Essays on Financial Economics and Macroeconomics

By

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ABSTRACT

ESSAYS ON FINANCIAL ECONOMICS AND MACROECONOMICS

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This thesis, entitled Essays on Financial Economics and Macroeconomics, studies the interactions between real macroeconomics and financial variables. There is an emerging literature aims to investigate how can we reduce the impacts from the financial crisis by considering both macroeconomics and finance conditions together. For example, decision-makers should consider the financial market conditions first before policies are made. Meanwhile, the forecasting of short term financial variables’ returns should take long term macroeconomic conditions into consideration. This has motivated us to explore further in the relationship between the macroeconomic factors and financial market conditions.

In the first chapter, we examine the short-run and long-run dynamics of the correlation between exchange rate and commodity returns, and assess the extent to which the long-run correlation is determined by economic fundamentals. Our empirical analysis is based on the dynamic conditional correlation model with mixed data sampling (DCC-MIDAS) of Colacito, Engle and Ghysels (2011). This model provides a framework that captures the high-frequency relation between exchange rate and commodity returns as well as the low-frequency relation of volatility and correlation to economic fundamentals. Using both economic and statistical criteria, we find that the DCC-MIDAS model augmented with economic fundamentals performs better than competing models in sample and out of sample.

In the second chapter, we investigate the direction of Granger causality between business and financial cycles. Our analysis is based on a vector autoregression model applied on mixed frequency data. This allows us to condition on data from higher frequency variables...
(such as monthly industrial production) and lower frequency variables (such as quarterly aggregate credit) in a way that avoids the effects on data aggregation. Our empirical investigation focuses on five industrialized countries: USA, Canada, UK, Germany and Japan. Firstly, we examine whether the monthly industrial production index causes quarterly aggregate credit or vice versa. Then, we determine the timing of when causality is statistically significant. We find that there is strong bidirectional causality between business and financial cycles. The timing of causality varies across countries, but for all countries, bidirectional causality is significant during the financial crisis.

The third and final chapter, which is an extension of the second chapter, investigates the role of the US as a global leader. Specifically, by paring US with other country (i.e., Canada, UK, Germany and Japan), we examine whether the US industrial production or credit causes the industrial production or credit of the other countries. In addition, we investigate whether causality is affected by the nominal interest rate. Our main finding is that the US business cycle strongly causes the business cycles of Canada, the UK and Germany. Finally, there is strong evidence that causality tends to be significant when the US interest rate is higher.
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CHAPTER 1
ON THE ECONOMIC DETERMINANTS OF THE CORRELATION BETWEEN EXCHANGE RATES AND COMMODITIES

1.1 Introduction

This chapter focuses on commodity currencies. This is a group of currencies identified by recent contributions to the literature on exchange rate predictability as currencies whose movements are primarily determined by movements in commodity prices (e.g., Chen and Rogoff, 2003; and Chen, Rogoff and Rossi, 2010). For example, the US-Canadian dollar exchange rate is often thought of as following oil price movements. This is because Canada is a typical small open economy in which crude oil is a substantial part of its total exports. In such an economy, it is natural to expect that the exchange rate will reflect movements in commodity prices. Other examples of commodity currencies include the US-Norwegian exchange rate and oil prices or the US-South African exchange rate and gold prices.¹

For these commodity currencies, the focus of recent research has been on whether commodity returns can predict exchange rate returns out of sample at the daily frequency (Ferraro, Rogoff and Rossi, 2015). In contrast, this chapter addresses a more general aspect of the links between exchange rates and commodities: the short-term and long-term dynamics of the correlation between exchange rate returns and commodity returns. We also link this correlation to the state of the economy by assessing the extent to which it is determined by economic fundamentals.

Understanding the correlation between exchange rate returns and commodity returns

¹There is a very large literature on the relation between exchange rates and oil. See, among others, Amano and Van Norden (1998a, 1998b), Ding and Vo (2012), and Aloui, Aissa and Nguyen (2013). For a review of the literature on exchange rate predictability see Della Corte and Tsiakas (2012), Rossi (2013), and Li, Tsiakas and Wang (2015).
is central to understanding several aspects of exchange rates and commodities. Given for example, that oil is typically quoted in US dollars, the price of oil from the perspective of Canadian consumer or producer will depend on the US-Canadian dollar exchange rate. Then, the volatility of the Canadian price of oil will depend on oil price volatility, exchange rate volatility and their correlation. More generally, the risk taken by any foreign consumer or producer of a commodity or, equivalently, the risk taken by any investor that includes a commodity in their asset allocation will depend on the correlation between commodity prices and exchange rates.

Our empirical analysis is based on the dynamic conditional correlation model with mixed data sampling (DCC-MIDAS) of Colacito, Engle and Ghysels (2011). The DCC-MIDAS model is well suited for this study because it achieves three distinct objectives: (i) it allows us to exploit the daily predictability of exchange rates when conditioning on commodity returns, (ii) it accounts for the short-term dynamics of volatility and correlation, and (iii) it also captures the long-run component of volatility and correlation that matches the lower frequency of economic fundamentals.

Following Ferraro, Rogoff and Rossi (2015), our main focus is on the predictive ability of oil prices on the US-Canadian dollar (USD/CAD) exchange rate because this is the typical pair of exchange rate and commodity examined in the literature. In the robustness section, we augment the scope of our study by considering additional exchange rates and commodities. We use daily data on exchange rates and oil prices to capture the short-term dynamics of returns, volatility and correlation. We also use monthly economic fundamentals to capture the long-term dynamics of volatility and correlation. Following Asgharian, Christiansen and Hou (2016), economic fundamentals are divided in four groups: interest rates and prices, state of economy variables (such as industrial production and money supply), uncertainty variables (such as the TED spread and the VIX), and lagged returns. Given the large number of economic fundamentals, we combine their predictive information using principle component analysis, which is a standard approach in the literature (see,
Following Asgharian, Christiansen and Hou (2016), we employ a statistical methodology for evaluating exchange rate predictability that involves using an information criterion (AIC) for evaluating the performance of alternative DCC-MIDAS specifications relative to the standard DCC benchmark with GARCH volatility. We also assess the statistical significance of the parameters that capture the effect of economic fundamentals on volatility and correlation.

In addition to the statistical evaluation, we also assess the economic value of exchange rate predictability in the context of dynamic asset allocation. A purely statistical analysis is not particularly informative to an investor as it falls short of measuring the tangible economic gains from predictability in exchange rates and commodities. Following Della Corte, Sarno and Tsiakas (2009, 2011), among others, we design an international asset allocation strategy that exposes a US investor to FX and commodity risk. We then evaluate the performance of dynamically rebalanced portfolios based on one-month ahead forecasts generated by the empirical models we estimate. We use mean-variance analysis, which allows us to measure how much a risk-averse investor is willing to pay for switching from a portfolio strategy based on the random walk benchmark to more sophisticated models, including the DCC-MIDAS that conditions on economic fundamentals.

