined as the period from the peak (exclusive) to the trough (inclusive), and the recovery phase is the period from the trough (exclusive) to the peak (inclusive).

## 2.3 Defining Financial Cycles

Following Claessens, Kose, and Terrones (2012), we identify the phases of the financial cycle based on contractions and expansions of real credit. We identify the turning points in the log of real credit using the algorithm introduced by Harding and Pagan (2002). This is a well-established and reproducible methodology for dating different phases of a cycle. The algorithm requires a complete cycle to last at least five quarters and each phase to last at least two quarters. Specifically, a peak in the quarterly log-credit series $y_t$ occurs at time $t$ if:

$$\begin{cases} (y_t - y_{t-2}) > 0, (y_t - y_{t-1}) > 0, \\ (y_{t+2} - y_t) < 0, (y_{t+1} - y_t) < 0. \end{cases}$$

Similarly, a trough occurs at time $t$ if:

$$\begin{cases} (y_t - y_{t-2}) < 0, (y_t - y_{t-1}) < 0, \\ (y_{t+2} - y_t) > 0, (y_{t+1} - y_t) > 0. \end{cases}$$

Using the terminology of Claessens, Kose, and Terrones (2012), the recovery phase of the financial cycle (from trough to peak) is called the "upturn," whereas the contraction phase (from peak to trough) is called the "downturn."

### 2.4 Interaction of Business and Financial Cycles

Our analysis accounts for the interaction between business and financial cycles by reporting results for four phases: (1) severe recessions, which are business cycle recessions that coincide with a financial cycle downturn; (2) standard business cycle recessions; (3) standard business cycle expansions; and (4) strong expansions, which are business cycle expansions that coincide with a financial cycle upturn.[5]

Table 2 reports the growth rates for the monthly industrial production and quarterly aggregate credit during the four phases. In almost all cases, there is a monotonic relation between IPI or credit with the four cycle phases: IPI and credit gradually improve as we move from a severe recession to a recession, then to an expansion and, finally, to a strong expansion. This finding is consistent with previous literature (e.g., Claessens, Kose, and Terrones (2012); Borio (2014)) as it indicates that: (1) IPI and credit display strong cyclical behaviour; and (2) there is strong interaction between the two cycles since they seem to be moving in the same direction. Having thus established this cyclical behaviour the natural question to consider next is whether one cycle causes the other one.

## 3 Testing for Causality

An important aspect of our analysis is the use of both same frequency (quarterly) data and mixed frequency (monthly plus quarterly) data. This is primarily driven by data availability: industrial production is available monthly but aggregate credit is available quarterly. We use monthly industrial production, rather than quarterly GDP, as the determinant of the business cycle because these two variables are almost perfectly correlated, but industrial production is available at a higher frequency (i.e., monthly). For this reason, industrial production has become the standard monthly variable to capture fluctuations in the real

[5]We use standard business cycle recessions and expansions to be consistent with the literature on business cycles. Note, however, that each of the two business cycle phases overlaps with both upturns and downturns of the financial cycle. Therefore, the four phases we consider are not mutually exclusive.

economy. In contrast, aggregate credit, which is the standard determinant of the financial cycle, is only available quarterly.

The benchmark for our empirical analysis is using same frequency data, where monthly industrial production is aggregated to the quarterly frequency. Hence the benchmark causality tests employ quarterly data for both industrial production and aggregate credit. The issue with the same frequency benchmark is that, as shown by Breitung and Swanson (2002), tests of Granger causality are aggregation dependent. For example, it is possible that monthly variables exhibit no causality, but when aggregated to the quarterly frequency they might exhibit spurious causality. The extent to which low-frequency causality becomes spurious depends on the aggregation interval (i.e., monthly to quarterly) and the dynamics in the monthly variables. Mixed frequency causality tests resolve this issue because they do not involve aggregation. For these reasons, in addition to the benchmark causality results based on quarterly data, our empirical analysis relies primarily on mixed frequency causality tests.

In what follows, we describe the two sets of causality tests. Note that the quarterly frequency causality tests are a simple case of the more general mixed frequency causality tests. Therefore, first we describe the mixed frequency tests and then the benchmark tests based on the quarterly frequency.

## 3.1 Mixed Frequency

We begin by introducing formal notation that distinguishes between three frequencies: monthly, quarterly and mixed frequency. The monthly variable is defined as $x_M(\tau, k)$, where $\tau \in \{1, ..., T\}$ denotes the quarterly time index, $k \in \{1, ..., m\}$ denotes the monthly time index, and $m = 3$ is the number of months in one quarter. The quarterly variable is simply defined as $x_Q(\tau)$.

The mixed frequency process combines both the monthly and the quarterly variable by stacking them as follows:

$$X(\tau) = [\tilde{x}_M(\tau), x_Q(\tau)]', \tag{1}$$

where $\tilde{x}_M(\tau) = [x_M(\tau, 1), x_M(\tau, 2), x_M(\tau, 3)]'$. Therefore, at each quarter $\tau$, $X(\tau)$ contains three monthly observations for $\tilde{x}_M$ and one quarterly observation for $x_Q$.

## 3.2 Definition of Causality

In order to define causality, we must first define the mixed frequency information set in period $\tau$ as follows:

$$F(\tau) = \{X(-\infty, \tau]\} = \{\tilde{x}_M(-\infty, \tau], x_Q(-\infty, \tau]\}.$$

In other words, $F(\tau)$ contains all the information in $\tilde{x}_M$ and $x_Q$ up to quarter $\tau$.

Then, consistent with the literature (e.g., Granger (1969)), we assert that $x_M$ does *not* cause $x_Q$ at the quarterly horizon $h$ given $F(\tau)$, a statement denoted as $x_M \nrightarrow x_Q(\tau+h)|F(\tau)$, if:

$$P[x_Q(\tau+h)|F(\tau)] = P[x_Q(\tau+h)|x_Q(-\infty, \tau)] \qquad \forall \tau. \tag{2}$$

Equation (2) implies that the $h$-quarter ahead prediction of the quarterly variable $x_Q(\tau+h)$ is uncorrelated with the past and present values of the monthly variable $\tilde{x}_M$.

Similarly, $x_Q$ does *not* cause $\tilde{x}_M$ at horizon $h$ given $F(\tau)$, a statement denoted as $x_Q \nrightarrow \tilde{x}_M(\tau+h)|F(\tau)$, if:

$$P[\tilde{x}_M(\tau)|F(\tau)] = P[\tilde{x}_M(\tau+h)|\tilde{x}_M(-\infty, \tau]] \qquad \forall \tau. \tag{3}$$

Equation (3) implies that the $h$-quarter ahead prediction of the monthly variable $\tilde{x}_M$ (a vector containing three months) is uncorrelated with the past and present values of the quarterly variable $x_Q$.

## 3.3 The MF-VAR model

We test for the causal relation between the high frequency variable (monthly industrial production) and the low frequency variable (quarterly credit) in the context of a mixed frequency vector autoregression (MF-VAR) model introduced by Ghysels (2016). We illustrate the model below for the simple case where $x_Q$ and $x_M$ follow an AR(1) process:

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ -d & 1 & 0 & 0 \\ 0 & -d & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{\equiv \mathbf{N}} \begin{bmatrix} x_M(\tau,1) \\ x_M(\tau,2) \\ x_M(\tau,3) \\ x_Q(\tau) \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 0 & d & c_1 \\ 0 & 0 & 0 & c_2 \\ 0 & 0 & 0 & c_3 \\ b_1 & b_2 & b_3 & a \end{bmatrix}}_{\equiv \mathbf{M}} \begin{bmatrix} x_M(\tau-1,1) \\ x_M(\tau-1,2) \\ x_M(\tau-1,3) \\ x_Q(\tau-1) \end{bmatrix} + \underbrace{\begin{bmatrix} \epsilon_M(\tau,1) \\ \epsilon_M(\tau,2) \\ \epsilon_M(\tau,3) \\ \epsilon_Q(\tau) \end{bmatrix}}_{\equiv \epsilon(\tau)}, \tag{4}$$

or

$$NX(\tau) = MX(\tau-1) + \epsilon(\tau). \tag{5}$$

In this MF-VAR specification, the parameters $c_1$, $c_2$ and $c_3$ measure the impact of the lagged $x_Q$ on $x_M$. Similarly, the parameters $b_1$, $b_2$ and $b_3$ measure the impact of the lagged $x_M$ on $x_Q$. It is straightforward to show that the model is of the form:

$$X(\tau) = AX(\tau-1) + \varepsilon(\tau), \tag{6}$$

where

$$A = N^{-1}M = \begin{bmatrix} 0 & 0 & d & \sum_{i=1}^{1} d^{1-i}c_i \\ 0 & 0 & d^2 & \sum_{i=1}^{2} d^{2-i}c_i \\ 0 & 0 & d^3 & \sum_{i=1}^{3} d^{3-i}c_i \\ b_1 & b_2 & b_3 & a \end{bmatrix},$$

and $\varepsilon(\tau) = N^{-1}\epsilon(\tau)$.[6]