Using both statistical and economic methods for assessing in-sample and out-of-sample predictability, we find that the MIDAS specification for volatility and correlation performs better than any alternative. This indicates that there is considerable value in using models that decompose volatility and correlation into a short-run and a long-run component. Furthermore, conditioning on economic fundamentals improves the MIDAS specification, especially for volatility. Finally, the DCC-MIDAS model delivers a sizeable certainty equivalent return over the benchmark for a mean-variance investor who implements an out-of-sample dynamic asset allocation strategy facing exchange rate risk and commodity price risk. These results hold for the US-Canadian dollar exchange rate and oil prices but are
also confirmed for the US-Norwegian krone and oil prices and the US-South African Rand and gold prices.

The remainder of the chapter is organized as follows. In the next section we describe the DCC-MIDAS model used throughout our analysis. Section 3 first describes our data on exchange rates, commodities and economic fundamentals, and then also reports our in-sample empirical results using the in-sample statistical criteria. Section 4 discusses the out-of-sample results and presents the dynamic asset allocation framework for assessing the economic value of exchange rate predictability. Section 5 reports robustness checks and, finally, Section 6 concludes.

1.2 The DCC-MIDAS Model

Our analysis is based on the dynamic conditional correlation model with mixed data sampling (DCC-MIDAS) of Colacito, Engle and Ghysels (2011). The DCC-MIDAS model is a combination of the DCC model of Engle (2002) and the GARCH-MIDAS model of Engle, Ghysels and Sohn (2013). The DCC-MIDAS model is well suited for this study because it achieves two distinct objectives: (i) it allows us to exploit the daily predictability of exchange rates when conditioning on commodity returns, and (ii) it also captures the long-run component of volatility and correlation that matches the lower frequency of economic fundamentals.

We focus on the returns of two assets: the foreign exchange (FX) return and the oil return. Following Ferraro, Rogoff and Rossi (2015), we condition FX returns on lagged oil returns. This is consistent with the finding that commodities can predict exchange rates out of sample at the daily frequency. The conditional mean specification for FX returns is as follows:

\[
\mu_{fx,i} = \mu_0 + \mu_1 r_{oil,i-1},
\]  

(1.1)
where $\mu_{fx,i}$ is the conditional FX mean return on day $i$, and $r_{oil,i-1}$ is the oil return on day $i-1$. Note that we do not condition oil returns on lagged FX returns, and hence $\mu_{oil,t} = \mu_{oil}$.

To simplify notation, in what follows we use the generic term $\mu$, whether $\mu$ is conditional as in the case of FX returns or unconditional as in the case of oil returns.

We use the DCC-MIDAS model as specified by Asgharian, Christiansen and Hou (2016). Consider the following process for the return on each of the two assets on day $i$ in month $t$:

$$r_{i,t} = \mu + \sqrt{\tau_t} g_{i,t} \varepsilon_{i,t}, \quad \varepsilon_{i,t} | F_{i-1,t} \sim N(0, 1), \quad i = 1, \ldots, N_t,$$  

(1.2)

where $N_t$ is the number of trading days in month $t$, and $F_{i-1,t}$ is the information set up to day $(i-1)$ of month $t$. Equation (1.2) decomposes the conditional variance $\sigma_{i,t}^2 = \tau_t g_{i,t}$ into the product of the short-run (daily) component $g_{i,t}$, and the long-run (monthly) component $\tau_t$.

The short-run component, $g_{i,t}$, is specified as a GARCH (1,1) process:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i,t-1},$$  

(1.3)

where $\alpha \geq 0$, $\beta \geq 0$, and $\alpha + \beta < 1$.

The long-run component $\tau_t$ follows a MIDAS regression:

$$\log (\tau_t) = m + \theta \sum_{k=1}^{K} \phi_k (w) X_{t-k}, \quad k = 1, \ldots, K,$$  

(1.4)

$$\phi_k (w) = \frac{(1 - k/K)^{w-1}}{\sum_{k=1}^{K} (1 - k/K)^{w-1}}.$$  

(1.5)

$X_t$ is a generic covariate, which we specify as either (i) the monthly realized volatility $RV_t = \sqrt{\sum_{i=1}^{N_t} r_{i,t}^2}$ or (ii) the monthly macro-finance factor $PCA_{j,t}$ (to be defined later). $K$ is the number of lags over which we smooth $X_{t-k}$. The weighting scheme for $\phi_k (w)$ guarantees a decaying pattern, where the rate of decay is determined by $w$. The smaller the
\( w \) the smoother the weights.

The conditional covariance between the FX and oil returns is given by:

\[
q_t = \bar{\rho}_t (1 - a - b) + a \varepsilon_{fx,t-1} \varepsilon_{oil,t-1} + bq_{t-1}, \tag{1.6}
\]

\[
\bar{\rho}_t = \frac{\exp(2z_t) - 1}{\exp(2z_t) + 1}, \tag{1.7}
\]

\[
z_t = m + \theta \sum_{k=1}^{K} \phi_k(w) X_{t-k}. \tag{1.8}
\]

In Equation (1.6), \( \varepsilon_{fx,t-1} \) and \( \varepsilon_{oil,t-1} \) are the standardized residuals from the univariate GARCH-MIDAS volatility model defined in Equation (1.2) above. Again, \( X_{t-k} \) is a generic covariate, which now is specified as either (i) the monthly realized correlation \( RC_t = \frac{\sum_{i=1}^{N_t} \varepsilon_{fx,i} \varepsilon_{oil,i}}{\sqrt{\sum_{k=1}^{N_t} \varepsilon_{fx,i}^2} \sqrt{\sum_{k=1}^{N_t} \varepsilon_{oil,i}^2}} \) or (ii) the monthly macro-finance factor \( PCA_{j,t} \) (again, to be defined later). \(^2\)

The model in Equation (1.6) can be written in matrix form as:

\[
Q_t = (1 - a - b) \tilde{R}_t + a \varepsilon_{t-1} \varepsilon'_{t-1} + bq_{t-1}. \tag{1.9}
\]

The matrix \( Q_t \) is a weighted average of three matrices and is always positive semi-definite if \( a \geq 0, b \geq 0 \) and \( a + b < 1 \). This is because the matrix \( \varepsilon_{t-1} \varepsilon'_{t-1} \) is always positive semi-definite by construction. Also, the matrix \( \tilde{R}_t \) is positive semi-definite if it computed as the weighted average of realized correlations as in Colacito, Engle and Ghysels (2011). In our analysis, we use Equation (1.8) to define the long-run correlation and we relate it to the covariate \( X_{t-k} \). We normalize the correlation in Equation (1.7) using the Fisher transformation, which follows Christodoulakis and Satchell (2002). This ensures that the off-diagonal elements of \( \tilde{R}_t \) are less than 1 in absolute value, and combined with the fact that the diagonal elements are all equal to 1, this fulfills the necessary conditions for the

\(^2\)Following Ghysels (2016), we use \( K = 36 \) months for the history of realized volatility in Equation (1.4) and \( K = 144 \) months for the history of realized correlation in Equation (1.8). Our simulations confirm that these values work well.
matrix to be positive semi-definite. This is true regardless of the weighting scheme in 
Equation (1.8) or the choice of the covariate $X_{t-k}$.

1.3 Empirical Results

1.3.1 Data on Exchange Rates, Commodities and Economic Fundamentals

Our empirical analysis employs data on spot exchange rates, commodity prices and a set 
of economic fundamentals. Following Ferraro, Rogoff and Rossi (2015), our main focus is 
on the predictive ability of oil prices on the US-Canadian dollar (USD/CAD) exchange rate 
because this is the typical pair of exchange rate and commodity examined in the literature. 
In the robustness section, we augment the scope of our study by considering additional 
exchange rates and commodities.

Daily data on the nominal USD/CAD spot exchange rate are obtained from Thomson 
Reuters Datastream. The exchange rate is defined as the US dollar price of a unit of foreign 
currency so that an increase in the exchange rate implies a depreciation of the US dollar. 
Daily data on the spot price of West Texas Intermediate (WTI) crude oil is also obtained 
from Thomson Reuters Datastream. We compute returns for exchange rates and oil by 
taking the difference between the log prices over two consecutive days. The sample period 
ranges from January 2, 1986 to December 31, 2015.

Our analysis also uses several economic fundamentals which, following Asgharian, 
Christiansen and Hou (2016), are divided in four groups: interest rates and prices, state of 
economy variables, uncertainty variables, and lagged returns. All economic fundamentals 
are monthly using end-of-month observations.

1. Group 1 on interest rates and prices includes the following variables:

   (a) the short-term interest rate spread between the US and Canada measured by the 
       yield difference in one-month Eurodeposit rates;
(b) the long-term interest rate spread between the US and Canada measured by the yield difference in 10-year bonds; and
(c) the inflation difference between the US and Canada measured by the log-difference of the seasonally adjusted monthly Consumer Price Index (CPI).

2. Group 2 on the state of economy includes the following variables:

   (a) the log-difference between the US and Canada in the monthly industrial production index; and
   (b) the log-difference between the US and Canada in the monthly money supply (M1).

All Group 1 and 2 variables are obtained from Thomson Reuters Datastream.

3. Group 3 on uncertainty includes the following variables:

   (a) the monthly TED spread defined as the difference between the 3-month LIBOR and the 3-month T-Bill rate; and
   (b) the VIX volatility index.

All Group 3 variables are obtained from the FRED database of the Federal Reserve Bank of St. Louis.

4. Group 4 simply includes the lagged monthly returns for FX and oil.

Given the large number of economic fundamentals, we combine their predictive information using principle component analysis. This is a standard approach in the literature (see, e.g., Neely, Rapach, Tu and Zhou, 2014); Asgharian, Christiansen and Hou, 2016). Specifically, we generate four additional macro-finance factors (\textit{PC 1}, \textit{PC 2}, \textit{PC 3}, \textit{PC 4}) using the first principle component for each group of economic fundamentals. We also generate a grand combination of all fundamentals (\textit{PC all}) by taking the first principle
component of all economic fundamentals. Table 1.1 reports descriptive statistics for all variables.

1.3.2 In-Sample Estimation

Univariate GARCH-MIDAS for Volatility

We begin our discussion of the in-sample estimation results by describing the model specifications used in our analysis. First, we estimate a set of univariate volatility models for the FX returns and the oil returns. In each case, the benchmark model is the standard GARCH. We augment the standard GARCH with a MIDAS specification which either conditions on realized variance (RV) or on a group of economic fundamentals (PC1, PC2, PC3, PC4, PC_all). The results are reported in Table 1.2.

Our findings indicate that using the AIC criterion the MIDAS specifications perform better than the standard GARCH. The best specification for exchange rates is GARCH-PC_all, which is the GARCH-MIDAS model that conditions on all economic fundamentals. Similarly, for oil returns GARCH-PC_all is one of the better performing models, only second to GARCH-PC_4. It is also noteworthy that the MIDAS parameters are statistically significant in most cases. Finally, the long-term component of FX return variance and oil return variance is plotted over time in Figures 1.1 and 1.2.

Multivariate DCC-MIDAS for Correlation

Next, we estimate several specifications of the DCC-MIDAS model for correlation. In this case, the benchmark model is the standard DCC with standard GARCH volatility. The DCC-MIDAS models augment the benchmark in three ways: first by conditioning on realized variance (RV) and realized correlation (RC); second, by conditioning on economic fundamentals in volatility and RC in correlation; and, finally, by conditioning on economic fundamentals in both volatility and correlation. The results are reported in Table 1.3.

3Note that the AIC criterion is exactly the same used by Asgharian, Christiansen and Hou (2016).
Our findings again indicate that the DCC-MIDAS specifications perform better than the standard DCC. This time, however, it is the RV/RC specification that performs the best. Although the MIDAS specifications conditioning on economic fundamentals outperform the standard DCC, they do not perform as well as the simpler RV/RC specification. Having said that, however, the $w$ parameter governing the MIDAS component tends to be significant for most specifications. This indicates that there is value in economic fundamentals. Finally, the short-term and long-term components of FX-oil return correlation are plotted over time in Figures 1.3 and 1.4.

In conclusion, the in-sample estimation results demonstrate that the MIDAS specifications dominate the performance of standard DCC-GARCH models. Therefore, it is important in modeling the dynamics of volatility and correlation to separate the short-term from the long-term component. In addition, low-frequency economic fundamentals have an important role in determining long-term volatility and correlation.