[6] For notational simplicity, in this specification we ignore the vector of constants, but we add it later to

## 3.4 Causality Tests

### 3.4.1 Does monthly industrial production cause quarterly credit?

In the context of the MF-VAR model, we test whether monthly industrial production causes quarterly credit by estimating the following regression with ordinary least squares (OLS):

$$x_Q(\tau) = \alpha_0 + \sum_{p=1}^{P} \alpha_p x_Q(\tau - p) + \sum_{r=1}^{R} \beta_r x_M(\tau - 1, r) + \varepsilon(\tau). \tag{7}$$

This regression follows Ghysels, Hill, and Motegi (2016, 2018). We test whether $x_M(\tau - 1, r)$ causes $x_Q(\tau)$ by testing the null hypothesis that $\beta_r = 0 \ \forall r$ using a Wald test statistic. Following Ghysels, Hill, and Motegi (2016, 2018), the calculation of the Wald test statistic is based on a bootstrap method with a heteroskedasticity-robust covariance matrix.

### 3.4.2 Does quarterly credit cause monthly industrial production?

We test whether quarterly credit causes monthly industrial production by estimating the following regression with OLS:

$$x_Q(\tau) = \alpha_0 + \sum_{p=1}^{P} \alpha_p x_Q(\tau - p) + \sum_{r=1}^{R} \beta_r x_M(\tau - 1, r) + \sum_{s=1}^{S} \gamma_s x_M(\tau + 1, s) + \varepsilon(\tau). \tag{8}$$

This is a two-sided regression, which incorporates both leads and lags for $x_M$. This type of regression was originally introduced by Sims (1972) and follows Ghysels, Hill, and Motegi (2018).

The main difference between regression models (7) and (8) is the lead variable $x_M(\tau + 1, s)$. The coefficient of the lead variable $\gamma_s$ is the focus of the quarterly-to-monthly causality test. From the point of view of $\tau + 1$, the coefficient $\gamma_s$ represents the predictive relation between the lagged $x_Q(\tau)$ variable and the $x_M(\tau + 1, s)$ variable. Hence $\gamma_s$ determines the quarterly-to-monthly causality. We test whether $x_Q(\tau)$ causes $x_M(\tau + 1, s)$ by testing the

the notation used for the causality tests.

null hypothesis that $\gamma_s = 0 \; \forall s$ using a Wald test statistic. Again, the Wald test statistic is based on a bootstrap method with a heteroskedasticity-robust covariance matrix.[7]

### 3.4.3 Lag selection

For both directions of causality, we follow Ghysels, Hill, and Motegi (2018) in using 4 quarterly lags ($P = 4$) and 12 monthly lags ($R = S = 12$). This implies that for each causality test we test 12 zero restrictions. This lag selection exhibits good performance with respect to Ljung-Box tests for the serial correlation of residuals. The Ljung-Box tests applied on Equation (7) are based on the double blocks-of-blocks bootstrap method of Ghysels, Hill, and Motegi (2018) with 10,000 replications.

In general, there is a tradeoff between adding more lag terms and the performance of Ljung-Box tests. Adding more lags reduces the serial correlation of the residuals but augments the effect of parameter proliferation, which may cause a size distortion to the asymptotic properties of the Wald test. Our lag selection is designed to balance this tradeoff and is also effective in dealing with intra-year seasonalities since the lags use a full year of information.[8]

## 3.5 Testing for the US as a Global Leader

The empirical framework we described so far is designed to test whether the industrial production of a country causes the credit of the same country or vice versa. This approach considers each country in isolation. We now turn to testing for the role of the US as a global leader in causing the business and financial cycles of another country.

Specifically, we test whether US industrial production (or credit) causes the industrial production (or credit) of another country. In order to do this, we estimate a variation of

[7] Note that this framework is broadly consistent with the Max test statistic for causality, which is discussed later for robustness.

[8] The Ljung-Box tests are used extensively by Ghysels, Hill, and Motegi (2018). These tests are appropriate in this context because they assess whether the set of all VAR autocorrelations is significantly different from zero instead of individually testing each lag. Unreported results on Ljung-Box tests are available upon request.

the original MF-VAR specification with two countries: the US and the domestic country denoted by D. This MF-VAR model is specified as follows:

$$\begin{bmatrix} \tilde{x}_M^{US}(\tau) \\ \tilde{x}_M^{D}(\tau) \\ x_Q^{US}(\tau) \\ x_Q^{D}(\tau) \end{bmatrix} = \sum_{p=1}^{P} A_p \begin{bmatrix} \tilde{x}_M^{US}(\tau-p) \\ \tilde{x}_M^{D}(\tau-p) \\ x_Q^{US}(\tau-p) \\ x_Q^{D}(\tau-p) \end{bmatrix} + \begin{bmatrix} \tilde{\varepsilon}_M^{US}(\tau) \\ \tilde{\varepsilon}_M^{D}(\tau) \\ \varepsilon_Q^{US}(\tau) \\ \varepsilon_Q^{D}(\tau) \end{bmatrix}, \tag{9}$$

where $\tilde{x}_M^{US}(\tau) = [x_M^{US}(\tau,1), x_M^{US}(\tau,2), x_M^{US}(\tau,3)]'$, and $\tilde{x}_M^{D}(\tau) = [x_M^{D}(\tau,1), x_M^{D}(\tau,2), x_M^{D}(\tau,3)]'$ are the monthly US and domestic variables respectively; $x_Q^{US}(\tau)$ and $x_Q^{D}(\tau)$ are the quarterly US and domestic variables respectively; $\tilde{\varepsilon}_M^{US}(\tau) = [\varepsilon_M^{US}(\tau,1), \varepsilon_M^{US}(\tau,2), \varepsilon_M^{US}(\tau,3)]'$ and $\tilde{\varepsilon}_M^{D}(\tau) = [\varepsilon_M^{D}(\tau,1), \varepsilon_M^{D}(\tau,2), \varepsilon_M^{D}(\tau,3)]'$ are the monthly error terms respectively; and $\varepsilon_Q^{US}(\tau)$ and $\varepsilon_Q^{D}(\tau)$ are the quarterly error terms.

The causality tests for the US as a global leader are set up in a similar way to the case of individual countries in isolation. The main difference here is that because the introduction of the US in the MF-VAR model substantially increases the dimension of the parameters to be estimated, the number of lags must be lower. We set $P = 2$ quarterly lags and $R = 6$ monthly lags, which is the highest number of lags that avoids estimation problems due to parameter proliferation. In other words, we test for 12 zero restrictions, which is the same number of restrictions estimated for the individual country results: here we have half the number of lags but double the number of countries, hence the same number of zero restrictions. Note that the Wald test follows Ghysels, Hill, and Motegi (2016) and is based on a bootstrap method with a heteroskedasticity-robust covariance matrix.

## 3.6 Testing for Causality at the Quarterly Frequency

The mixed frequency causality tests are assessed against the benchmark of quarterly frequency causality tests. The two sets of tests (mixed vs. quarterly) are designed to have the same structure so that they are directly comparable. Specifically, we estimate the same regressions as in Equations (7) and (8), the only difference being that monthly industrial production is replaced by quarterly industrial production. As a result, all lags are set at 4 quarters. We implement a similar change in testing for the role of the US as a global leader. The VAR structure remains the same but now all variables are quarterly.

# 4 Results

## 4.1 Individual Countries

We begin by assessing the extent, significance and direction of Granger causality between business cycles and financial cycles of individual countries. Table 3 reports the $p$-values of the Wald test over the full sample for two cases: quarterly frequency and mixed frequency. As previously shown in Table 1, the full sample period is slightly different across countries, the longest one ranging from January 1961 to June 2016.[9]

The empirical evidence reported in Table 3 indicates that there is a strong causality between business and financial cycles and it goes in both directions. This finding holds for both quarterly and mixed frequency since the results are effectively the same across the two frequencies. Specifically, we find that IPI causes credit for 3 out of 5 countries, whereas credit causes IPI for 4 out of 5 countries. For the US, Canada and Japan, there is strong bidirectional causality. For the UK, it is credit that significantly causes IPI. Finally, for Germany, causality is not significant in either direction.

The full sample results in Table 3 are complemented by Figures 1 and 2, which display the $p$-values period-by-period using a rolling window of 20 years beginning from January 1981 onwards. Given that the full sample results are effectively the same for quarterly and mixed frequency, the figures (as well as most of the ensuing analysis) report results for the mixed frequency case, which is more general. The contribution of the figures is that they indicate

[9]The first data point is for January 1960 but since we are computing the annual growth rate, the analysis effectively begins on January 1961.

which time periods are associated with significant causality and which are not. According to the figures, the strongest results relate to IPI causing credit in the US and credit causing IPI in Canada. In addition, in almost all cases, bidirectional causality is significant around the 2007-2008 financial crisis.

## 4.2 The US as a Global Leader

Next, we turn to the role of the US as a global leader, where we examine the following four cross-country causal relations: (1) US IPI causing the IPI of another country; (2) US IPI causing the credit of another country; (3) US credit causing the IPI of another country; (4) US credit causing the credit of another country. The mixed frequency results are reported in Table 4 and Figures 3 and 4.

Our main finding here is that the US IPI strongly causes the IPI of other countries: for mixed frequency, the $p$-value is significant for 3 out of 4 countries (the exception being Japan), whereas for quarterly frequency, the $p$-value is significant for all 4 countries. The other causal relations are predominantly insignificant, which indicates that the primary way that the US affects other countries is through its business cycle. Therefore, we conclude that the US business cycle strongly causes the business cycle of Canada, the UK and Germany, whereas for Japan it depends on the frequency used in the analysis.

## 4.3 Is Causality Cyclical?

Having established the bidirectional causality of domestic business and financial cycles as well as the leading effect of US business cycles on other countries' business cycles, we now turn to relating causality to the phase of the cycles. In other words, we ask the following question: when is causality the strongest? Is it during severe recessions, recessions, expansions or strong expansions? To answer this question, we compute how often (as a percentage of all time periods) the $p$-value is less than or equal to 0.1 during a particular phase. Table 5 has the mixed frequency results for individual countries, whereas Table 6 has the mixed frequency results for the US as a global leader.

For individual countries the results are mixed. For example, for the US and Canada, IPI causes credit more often during strong expansions. For the UK, Germany and Japan, IPI causes credit more often during severe recessions. Hence the evidence on the cyclicality of causality for individual countries is inconclusive.

In assessing the role of the US as a global leader, however, the results are more clear: the US IPI causes other countries' IPI more often during severe recessions. This is true whether we look at cycle phases from the point of view of the US or from the point of view of the other country. Overall, this is an important finding because it indicates that the US is a global leader in exporting its (severe) recessions to other countries. To be precise, it also exports its strong expansions to other countries but the former effect is much stronger than the latter. To conclude, therefore, from an individual country's point of view, there is no distinct pattern in whether the causality between cycles is stronger during one particular phase. There is, however, a clear pattern in that the causality of the US business cycle to other countries' business cycles is stronger during bad times.

## 4.4 Causality and the Interest Rate

The interest rate is perhaps the most relevant economic variable in terms of affecting both the business and the financial cycle. We relate causality to the interest rate by forming of a dummy variable that takes the value of 1 if the $p$-value for causality at a given time period is less than 0.1, and 0 otherwise. The $p$-value is taken from the mixed frequency rolling-window regressions. Then, for individual country analysis, we estimate a probit regression of the dummy variable on the domestic nominal interest rate. In other words, we assess whether interest rates are related to low $p$-values for causality.

For the cross-country analysis (i.e., assessing the leading role of the US), we estimate a probit regression of the dummy variable on the difference between the domestic and the US nominal interest rate. Note that interest rates are the 3-month Treasury Bill rates obtained from the FRED database of the Federal Reserve Bank of St. Louis. The results are reported in Table 7.

We find that for the individual country analysis, causality consistently displays a significant relation to the nominal interest rate but the sign of the relation differs across countries. For example, for the US and the UK, IPI causes credit when interest rates tend to be low, whereas credit causes IPI when interest rates tend to be high. For Canada, both causal relations are related to higher interest rates, whereas for Germany they are both related to low interest rates. Therefore, although the interest rate is significantly related to causality in most cases, the direction of this relation is not consistent across countries.

For the cross-country analysis, causality is significantly related to the interest rate differential for about half of the cases, but when it does the relation tends to be negative. This implies that causality is high when either the domestic interest rate is low or the US interest rate is high (or both). In other words, the US tends to export its cycles to other countries when the US interest rate is higher than the domestic interest rate.

# 5 Housing Prices, Equity Prices and Credit

In this section, we add two further variables to our analysis of the financial cycle: housing prices and equity prices. Although aggregate credit is the primary variable used in the literature for the study of financial cycles, housing and equity prices have also been used, in addition to credit, to provide a comprehensive view of financial cycles (see, e.g., Claessens, Kose, and Terrones (2012)).

## 5.1 Housing and Equity Price Data

The monthly housing price index (HPI) is obtained from the OECD Main Economic Indicators for all countries except for the UK. For the UK, we use the Halifax Housing Price Index obtained from Datastream because it is not available from the OECD. The HPI data are converted to real terms by dividing by the CPI of each country. The sample period for HPI begins on the following dates: January 1970 for Canada and Germany; January 1971 for Japan; and January 1984 for the US and the UK. For all countries, the HPI data sample ends in June 2016.

For the monthly equity price index (EPI) of each country we use the MSCI stock price index, which is obtained from Datastream. The EPI data are converted to real terms in the same way as the HPI data above. The EPI sample period for all five countries ranges from January 1970 to June 2016. Similar to industrial production and credit, our empirical analysis is based on annual growth rates. Table 8 reports descriptive statistics for the real annual growth rates of the housing and equity price indexes.

### 5.2 Causality Tests using Housing and Equity Prices

We take a deeper look into the workings of the financial cycle by assessing the extent to which: (1) monthly housing prices cause quarterly credit or vice versa; and monthly equity prices cause quarterly credit or vice versa. To do so, we perform the quarterly frequency and mixed frequency causality tests (with the same regressions, the same lags and the same Wald tests) used to assess the causal relation between industrial production and credit. The mixed frequency analysis is again a natural framework to use since housing and equity prices are available at the monthly frequency but credit is only available quarterly. The full sample results are reported in Table 9.

We find that there is a strong causal relation between HPI and credit and a bit less so between EPI and credit. For example, HPI causes credit for 3 of the 5 countries, whereas the inverse relation holds for 2 of the 5 countries. Similarly, EPI causes credit for 2 of the 5 countries but the inverse relation only holds for 1 of the 5 countries. In conclusion, therefore, there is evidence of a causal relation between housing prices, equity prices and credit with the strongest causality running from housing prices to credit.

# 6 The Max Test for Causality

Our main analysis is based on causality tests using the Wald test statistic. In a recent contribution, Ghysels, Hill, and Motegi (2018) propose an alternative statistic for mixed frequency causality tests: the Max test statistic. The Max and the Wald statistics are similar in many respects, except for two: (1) the Max statistic is more effective in dealing with parameter proliferation because it breaks down the main VAR regression into several regressions with less parameters; however, (2) the Max statistic is infeasible for VAR regressions with the US as a global leader (i.e., adding a second country to the analysis) due to the higher number of variables and parameters. For these reasons, we choose the Wald test for our main analysis and the Max test for robustness.