1.4 Out-of-Sample Analysis

All empirical models are evaluated out-of-sample relative to the random walk (RW) benchmark. Following Asgharian, Christiansen and Hou (2016), we generate out-of-sample forecasts for monthly returns, volatility and correlation using a 10-year rolling estimation window. For the DCC-MIDAS models, this requires an additional 12-year window that begins on the first sample observation (January 1986) to provide initial values for the dynamic correlations. Using these rolling estimates, we form monthly exchange rate forecasts for the spot USD/CAD returns and the spot oil returns. We also form monthly forecasts for volatilities and correlations using the long-run conditional variances and correlations from the DCC-MIDAS models. Given the initial estimation requirements, the out-of-sample period ranges from January 2008 to December 2015.
1.4.1 Statistical Evaluation

The statistical evaluation of out-of-sample predictability is based on the Mean Absolute Error (MAE) of the forecasts. Table 1.4 reports MAE for three cases: (1) the univariate GARCH-MIDAS for FX returns, where we compare the forecasted variance of alternative models to the realized variance (RV) of FX returns; (2) the univariate GARCH-MIDAS for oil returns, where we compare the forecasted variance of alternative models to the RV of oil returns; and (3) select specifications of the multivariate DCC-MIDAS for FX returns, where we compare the forecasted correlation of alternative models to the realized correlation between FX and oil returns. Our statistical evaluation is consistent with Asgharian, Christiansen and Hou (2016).

Our main findings can be summarized as follows. For the two univariate cases, the standard GARCH performs better than the RW benchmark. For FX returns only, two GARCH-MIDAS specifications (RV and PC 4) outperform the standard GARCH model. For the multivariate models, the most sophisticated PC all/RC model displays the same MAE as the benchmark RW model. In short, therefore, the statistical evaluation provides moderate out-of-sample evidence in favour of dynamic volatility and correlation with MIDAS structure.

1.4.2 Economic Evaluation

The Dynamic FX Strategy

The economic evaluation of out-of-sample predictability is based on the dynamic asset allocation methodology of Della Corte, Sarno and Tsiakas (2009, 2011, 2012). We begin by designing a dynamic trading strategy for a US investor who has a one-month horizon and constructs a dynamically rebalanced portfolio by allocating her wealth between a US bond, a Canadian bond and oil.

We focus on the PC all/RC specification for the DCC-MIDAS as opposed to the PC all/PC all because the latter is numerically infeasible to estimate every month out of sample.
Investing in the Canadian bond exposes the US investor to purely FX risk in the following way. At each period \( t + 1 \), the Canadian bond yields a riskless return in Canadian dollars but a risky return \( r_{t+1} \) in US dollars. The expected US dollar return of investing in the Canadian bond is equal to \( r_{t+1|t} = i_t^* + \mu_{fx,t+1} \), where \( r_{t+1|t} = E_t [r_{t+1}] \) is the conditional expectation of \( r_{t+1} \), \( i_t^* \) is the Canadian nominal interest rate, and \( \mu_{fx,t+1} = E_t [r_{fx,t+1}] \) is the conditional expectation of \( r_{fx,t+1} \). As the interest rate \( i_t^* \) is known in advance at time \( t \), the only risk the US investor is exposed to from time \( t \) to \( t + 1 \) by investing in the Canadian bond is FX risk. Similarly, investing in the US bond is riskless, and hence the riskless rate \( r_f \) is equal to the yield of the US bond.

In addition to FX risk, the investor is also subject to oil price risk. In other words, the trading strategy is designed to reflect changes in the variables that we model. In a more realistic trading strategy, an investor is more likely to trade futures contract in oil rather than taking a spot position in the physical commodity. We use spot contract in our hypothetical trading strategy because we model the returns, volatilities and correlations of spot oil returns as is standard in the FX literature on commodity currencies. It is likely that his assumptions do not affect our results substantively. Bessler and Wolff (2015) show that whether the investor trades commodity futures contracts or spot physical commodity, the optimal portfolios are very similar.

**Mean-Variance Asset Allocation**

Our analysis focuses on the maximum expected return strategy, which leads to an allocation on the efficient mean-variance frontier and is often used in active currency management (e.g., Della Corte, Sarno and Tsiakas, 2009, 2011, 2012). This strategy maximizes the expected portfolio return at each month \( t \) for a given target portfolio volatility:

\[
\max_{w_t} \ r_{p,t+1|t} = w_t' r_{t+1|t} + (1 - w_t') r_f \\
\text{s.t.} \quad \sigma_p^* = (w_t' \Sigma_{t+1|t} w_t)^{1/2},
\]

(1.10)
where $r_{t+1}$ denotes the $N \times 1$ vector of risky asset returns at time $t+1$, $\Sigma_{t+1|t} = E_t[(r_{t+1} - r_{t+1|t})(r_{t+1} - r_{t+1|t})']$ the $N \times N$ conditional variance-covariance matrix of $r_{t+1}$, $\sigma_p^*$ is the target conditional volatility of the portfolio returns, and $\iota$ is an $N \times 1$ vector of ones. We set $\sigma_p^* = 5\%$ to account for the low average volatilities of FX and oil.

The solution to the maximum expected return rule gives the following risky asset weights:

$$w_t = \frac{\sigma_p^*}{\sqrt{C_t}} \Sigma_{t+1|t}^{-1} (\mu_{t+1|t} - \iota r_f), \quad (1.11)$$

where $C_t = (\mu_{t+1|t} - \iota r_f)' \Sigma_{t+1|t}^{-1} (\mu_{t+1|t} - \iota r_f)$.

Then, the return on the investor’s portfolio is:

$$r_{p,t+1} = w_t' r_{t+1} + (1 - w_t') r_f. \quad (1.12)$$

Every month the investor takes two steps. First, she uses each model to forecast the one-month ahead returns, volatilities and correlations. Second, conditional on the forecasts of each model, she dynamically rebalances her portfolio by computing the new optimal weights. By design, in this setting the optimal weights will vary across models only to the extent that forecasts of the conditional mean, volatility and correlation will vary, which is precisely what the empirical models provide. Therefore, this setup assesses the predictive ability of the forecasts generated by the DCC-MIDAS model by informing us whether these forecasts lead to a better performing allocation strategy than conditioning on the benchmark RW model.

**Performance Evaluation**

We evaluate the performance of optimally rebalanced portfolios using the Sharpe ratio (SR) and the certainty equivalent return (CER). The Sharpe ratio is perhaps the most commonly used performance measure and is defined as the average excess return of a portfolio divided by the standard deviation of the portfolio returns.
The certainty equivalent return is defined as:

\[ CER = \left( \bar{r}_p - \frac{\gamma}{2} \sigma^2_p \right), \]  

(1.13)

where \( \bar{r}_p \) is the mean portfolio return, \( \gamma \) denotes the investor’s degree of relative risk aversion (RRA), and \( \sigma^2_p \) is the portfolio variance over the forecast evaluation period. The CER can be interpreted as the performance fee the risk-averse investor is willing to pay for switching from the riskless asset to the risky portfolio. We focus on the difference in CER (\( \Delta CER \)), which is equal to the CER of the portfolio generated by the forecasts of the alternative model minus the CER of the portfolio generated by the RW benchmark. \( \Delta CER \) measures the performance fee the risk-averse investor is willing to pay for switching from the risky portfolio generated by the benchmark model to the risky portfolio generated by the alternative model. We report \( \Delta CER \) in annualized basis points (bps).\(^5\)

**Results**

Table 1.4 reports the economic out-of-sample evaluation results for four select models: (1) the RW benchmark; (2) the standard DCC-GARCH model; (3) the DCC-MIDAS model with \( RV/RC \) covariates in volatility and correlation; and the augmented DCC-MIDAS model with \( PC \ all \) volatility and \( RC \) correlation specification. We report results for three degrees of relative risk aversion: \( \gamma = \{2, 6, 10\} \).

Our main findings can be summarized as follows. The worst performing model is the RW (annualized \( SR = -0.105 \)). Next is the standard DCC-GARCH model (\( SR = 0.137 \)). The two best performing models are the DCC-MIDAS, where \( PC \ all/RC \) outperforms the \( RV/RC \) specification (\( SR = 0.411 \) for the former vs. \( SR = 0.367 \) for the latter). This is also reflected in the \( \Delta CER \) values. For example, an investor with low risk aversion (\( \gamma = 2 \)) will pay 28 bps to use the more sophisticated \( PC \ all/RC \) DCC-MIDAS model as opposed

\(^5\)Note that the Sharpe ratio is a performance measure that is specific to a model, whereas \( \Delta CER \) is a relative performance measure for a model relative to the benchmark.
to the RW.\footnote{It is interesting to note that the less risk-averse the investor (hence the more she is willing to take risks), the more she values dynamic volatilities and correlations in asset allocation.}

We conclude, therefore, that the economic evaluation provides stronger out-of-sample evidence than the statistical evaluation. Specifically, the empirical evidence indicates that there is incremental value in (1) modeling the dynamics of volatilities and correlation with a DCC-GARCH model; (2) modeling separately the short term and long term dynamics of volatility and correlation with a DCC-MIDAS model; and (3) conditioning on economic fundamentals in dynamic volatility.

\subsection*{1.5 Robustness}

Following Ferraro, Rogoff and Rossi (2015), the main focus of our analysis is the USD/CAD for the exchange rate and oil for the commodity. In this section, we augment the scope of our study by considering the correlation between two additional pairs of exchange rates and commodities: the US-Norwegian (USD/NOK) exchange rate with oil prices, and the US-South African (USD/ZAR) exchange rate with gold prices. We estimate a set of select DCC-MIDAS specifications and report the estimation results in Table 1.5.

We find that the best performing model is the DCC-MIDAS with all economic fundamentals in both volatility and correlation. This is assessed using the AIC criterion and is the case for USD/NOK and for USD/ZAR. Furthermore, the MIDAS-DCC parameter is statistically significant. We conclude, therefore, that our main results are not specific to the USD/CAD. They also hold for additional exchange rates and commodities among the group of commodity currencies typically investigated in this line of research. Overall, this is further evidence that the DC-MIDAS model is a powerful tool for assessing the dynamics of volatility and correlation between exchange rates and commodities.
A central issue relating to commodity currencies is the correlation between exchange rate returns and commodity returns. We study the short-term and long-term dynamics of this correlation. We also link this correlation to a large set of economic fundamentals. Our empirical analysis is based on the dynamic conditional correlation model with mixed data sampling (DCC-MIDAS) of Colacito, Engle and Ghysels (2011). This model is well suited to achieve the stated objectives of our study.

We find that the best performing models for volatility and correlation are those using the MIDAS specification, which decomposes the short-term dynamics from the long-term dynamics of volatility and correlation. In addition, conditioning on economic fundamentals improves the MIDAS specification, especially for volatility. Finally, the DCC-MIDAS model delivers sizeable economic value for a mean-variance investor who implements an out-of-sample dynamic asset allocation strategy facing exchange rate risk and commodity price risk. These results hold for the standard case of the US-Canadian dollar exchange rate and oil prices but are also confirmed for the US-Norwegian krone and oil prices and the US-South African Rand and gold prices.
Table 1.1: Descriptive Statistics

The table reports descriptive statistics for daily FX returns, daily oil returns and monthly macro-finance factors. FX return is the spot daily return of the USD/CAD exchange rate. Oil return is the spot daily return of WTI crude oil. The macro-finance factors are based on the first principal component of the following economic fundamentals: $PC_1$ is based on the difference of the one-month interest rate ($i_{1M}$), the difference of the 10-year bond yield ($i_{10Y}$) and the log difference in the consumer price index ($p$); $PC_2$ is based on the log difference of the industrial production index ($y$) and the log difference of the money supply ($m$); $PC_3$ is based on the TED spread and the VIX volatility index; $PC_4$ is based on the lagged FX ($r_{fx,i-1}$) and oil returns ($r_{oil,i-1}$); and $PC_{all}$ is based on all economic fundamentals. (Log) differences are the (log of the) US variable minus the (log of the) Canadian variable and are indicated by a $\Delta$. $N$ is the number of observations. The sample period ranges from January 1986 to December 2015.

<table>
<thead>
<tr>
<th>Panel A: FX and Oil Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>FX Return Daily</td>
</tr>
<tr>
<td>Oil Return Daily</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Macro-Finance Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>PC 1 Monthly</td>
</tr>
<tr>
<td>PC 2 Monthly</td>
</tr>
<tr>
<td>PC 3 Monthly</td>
</tr>
<tr>
<td>PC 4 Monthly</td>
</tr>
<tr>
<td>PC all Monthly</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Correlations of PC with with Economic Fundamentals</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta i_{1M}$</td>
</tr>
<tr>
<td>PC 1</td>
</tr>
<tr>
<td>PC 2</td>
</tr>
<tr>
<td>PC 3</td>
</tr>
<tr>
<td>PC 4</td>
</tr>
<tr>
<td>PC all</td>
</tr>
</tbody>
</table>
Table 1.2: Univariate GARCH-MIDAS Estimation Results