## 6.1 Max Test: Monthly-to-Quarterly Causality

In implementing the Max test for monthly-to-quarterly causality, Ghysels, Hill, and Motegi (2018) address the problem of parameter proliferation by estimating $R$ separate parsimonious regressions as follows:

$$x_Q(\tau) = \alpha_0 + \sum_{p=1}^{P} \alpha_p x_Q(\tau - p) + \beta_r x_M(\tau - 1, r) + \varepsilon(\tau), \quad r = 1, ..., R. \tag{10}$$

Each regression requires estimation of only $P+2$ parameters, which thus avoids the parameter proliferation problem. Recall that for the Wald test, Equation (7) requires estimation of $P + R + 1$ parameters.

The null hypothesis $H_0$ is similar to the Wald test: $\beta_r = 0 \quad \forall r$. Then, the Max test statistic is defined as follows:

$$\underset{1 \leq r \leq R}{max} (\sqrt{T} w' \hat{\beta})^2, \tag{11}$$

where $w$ is an $R \times 1$ sequence of non-negative scalar weights applied on the $R \times 1$ vector of $\hat{\beta}$ estimates such that $\sum_{r=1}^{R} w_r = 1$.

## 6.2 Max Test: Quarterly-to-Monthly Causality

Similarly, for the quarterly-to-monthly Max causality test we estimate the following $S$ separate parsimonious regressions:

$$x_Q(\tau) = \alpha_0 + \sum_{p=1}^{P} \alpha_p x_Q(\tau - p) + \sum_{r=1}^{R} \beta_r x_M(\tau - 1, r) + \gamma_s x_M(\tau + 1, s) + \varepsilon(\tau), \quad s = 1, ..., S. \tag{12}$$

Now, each regression requires estimation of $P + R + 2$ parameters in contrast to Equation (8) for the Wald test that requires estimation of $P + R + S + 1$ parameters.

The Max statistic tests the null hypothesis $H_0 : \gamma_s = 0 \quad \forall s$, and is defined as:

$$\underset{1 \leq s \leq S}{max} (\sqrt{T} w' \hat{\gamma})^2, \tag{13}$$

where $w$ is an $S \times 1$ sequence of non-negative scalar weights applied on the $S \times 1$ vector of $\hat{\gamma}$ estimates such that $\sum_{s=1}^{S} w_s = 1$. Note that for the Max test, we use the same number of lags as for the Wald test.

## 6.3 Max Test: Results

The full empirical evidence for IPI, Credit, HPI and EPI is reported in Table 10. Overall, the Max test results are consistent with the Wald test results. The Max test results are a bit weaker in some cases (e.g., credit causes industrial production for one less country) but also a bit stronger in other cases (e.g., credit causes housing prices for two more countries). Whether we use the Max or the Wald test, the main finding remains the same: there is strong causality between business and financial cycles and it goes in both directions.

# 7 Conclusion

An emerging literature in financial economics has established the presence of financial cycles, which are primarily based on the cyclical behaviour of aggregate real credit issued by banks. These financial cycles are distinct but correlated to the standard business cycles of real economic activity. When both cycles are close to their peak, the economic and financial conditions are extraordinarily good. Similarly, when both cycles are close to their trough, the economic and financial conditions are extraordinarily bad. An open question in this literature remains the question of whether business cycles cause financial cycles or vice versa. This is a question with fundamental implications for research, policy and financial practice.

Our paper bridges this gap in the literature by investigating the extent, significance and direction of Granger causality between the two cycles. Our methodology is primarily based on a mixed frequency vector autoregression that exploits the fact that real economic activity is measured at a higher frequency than aggregate credit. The empirical evidence establishes three main findings: (1) there is a significant causal relation between business and financial cycles for five industrialized economies; (2) the causal relation is bidirectional: business cycles cause financial cycles and vice versa; and (3) the US is a global leader in that the US business cycle causes the business cycles of the other countries. This relation is true at all times but is especially strong during recessions. Overall, these findings indicate that in several countries Main Street and Wall Street are not only correlated but are in fact causing each other with the US Main Street playing a leading role in this causal relation.

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## Table 1. Descriptive Statistics for Industrial Production and Credit

The table reports descriptive statistics for 100 × annual log-difference of the monthly industrial production index and quarterly credit. AR(1) is the serial correlation at 1 lag. Corr is the correlation between industrial production and credit (both at quarterly frequency). All data are in real terms.

| | Sample Period | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Begin | End | Mean | SDev | Skew | Kurt | Min | Max | AR(1) | Corr |
| Panel A: USA | | | | | | | | | | |
| Industrial production | 1961M1 | 2016M6 | 2.63 | 4.76 | −1.11 | 5.15 | −16.64 | 12.56 | 0.98 | 0.50 |
| Credit | 1961Q1 | 2016Q2 | 3.23 | 4.92 | −0.63 | 2.99 | −12.89 | 12.52 | 0.96 | |
| Panel B: Canada | | | | | | | | | | |
| Industrial production | 1962M1 | 2016M6 | 2.65 | 5.32 | −0.52 | 3.53 | −16.80 | 15.77 | 0.96 | 0.18 |
| Credit | 1962Q1 | 2016Q2 | 6.66 | 5.68 | 0.20 | 3.28 | −8.82 | 22.28 | 0.95 | |
| Panel C: UK | | | | | | | | | | |
| Industrial production | 1964M1 | 2016M6 | 0.96 | 3.98 | −0.55 | 5.31 | −12.72 | 20.40 | 0.89 | 0.44 |
| Credit | 1964Q1 | 2016Q2 | 5.17 | 5.67 | −0.06 | 2.69 | −8.86 | 18.30 | 0.96 | |
| Panel D: Germany | | | | | | | | | | |
| Industrial production | 1961M1 | 2016M6 | 2.28 | 5.57 | −1.27 | 7.57 | −27.67 | 16.07 | 0.91 | 0.30 |
| Credit | 1961Q1 | 2016Q2 | 3.67 | 3.83 | 0.07 | 2.13 | −3.03 | 12.24 | 0.98 | |
| Panel E: Japan | | | | | | | | | | |
| Industrial production | 1965M10 | 2016M6 | 2.87 | 8.07 | −1.07 | 7.14 | −40.55 | 24.15 | 0.96 | 0.44 |
| Credit | 1965Q4 | 2016Q2 | 3.35 | 5.12 | 0.46 | 2.58 | −7.43 | 17.46 | 0.96 | |

## Table 2. Business and Financial Cycles

The table reports the mean of 100 × log-difference of the monthly industrial production index (IPI) and quarterly credit during different phases of business and financial cycles. For the US, recessions and expansions are according to the NBER. For Canada, the UK, Germany and Japan recessions and expansions are according to the OECD-based recession indicators. A severe recession is a business cycle recession that coincides with a financial cycle downturn. A strong expansion is a business cycle expansion that coincides with a financial cycle upturn. Financial cycle upturns and downturns are defined as in Claessens, Kose, and Terrones (2012).

| | USA | | Canada | | UK | | Germany | | Japan | |
|---|---|---|---|---|---|---|---|---|---|---|
| | IPI | Credit | IPI | Credit | IPI | Credit | IPI | Credit | IPI | Credit |
| Severe Recession | −0.85 | 0.06 | −0.24 | −0.54 | −0.29 | −2.34 | −0.36 | −1.66 | −0.14 | −0.20 |
| Recession | −0.68 | 0.53 | −0.11 | 0.69 | −0.13 | 0.36 | −0.16 | 1.20 | −0.28 | 1.04 |
| Expansion | 0.37 | 1.01 | 0.48 | 1.45 | 0.25 | 1.19 | 0.48 | 1.38 | 0.62 | 1.73 |
| Strong Expansion | 0.41 | 1.17 | 0.57 | 2.61 | 0.25 | 3.73 | 0.57 | 3.54 | 0.53 | 4.94 |