The table displays the parameter estimates for several univariate GARCH-MIDAS models applied on daily FX and oil returns. AIC is the Akaike information criterion. The sample period ranges from January 1986 to December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>$\mu_0$</th>
<th>$\mu_1$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\theta$</th>
<th>$w$</th>
<th>$m$</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: FX Returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard GARCH</td>
<td>$1 \times 10^{-6}$</td>
<td>0.009***</td>
<td>0.07***</td>
<td>0.93***</td>
<td></td>
<td></td>
<td></td>
<td>-57907</td>
</tr>
<tr>
<td>GARCH-RV</td>
<td>$1 \times 10^{-6}$</td>
<td>0.009***</td>
<td>0.11***</td>
<td>0.88***</td>
<td>5.11</td>
<td>5.24</td>
<td>0.04</td>
<td>-57335</td>
</tr>
<tr>
<td>GARCH-PC 1</td>
<td>$1 \times 10^{-6}$</td>
<td>0.009***</td>
<td>0.04***</td>
<td>0.96***</td>
<td>-0.01</td>
<td>5.58</td>
<td>-12.0</td>
<td>-57923</td>
</tr>
<tr>
<td>GARCH-PC 2</td>
<td>$1 \times 10^{-6}$</td>
<td>0.009***</td>
<td>0.05***</td>
<td>0.95***</td>
<td>2.12***</td>
<td>3.63</td>
<td>-22.2</td>
<td>-57990</td>
</tr>
<tr>
<td>GARCH-PC 3</td>
<td>$1 \times 10^{-6}$</td>
<td>0.009***</td>
<td>0.04***</td>
<td>0.96***</td>
<td>0.03***</td>
<td>49.7*</td>
<td>-11.6***</td>
<td>-57977</td>
</tr>
<tr>
<td>GARCH-PC 4</td>
<td>$1 \times 10^{-6}$</td>
<td>0.009***</td>
<td>0.04***</td>
<td>0.96***</td>
<td>-2.94</td>
<td>24.0</td>
<td>-11.6***</td>
<td>-57926</td>
</tr>
<tr>
<td>GARCH-PC all</td>
<td>$1 \times 10^{-6}$</td>
<td>0.009***</td>
<td>0.04***</td>
<td>0.96***</td>
<td>-0.03***</td>
<td>49.7*</td>
<td>-11.6***</td>
<td>-57977</td>
</tr>
<tr>
<td><strong>Panel B: Oil Returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard GARCH</td>
<td>$4 \times 10^{-6}$</td>
<td>0.08***</td>
<td>0.92***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-34281</td>
</tr>
<tr>
<td>GARCH-RV</td>
<td>$3 \times 10^{-4}$</td>
<td>0.13***</td>
<td>0.87***</td>
<td>0.29</td>
<td>21.8</td>
<td>0.05</td>
<td></td>
<td>-34067</td>
</tr>
<tr>
<td>GARCH-PC 1</td>
<td>$2 \times 10^{-4}$</td>
<td>0.08***</td>
<td>0.91***</td>
<td>-0.22***</td>
<td>1.00***</td>
<td>-6.91***</td>
<td></td>
<td>-34288</td>
</tr>
<tr>
<td>GARCH-PC 2</td>
<td>$2 \times 10^{-4}$</td>
<td>0.08***</td>
<td>0.92***</td>
<td>0.44**</td>
<td>42.3</td>
<td>-9.26***</td>
<td></td>
<td>-34278</td>
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<tr>
<td>GARCH-PC 3</td>
<td>$2 \times 10^{-4}$</td>
<td>0.10***</td>
<td>0.89***</td>
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<td>4.80***</td>
<td>-0.11</td>
<td></td>
<td>-33435</td>
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<tr>
<td>GARCH-PC 4</td>
<td>$2 \times 10^{-4}$</td>
<td>0.07***</td>
<td>0.93***</td>
<td>-9.71***</td>
<td>49.5***</td>
<td>-7.00***</td>
<td></td>
<td>-34296</td>
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<tr>
<td>GARCH-PC all</td>
<td>$2 \times 10^{-4}$</td>
<td>0.08***</td>
<td>0.91***</td>
<td>-0.05***</td>
<td>10.8***</td>
<td>-8.33***</td>
<td></td>
<td>-34294</td>
</tr>
</tbody>
</table>
**Table 1.3: Multivariate DCC-MIDAS Estimation Results**

The table displays the parameter estimates for several multivariate DCC-MIDAS models applied on daily FX and oil returns. AIC is the Akaike information criterion. The sample period ranges from January 1986 to December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th>GARCH</th>
<th>DCC</th>
<th>a</th>
<th>b</th>
<th>w</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard</td>
<td>Standard</td>
<td>0.02***</td>
<td>0.97***</td>
<td></td>
<td>59001</td>
</tr>
<tr>
<td>RV</td>
<td>RC</td>
<td>0.02***</td>
<td>0.98***</td>
<td>2.73*</td>
<td>24664</td>
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<tr>
<td>PC 1</td>
<td>RC</td>
<td>0.01***</td>
<td>0.99***</td>
<td>1.01</td>
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</tr>
<tr>
<td>PC 2</td>
<td>RC</td>
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<td>0.98***</td>
<td>1.01*</td>
<td>26955</td>
</tr>
<tr>
<td>PC 3</td>
<td>RC</td>
<td>0.01***</td>
<td>0.98***</td>
<td>1.01***</td>
<td>31370</td>
</tr>
<tr>
<td>PC 4</td>
<td>RC</td>
<td>0.01***</td>
<td>0.98***</td>
<td>3.57</td>
<td>26284</td>
</tr>
<tr>
<td>PC all</td>
<td>RC</td>
<td>0.01***</td>
<td>0.98***</td>
<td>5.69</td>
<td>27001</td>
</tr>
<tr>
<td>PC 1</td>
<td>PC 1</td>
<td>0.01***</td>
<td>0.99***</td>
<td>2.63*</td>
<td>26141</td>
</tr>
<tr>
<td>PC 2</td>
<td>PC 2</td>
<td>0.01***</td>
<td>0.99***</td>
<td>16.8</td>
<td>26141</td>
</tr>
<tr>
<td>PC 3</td>
<td>PC 3</td>
<td>0.01***</td>
<td>0.99***</td>
<td>5.17</td>
<td>26142</td>
</tr>
<tr>
<td>PC 4</td>
<td>PC 4</td>
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<td>0.99***</td>
<td>1.00*</td>
<td>26146</td>
</tr>
<tr>
<td>PC all</td>
<td>PC all</td>
<td>0.05***</td>
<td>0.95***</td>
<td>5.00*</td>
<td>26205</td>
</tr>
</tbody>
</table>
Table 1.4: Out-of-Sample Evaluation

The table shows the out-of-sample statistical and economic evaluation of select multivariate DCC-MIDAS models. We form monthly exchange rate forecasts for the spot USD/CAD returns and the spot oil returns for the out-of-sample period of January 2008 to December 2015. The results are based on a 10-year rolling estimation window that begins in January 1998 plus an additional 12-year window that begins in January 1986 to provide initial values on the dynamic correlations. For the statistical evaluation, we compute the Mean Absolute Error (MAE) of the forecasts. For the economic evaluation, we build a maximum expected return strategy subject to a target portfolio volatility $\sigma_p^* = 5\%$ for a US investor who each month dynamically rebalances her portfolio investing in a domestic US bond, a Canadian bond and oil. For each portfolio, we report the annualized Sharpe ratio ($SR$), and the certainty equivalent return ($\Delta CER$) a risk-averse investor is willing to pay to switch from the benchmark random walk strategy to a competing strategy. $\Delta CER$ is expressed in annual basis points and is reported for three degrees of relative risk aversion.

<table>
<thead>
<tr>
<th>GARCH</th>
<th>DCC</th>
<th>MAE</th>
<th>SR</th>
<th>$\Delta CER$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RW</td>
<td>RW</td>
<td>0.207</td>
<td>−0.105</td>
<td>$RRA = 2$</td>
</tr>
<tr>
<td>Standard</td>
<td>Standard</td>
<td>0.335</td>
<td>0.137</td>
<td>7.0</td>
</tr>
<tr>
<td>RV</td>
<td>RC</td>
<td>0.423</td>
<td>0.367</td>
<td>24.4</td>
</tr>
<tr>
<td>PC all</td>
<td>RC</td>
<td>0.207</td>
<td>0.411</td>
<td>28.1</td>
</tr>
</tbody>
</table>
Table 1.5: Robustness: Other Exchange Rates and Commodities

The table displays the parameter estimates for selective multivariate DCC-MIDAS models applied on two cases: the Norwegian Krone and Oil; and the South African rand and Gold. AIC is the Akaike information criterion. The sample period ranges from January 1986 to December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th>GARCH</th>
<th>DCC</th>
<th>a</th>
<th>b</th>
<th>w</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Norwegian Krone and Oil</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard</td>
<td>Standard</td>
<td>0.01***</td>
<td>0.99***</td>
<td></td>
<td>29962</td>
</tr>
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<td>RV</td>
<td>RC</td>
<td>0.01*</td>
<td>0.92***</td>
<td>2.75*</td>
<td>26284</td>
</tr>
<tr>
<td>PC all</td>
<td>RC</td>
<td>0.01*</td>
<td>0.89***</td>
<td>3.07*</td>
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<tr>
<td>PC all</td>
<td>PC all</td>
<td>0.09**</td>
<td>0.91***</td>
<td>4.98</td>
<td>26175</td>
</tr>
<tr>
<td>Panel B: South African Rand and Gold</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard</td>
<td>Standard</td>
<td>0.02***</td>
<td>0.95***</td>
<td></td>
<td>33483</td>
</tr>
<tr>
<td>RV</td>
<td>RC</td>
<td>0.02***</td>
<td>0.93***</td>
<td>2.29*</td>
<td>26401</td>
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<tr>
<td>PC all</td>
<td>RC</td>
<td>0.02***</td>
<td>0.96***</td>
<td>1.01***</td>
<td>27804</td>
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<tr>
<td>PC all</td>
<td>PC all</td>
<td>0.04***</td>
<td>0.97***</td>
<td>5.00</td>
<td>26302</td>
</tr>
</tbody>
</table>
Figure 1.1: The Long-Run Component of FX Return Variance

The figure plots the realized monthly FX return variance against the estimated long-run variance of the GARCH-MIDAS model. The top graph is for the model that uses only realized variance (RV) in the MIDAS equation and the bottom graph is for the model that uses the first principal component (PC) of all macro-finance variables in the MIDAS equation.
Figure 1.2: The Long-Run Component of Oil Return Variance

The figure plots the realized monthly oil return variance against the estimated long-run variance of the GARCH-MIDAS model. The top graph is for the model that uses only realized variance (RV) in the MIDAS equation and the bottom graph is for the model that uses the first principal component (PC) of all macro-finance variables in the MIDAS equation.
Figure 1.3: The Short-Run Component of FX-Oil Return Correlation

The figure plots the estimated short-run correlation for two specifications of the DCC-MIDAS model: the one that uses only realized correlation (RC) in the MIDAS equation and the one that uses the first principal component (PC) of all macro-finance variables in the MIDAS equation.
Figure 1.4: The Long-Run Component of FX-Oil Return Correlation

The figure plots the realized monthly FX-oil return correlation against the estimated long-run correlation of the DCC-MIDAS model. The top graph is for the model that uses only realized correlation (RC) in the MIDAS equation and the bottom graph is for the model that uses the first principal component (PC) of all macro-finance variables in the MIDAS equation.
CHAPTER 2
ON THE DIRECTION OF CAUSALITY BETWEEN BUSINESS
AND FINANCIAL CYCLES: EVIDENCE FROM INDIVIDUAL
COUNTRIES

2.1 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 are 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 chapter 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 indus-

\(^1\)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.
trial 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 industrial production index causes quarterly aggregate credit or vice versa. We also determine the timing of when causality is statistically significant. 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. 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 based on the standard Wald

\(^2\)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.
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.\(^3\)

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

\(^3\)See Breitung and Swanson (2002) for a detailed discussion of these issues.
are traded among investors (such as 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 chapter 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.

2.2 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.

2.2.1 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 2.1 reports descriptive statistics on the real annual growth rates of the two variables.

2.2.2 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 busi-
ness 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).

2.2.3 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.”
2.2.4 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 co-incide 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.4

Table 2.2 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.

2.3 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 economy. In contrast, aggregate credit, which is the standard determinant of the financial

---

4We 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.
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.

2.3.1 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 $\tau \in \{1, \ldots, T\}$ denotes the quarterly time index, $k \in \{1, \ldots, m\}$ 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:

$$X(\tau) = [\tilde{x}_M(\tau), x_Q(\tau)]', \quad (2.1)$$
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 $x_Q$.

### 2.3.2 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 $x_M \not\rightarrow x_Q(\tau + h)|F(\tau)$, if:

$$P[x_Q(\tau + h)|F(\tau)] = P[x_Q(\tau + h)|x_Q(-\infty, \tau)] \quad \forall \tau. \quad (2.2)$$

Equation (2.2) 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 $x_Q \not\rightarrow \tilde{x}_M(\tau + h)|F(\tau)$, if:

$$P[\tilde{x}_M(\tau)|F(\tau)] = P[\tilde{x}_M(\tau + h)|\tilde{x}_M(-\infty, \tau)] \quad \forall \tau. \quad (2.3)$$

Equation (2.3) 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 $x_Q$. 