## Table 3. Causality Tests for Individual Countries

The table displays the $p$-value for the Wald test used to assess the causality between the industrial production index (IPI) and aggregate credit. Panel A is for quarterly IPI and quarterly credit, whereas Panel B is for mixed frequency based on monthly IPI and quarterly credit. The notation, for example, "IPI $\nrightarrow$ Credit" denotes the null hypothesis of no causality from IPI to credit. The Wald test uses 4 quarterly lags and leads and 12 monthly lags and leads. The Wald test calculation is based on a heteroskedasticity-robust covariance matrix with 10,000 bootstrap replications. The full sample covers the sample periods reported in Table 1. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

| | USA | Canada | UK | Germany | Japan |
|---|---|---|---|---|---|
| | | Panel A: Quarterly Frequency | | | |
| IPI $\nrightarrow$ Credit | 0.011** | 0.001*** | 0.374 | 0.116 | 0.001*** |
| Credit $\nrightarrow$ IPI | 0.002*** | 0.021** | 0.001*** | 0.424 | 0.014** |
| | | Panel B: Mixed Frequency | | | |
| IPI $\nrightarrow$ Credit | 0.015** | 0.002*** | 0.560 | 0.159 | 0.004*** |
| Credit $\nrightarrow$ IPI | 0.007*** | 0.009*** | 0.001*** | 0.785 | 0.008*** |

## Table 4. Causality Tests for the US as a Global Leader

The table displays the $p$-value for the Wald test used to assess the causality between either the US industrial production index (IPI) or US credit and either the IPI or the credit of another country. Panel A is for quarterly IPI and quarterly credit, whereas Panel B is for mixed frequency based on monthly IPI and quarterly credit. The notation, for example, "$\text{IPI}_{USA} \nrightarrow \text{Credit}_{Other}$" denotes the null hypothesis of no causality from the US IPI to another country's credit. The Wald test uses 2 quarterly lags and 6 monthly lags. The Wald test calculation is based on a heteroskedasticity-robust covariance matrix with 1,999 bootstrap replications. The full sample covers the sample periods reported in Table 1. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

| | Canada | UK | Germany | Japan |
|---|---|---|---|---|
| **Panel A: Quarterly Frequency** | | | | |
| $\text{IPI}_{USA} \nrightarrow \text{IPI}_{Other}$ | 0.001*** | 0.001*** | 0.004*** | 0.023** |
| $\text{IPI}_{USA} \nrightarrow \text{Credit}_{Other}$ | 0.194 | 0.636 | 0.582 | 0.142 |
| $\text{Credit}_{USA} \nrightarrow \text{IPI}_{Other}$ | 0.681 | 0.962 | 0.424 | 0.162 |
| $\text{Credit}_{USA} \nrightarrow \text{Credit}_{Other}$ | 0.997 | 0.058* | 0.899 | 0.104 |
| **Panel B: Mixed Frequency** | | | | |
| $\text{IPI}_{USA} \nrightarrow \text{IPI}_{Other}$ | 0.003*** | 0.046** | 0.055* | 0.155 |
| $\text{IPI}_{USA} \nrightarrow \text{Credit}_{Other}$ | 0.194 | 0.706 | 0.174 | 0.058* |
| $\text{Credit}_{USA} \nrightarrow \text{IPI}_{Other}$ | 0.768 | 0.677 | 0.141 | 0.275 |
| $\text{Credit}_{USA} \nrightarrow \text{Credit}_{Other}$ | 0.322 | 0.100* | 0.911 | 0.021** |

## Table 5. Causality across Cycle Phases: Individual Countries

The table shows how often we observe statistically significant causality (i.e., Wald $p$-value$\leq$0.1) for different phases of the business and financial cycle. Each entry is the frequency of statistically significant causality using a 20-year-rolling window. For example, a value of 0.88 in the upper left corner implies that IPI has singificantly caused credit in the USA 88% of the time during severe recessions.

| | USA | Canada | UK | Germany | Japan |
|---|---|---|---|---|---|
| | | Panel A: IPI $\rightarrow$ Credit | | | |
| Severe Recession | 0.88 | 0.45 | 0.67 | 0.73 | 0.71 |
| Recession | 0.70 | 0.56 | 0.58 | 0.58 | 0.78 |
| Expansion | 0.93 | 0.53 | 0.49 | 0.58 | 0.72 |
| Strong Expansion | 0.93 | 0.51 | 0.47 | 0.50 | 0.63 |
| | | Panel B: Credit $\rightarrow$ IPI | | | |
| Severe Recession | 0.75 | 0.90 | 0.67 | 0.63 | 0.45 |
| Recession | 0.70 | 0.92 | 0.60 | 0.53 | 0.43 |
| Expansion | 0.41 | 0.91 | 0.86 | 0.46 | 0.37 |
| Strong Expansion | 0.42 | 0.87 | 0.81 | 0.36 | 0.29 |

## Table 6. Causality across Cycle Phases: The US as a Global Leader

The table shows how often we observe statistically significant causality (i.e., Wald $p$-value$\leq$0.1) for different phases of the business and financial cycle. Each entry is the frequency of statistically significant causality using a 20-year-rolling window. For example, a value of 0.71 in the upper left corner implies that IPI USA has singificantly caused IPI Canada 71% of the time during severe recessions according to the US cycle.

| | | | | |
|---|---|---|---|---|
| **Panel A: USA causing Canada** | | | | |
| | $\text{IPI}_{USA} \rightarrow \text{IPI}_{Canada}$ | | $\text{Credit}_{USA} \rightarrow \text{Credit}_{Canada}$ | |
| | US Cycle | Canada Cycle | US Cycle | Canada Cycle |
| Severe Recession | 0.71 | 0.70 | 0.14 | 0.18 |
| Recession | 0.74 | 0.62 | 0.32 | 0.25 |
| Expansion | 0.57 | 0.57 | 0.21 | 0.20 |
| Strong Expansion | 0.57 | 0.47 | 0.22 | 0.17 |
| **Panel B: USA causing UK** | | | | |
| | $\text{IPI}_{USA} \rightarrow \text{IPI}_{UK}$ | | $\text{Credit}_{USA} \rightarrow \text{Credit}_{UK}$ | |
| | US Cycle | UK Cycle | US Cycle | UK Cycle |
| Severe Recession | 0.57 | 0.41 | 0.71 | 0.19 |
| Recession | 0.43 | 0.27 | 0.43 | 0.10 |
| Expansion | 0.29 | 0.34 | 0.10 | 0.17 |
| Strong Expansion | 0.21 | 0.23 | 0.10 | 0.06 |
| **Panel C: USA causing Germany** | | | | |
| | $\text{IPI}_{USA} \rightarrow \text{IPI}_{Germany}$ | | $\text{Credit}_{USA} \rightarrow \text{Credit}_{Germany}$ | |
| | US Cycle | Germany Cycle | US Cycle | Germany Cycle |
| Severe Recession | 0.88 | 0.83 | 0.38 | 0.10 |
| Recession | 0.85 | 0.77 | 0.20 | 0.12 |
| Expansion | 0.74 | 0.74 | 0.15 | 0.19 |
| Strong Expansion | 0.71 | 0.72 | 0.17 | 0.08 |
| **Panel D: USA causing Japan** | | | | |
| | $\text{IPI}_{USA} \rightarrow \text{IPI}_{Japan}$ | | $\text{Credit}_{USA} \rightarrow \text{Credit}_{Japan}$ | |
| | US Cycle | Japan Cycle | US Cycle | Japan Cycle |
| Severe Recession | 0.00 | 0.47 | 0.29 | 0.53 |
| Recession | 0.21 | 0.49 | 0.50 | 0.61 |
| Expansion | 0.52 | 0.47 | 0.68 | 0.72 |
| Strong Expansion | 0.47 | 0.42 | 0.77 | 0.83 |

## Table 7. Causality Tests: The Role of Interest Rates

The table presents evidence on the relation between causality and the norminal interest rate. Panel A shows the $\beta_i$ estimates from the probit model: $P_{i,t} = \alpha_i + \beta_i r_{i,t} + \varepsilon_{i,t}$, for country $i$ at time $t$. $P_{i,t}$ is a dummy variable that takes a value of 1 if causality for country $i$ at time $t$ is significant at the 10% level, and 0 otherwise; $r_{i,t}$ is the nominal interest rate of country $i$ at time $t$. Panel B shows the $\beta_i$ estimates from the probit model: $P_{USA,i,t} = \alpha_i + \beta_i(r_{i,t} - r_{USA,t}) + \varepsilon_{USA,i,t}$, where $i$ refers to a country other than the USA, and $P_{USA,i,t}$ is a dummy variable that takes a value of 1 if causality from the USA to another country $i$ at time $t$ is significant at the 10%, and 0 otherwise. The numbers in parentheses are the $p$-values of the coefficients $\beta_i$.

| Panel A: Individual Countries | USA | Canada | UK | Germany | Japan |
|---|---|---|---|---|---|
| IPI → Credit | − 0.25<br>(<0.01) | 0.34<br>(<0.01) | − 0.10<br>(<0.01) | − 0.13<br>(<0.01) | 0.12<br>(0.04) |
| Credit → IPI | 0.08<br>(<0.01) | 0.42<br>(<0.01) | 0.03<br>(0.38) | −0.07<br>(0.05) | −0.02<br>(0.71) |

| Panel B: The US as a Global Leader | Canada | UK | Germany | Japan |
|---|---|---|---|---|
| $\text{IPI}_{USA} \rightarrow \text{IPI}_{Other}$ | −8.25<br>(0.13) | −19.44<br>(<0.01) | 0.22<br>(0.91) | 2.34<br>(0.49) |
| $\text{IPI}_{USA} \rightarrow \text{Credit}_{Other}$ | −34.37<br>(<0.01) | −15.82<br>(<0.01) | 1.27<br>(0.50) | −1.30<br>(0.70) |
| $\text{Credit}_{USA} \rightarrow \text{IPI}_{Other}$ | 1.21<br>(0.86) | 5.91<br>(0.15) | 0.30<br>(0.88) | −5.35<br>(0.15) |
| $\text{Credit}_{USA} \rightarrow \text{Credit}_{Other}$ | 11.91<br>(0.04) | −10.25<br>(0.04) | 1.02<br>(0.66) | −42.20<br>(<0.01) |

## Table 8. Descriptive Statistics for Housing and Equity Price

The table reports descriptive statistics for 100 × annual log-difference of the monthly housing price index and the monthly equity price index. AR(1) is the serial correlation at 1 lag. Corr is the correlation between housing price and credit or equity price and credit (all at quarterly frequency). All data are in real terms.

| | Sample Period | | | | | | | | | Corr with |
|---|---|---|---|---|---|---|---|---|---|---|
| | Begin | End | Mean | SDev | Skew | Kurt | Min | Max | AR(1) | Credit |
| **Panel A: USA** | | | | | | | | | | |
| Housing price | 1984M1 | 2016M6 | 0.57 | 1.35 | 0.03 | 3.42 | −3.04 | 4.78 | 0.96 | 0.33 |
| Equity price | 1971M1 | 2016M6 | 5.78 | 17.08 | −0.90 | 4.13 | −62.32 | 44.20 | 0.94 | 0.06 |
| **Panel B: Canada** | | | | | | | | | | |
| Housing price | 1970M1 | 2016M6 | −0.16 | 1.70 | 0.14 | 3.38 | −4.87 | 4.87 | 0.96 | 0.17 |
| Equity price | 1971M1 | 2016M6 | 5.28 | 18.45 | −0.55 | 3.81 | −60.83 | 56.12 | 0.94 | 0.19 |
| **Panel C: UK** | | | | | | | | | | |
| Housing price | 1984M1 | 2016M6 | 3.00 | 9.12 | −0.11 | 3.22 | −23.75 | 25.31 | 0.98 | 0.61 |
| Equity price | 1971M1 | 2016M6 | 5.38 | 19.52 | −1.41 | 7.83 | −94.51 | 69.66 | 0.93 | 0.15 |
| **Panel D: Germany** | | | | | | | | | | |
| Housing price | 1970M1 | 2016M6 | 0.47 | 1.54 | 1.46 | 6.42 | −2.42 | 6.66 | 0.95 | 0.53 |
| Equity price | 1971M1 | 2016M6 | 5.33 | 21.99 | −0.54 | 3.60 | −78.56 | 61.65 | 0.94 | 0.12 |
| **Panel E: Japan** | | | | | | | | | | |
| Housing price | 1971M1 | 2016M6 | 0.38 | 1.88 | −1.58 | 9.74 | −9.49 | 6.05 | 0.96 | 0.36 |
| Equity price | 1971M1 | 2016M6 | 4.00 | 23.17 | −0.17 | 3.25 | −64.37 | 72.12 | 0.95 | 0.30 |

## Table 9. Causality Tests for Housing and Equity Price

The table displays the $p$-value for the Wald test used to assess the causality between the housing price index (HPI) and aggregate credit as well as between the equity price index (EPI) and aggregate credit. Panel A is for quarterly HPI, EPI and credit, whereas Panel B is for mixed frequency based on monthly IPI, monthly EPI and quarterly credit. The notation, for example, "HPI $\nrightarrow$ Credit" denotes the null hypothesis of no causality from HPI to credit. The Wald test uses 4 quarterly lags and leads and 12 monthly lags and leads. The Wald test calculation is based on a heteroskedasticity-robust covariance matrix with 10,000 bootstrap replications. The full sample covers the sample periods reported in Tables 1 and 8. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

| | USA | Canada | UK | Germany | Japan |
|---|---|---|---|---|---|
| Panel A: Quarterly Frequency | | | | | |
| HPI $\nrightarrow$ Credit | 0.010*** | 0.110 | 0.003*** | 0.145 | 0.093* |
| Credit $\nrightarrow$ HPI | 0.003*** | 0.320 | 0.004*** | 0.889 | 0.001*** |
| EPI $\nrightarrow$ Credit | 0.009*** | 0.459 | 0.622 | 0.071* | 0.267 |
| Credit $\nrightarrow$ EPI | 0.677 | 0.251 | 0.069* | 0.965 | 0.009*** |
| Panel B: Mixed Frequency | | | | | |
| HPI $\nrightarrow$ Credit | 0.001*** | 0.206 | 0.024** | 0.205 | 0.003*** |
| Credit $\nrightarrow$ HPI | 0.129 | 0.200 | 0.023** | 0.531 | 0.001*** |
| EPI $\nrightarrow$ Credit | 0.004*** | 0.306 | 0.891 | 0.124 | 0.090* |
| Credit $\nrightarrow$ EPI | 0.297 | 0.494 | 0.069* | 0.774 | 0.010*** |

## Table 10. Max Causality Test

The table displays the $p$-value for the mixed frequency Max test used to assess the causality between monthly industrial production index (IPI), monthly housing price index (HPI), monthly equity price index (EPI) and quarterly credit. The notation, for example, "IPI $\nrightarrow$ Credit" denotes the null hypothesis of no causality from IPI to credit. The Max test uses 4 quarterly lags and leads and 12 monthly lags and leads. The Max test calculation is based on a heteroskedasticity-robust covariance matrix with 10,000 bootstrap replications. The full sample covers the sample periods reported in Tables 1 and 8. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

| | USA | Canada | UK | Germany | Japan |
|---|---|---|---|---|---|
| IPI $\nrightarrow$ Credit | 0.152 | 0.008*** | 0.826 | 0.197 | 0.057* |
| Credit $\nrightarrow$ IPI | 0.001*** | 0.206 | 0.002*** | 0.387 | 0.030** |
| HPI $\nrightarrow$ Credit | 0.012** | 0.198 | 0.079* | 0.086* | 0.074 |
| Credit $\nrightarrow$ HPI | 0.002*** | 0.017** | 0.033** | 0.477 | 0.001*** |
| EPI $\nrightarrow$ Credit | 0.020** | 0.264 | 0.468 | 0.067* | 0.659 |
| Credit $\nrightarrow$ EPI | 0.334 | 0.244 | 0.228 | 0.798 | 0.011** |

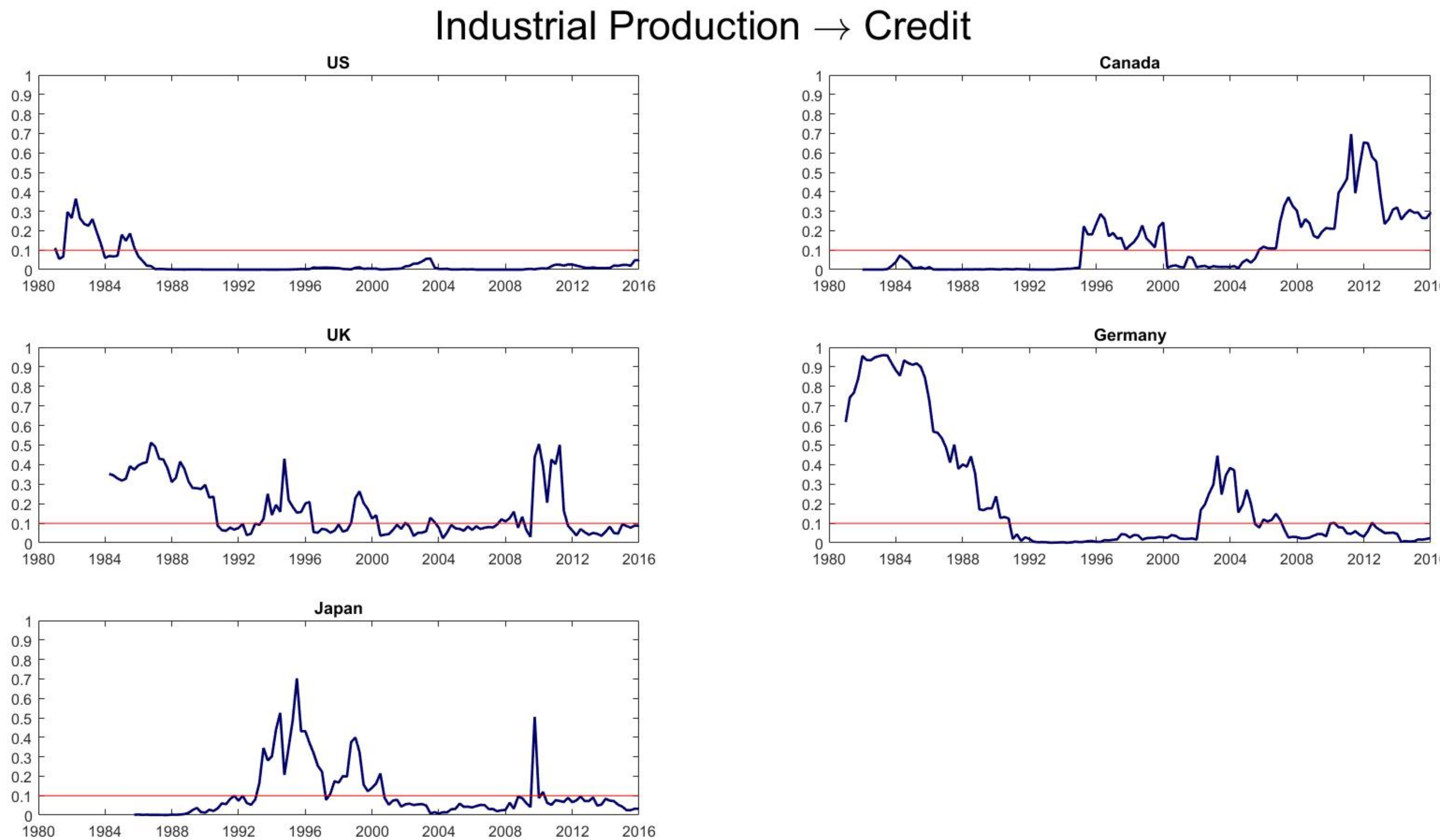


**Figure 1. Industrial Production Causing Credit - Mixed Frequency**

The figure plots the $p$-value for the mixed frequency Wald test used to assess the causality from the monthly industrial production index to quarterly credit. The $p$-value is estimated using a 20-year rolling window.

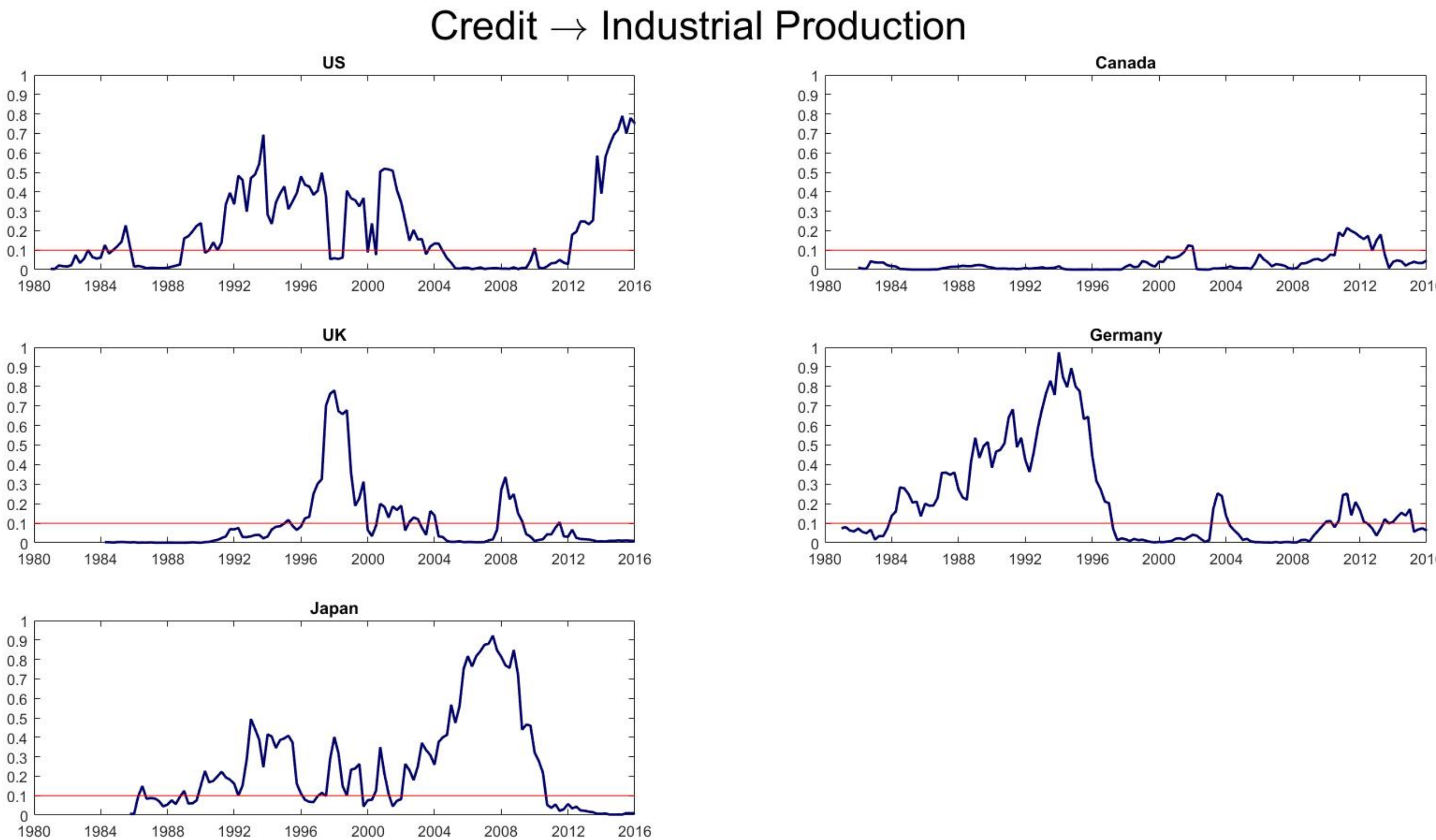


**Figure 2. Credit Causing Industrial Production - Mixed Frequency**

The figure plots the $p$-value for the mixed frequency Wald test used to assess the causality from quarterly credit to the monthly industrial production index. The $p$-value is estimated using a 20-year rolling window.

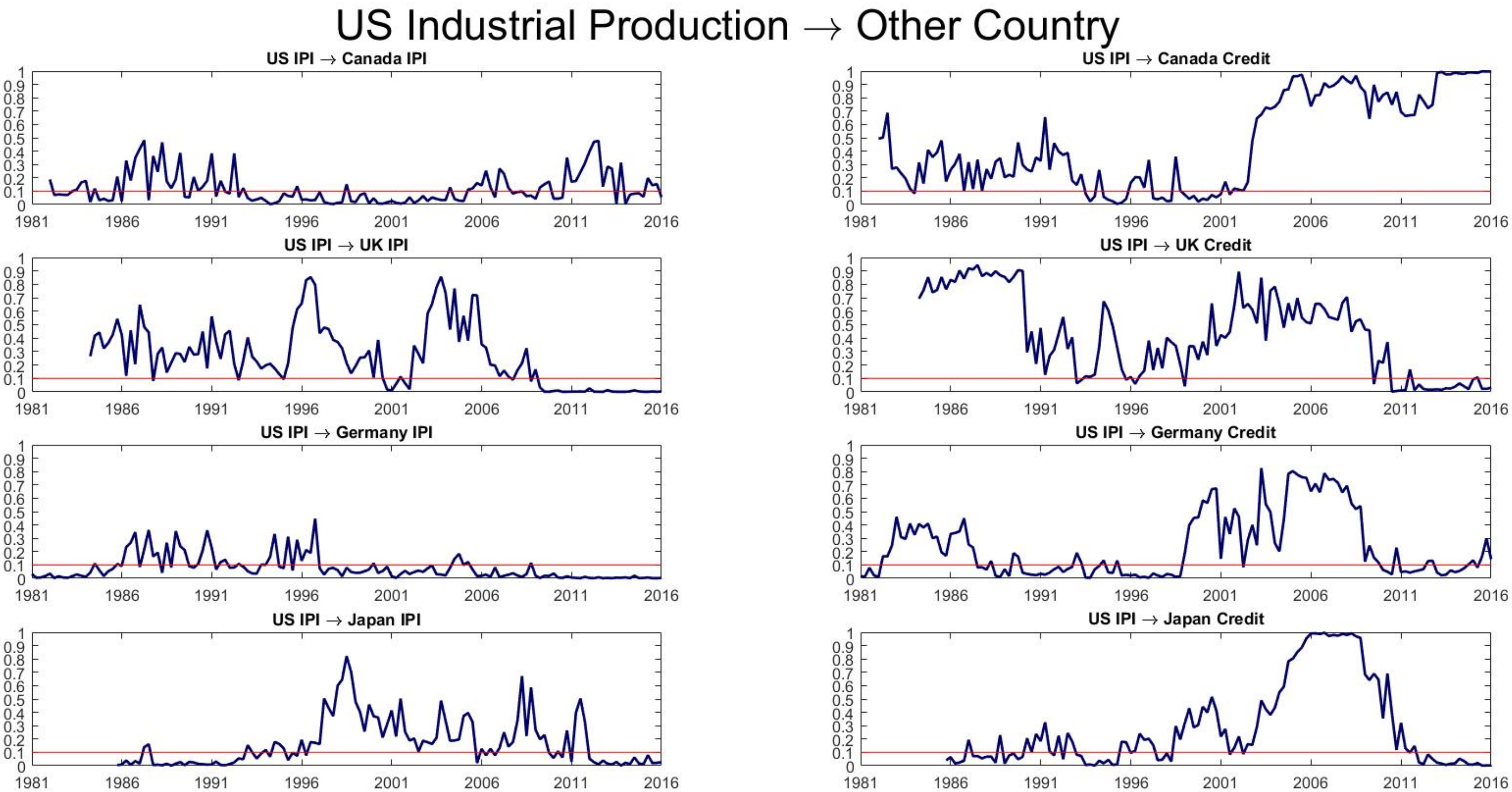


**Figure 3. US Industrial Production as a Global Leader - Mixed Frequency**

The figure plots the $p$-value for the mixed frequency Wald test used to assess the causality from the US monthly industrial production index to another country's monthly industrial production index or quarterly credit. The $p$-value is estimated using a 20-year rolling window.

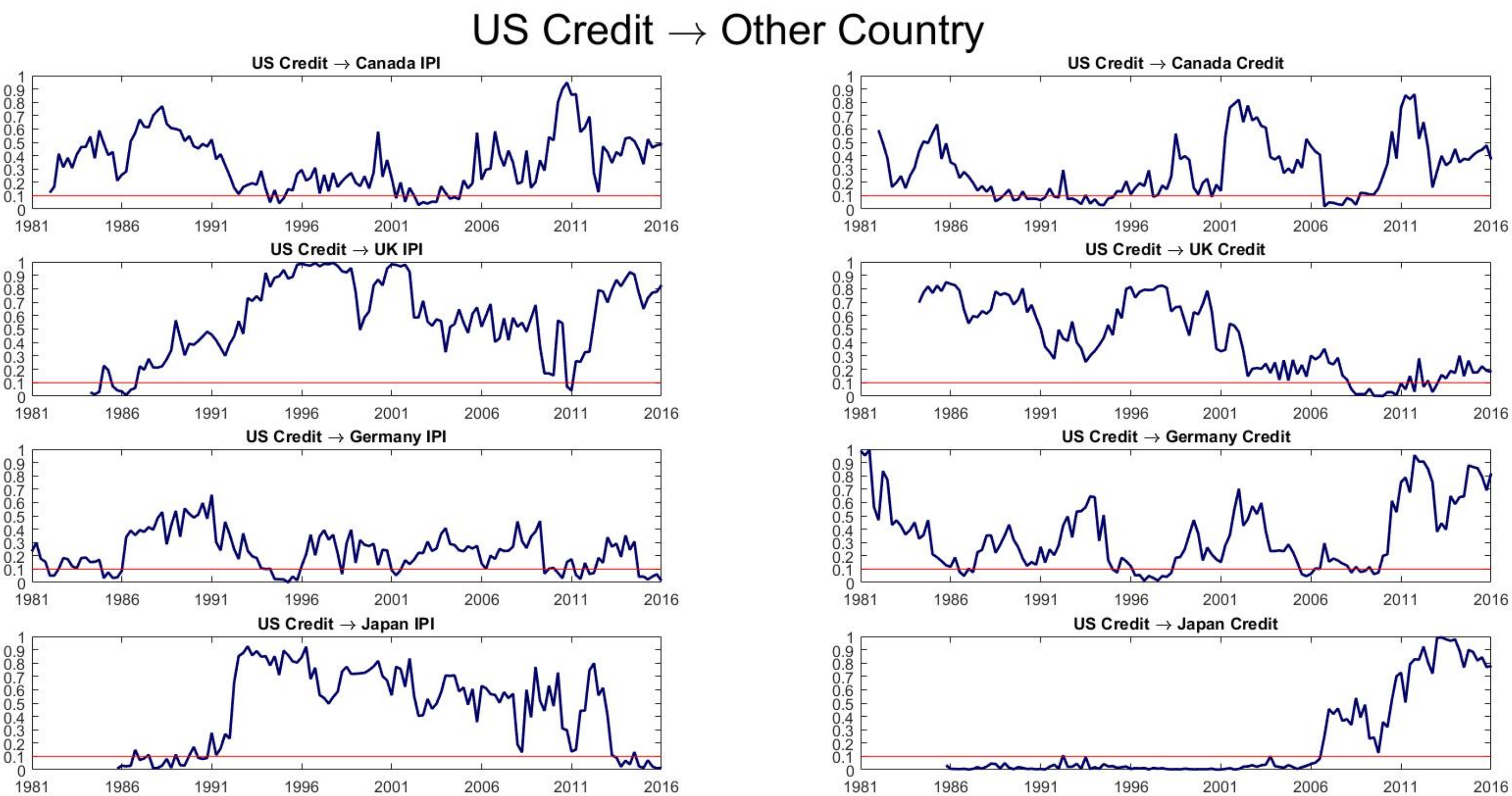


**Figure 4. US Credit as a Global Leader - Mixed Frequency**

The figure plots the $p$-value for the mixed frequency Wald test used to assess the causality from the US quarterly credit to another country's monthly industrial production index or quarterly credit. The $p$-value is estimated using a 20-year rolling window.