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2.3.3 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:

\[
\begin{pmatrix}
1 & 0 & 0 & 0 \\
-d & 1 & 0 & 0 \\
0 & -d & 1 & 0 \\
0 & 0 & 0 & 1 \\
\end{pmatrix}
\begin{pmatrix}
x_M(\tau, 1) \\
x_M(\tau, 2) \\
x_M(\tau, 3) \\
x_Q(\tau) \\
\end{pmatrix}
\equiv N
= 
\begin{pmatrix}
0 & 0 & d & c_1 \\
0 & 0 & 0 & c_2 \\
0 & 0 & 0 & c_3 \\
0 & 0 & b_1 & b_2 & b_3 & a \\
\end{pmatrix}
\begin{pmatrix}
x_M(\tau - 1, 1) \\
x_M(\tau - 1, 2) \\
x_M(\tau - 1, 3) \\
x_Q(\tau - 1) \\
\end{pmatrix}
\equiv M
+ 
\begin{pmatrix}
\epsilon_M(\tau, 1) \\
\epsilon_M(\tau, 2) \\
\epsilon_M(\tau, 3) \\
\epsilon_Q(\tau) \\
\end{pmatrix}
\equiv \epsilon(\tau),
\]

or

\[
NX(\tau) = MX(\tau - 1) + \epsilon(\tau).
\] (2.4)

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:

\[
X(\tau) = AX(\tau - 1) + \epsilon(\tau),
\] (2.6)

where

\[
A = N^{-1}M = 
\begin{pmatrix}
0 & 0 & d & \sum_{i=1}^1 d^{1-i}c_i \\
0 & 0 & d^2 & \sum_{i=1}^2 d^{2-i}c_i \\
0 & 0 & d^3 & \sum_{i=1}^3 d^{3-i}c_i \\
0 & 0 & b_1 & b_2 & b_3 & a \\
\end{pmatrix}
\]
2.3.4 Causality Tests

I. 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):

\[ x_Q(\tau) = \alpha_0 + \sum_{p=1}^{P} \alpha_p x_Q(\tau - p) + \sum_{r=1}^{R} \beta_r x_M(\tau - 1, r) + \varepsilon(\tau). \] (2.7)

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.

II. Does quarterly credit cause monthly industrial production?
We test whether quarterly credit causes monthly industrial production by estimating the following regression with OLS:

\[ x_Q(\tau) = \alpha_0 + \sum_{p=1}^{P} \alpha_p x_Q(\tau - p) + \sum_{r=1}^{R} \beta_r x_M(\tau - 1, r) + \sum_{s=1}^{S} \gamma_s x_M(\tau + 1, s) + \varepsilon(\tau). \] (2.8)

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 (2.7) and (2.8) 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

\[ \varepsilon(\tau) = N^{-1}\varepsilon(\tau). \] 5

\[ ^{5}\text{For notational simplicity, in this specification we ignore the vector of constants, but we add it later to the notation used for the causality tests.} \]
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 null hypothesis that $\gamma_s = 0$ for all $s$ using a Wald test statistic. Again, the Wald test statistic is based on a bootstrap method with a heteroskedasticity-robust covariance matrix.\(^6\)

**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 ($R = S = 12$).\(^7\) 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 (2.7) 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.\(^8\)

### 2.3.5 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 re-

---

\(^6\)Note that this framework is broadly consistent with the Max test statistic for causality, which is discussed later for robustness.

\(^7\)This implies that for each causality test we test 12 zero restrictions.

\(^8\)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.
gressions as in Equations (2.7) and (2.8), the only difference being that monthly industrial production is replaced by quarterly industrial production. As a result, all lags are set at 4 quarters. The VAR structure remains the same but now all variables are quarterly.

2.4 Results

2.4.1 Individual Countries

We begin by assessing the extent, significance and direction of Granger causality between business cycles and financial cycles of individual countries. Table 2.3 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 2.1, 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 2.3 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 2.3 are complemented by Figures 2.1 and 2.2, 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 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

\(^9\)The first data point is for January 1960 but since we are computing the annual growth rate, the analysis effectively begins on January 1961.
and credit causing IPI in Canada. In addition, in almost all cases, bidirectional causality is significant around the 2007-2008 financial crisis.

2.4.2 Is Causality Cyclical?

Having established the bidirectional causality of domestic business and financial 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 2.4 has the mixed frequency results. 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.

2.4.3 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, 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.

From Table 2.5, we find that 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.

2.5 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)).

2.5.1 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 2.6 reports descriptive statistics for the real annual growth rates of the housing and equity price indexes.
2.5.2 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 2.7.

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.

2.6 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.
2.6.1 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:

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

(2.9)

where $m = 3$ is the frequency difference. Each regression requires estimation of only $P + 2$ parameters, which thus avoids the parameter proliferation problem. Recall that for the Wald test, Equation (2.7) 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:

$$\max_{1 \leq r \leq R} \left( \sqrt{T} w' \hat{\beta} \right)^2,$$

(2.10)

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 $\sum_{r=1}^{R} w_r = 1$.

2.6.2 Max Test: Quarterly-to-Monthly Causality

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

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

(2.11)

Now, each regression requires estimation of $P + R + 2$ parameters in contrast to Equation (2.8) for the Wald test that requires estimation of $P + R + S + 1$ parameters.

---

The second term $x_M(\tau - 1, m + 1 - r)$ in equation (2.9) indicates the monthly variable in the past, for example, given the frequency difference $m$ equals to 3, when the monthly lag equals to 5, or $r = 5$, then we have $x_M(\tau - 1, -1)$ representing the variable of the third month in quarter $\tau - 2$. 

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

\[
\max_{1 \leq s \leq S} \left( \sqrt{T} w' \hat{\gamma} \right)^2,
\]

(2.12)

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.

### 2.6.3 Max Test: Results

The full empirical evidence for IPI, Credit, HPI and EPI is reported in Table 2.8. 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.

### 2.7 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.

This chapter 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; and (2) the causal relation is bidirectional: business cycles cause financial cycles and vice versa. Overall, these findings indicate that in several countries Main Street and Wall Street are not only correlated but are in fact causing each other.
Table 2.1: 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.

<table>
<thead>
<tr>
<th>Sample Period</th>
<th>Mean</th>
<th>SDev</th>
<th>Skew</th>
<th>Kurt</th>
<th>Min</th>
<th>Max</th>
<th>AR(1)</th>
<th>Corr</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: USA</strong></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industrial production</td>
<td>2.63</td>
<td>4.76</td>
<td>-1.11</td>
<td>5.15</td>
<td>-16.64</td>
<td>12.56</td>
<td>0.98</td>
<td>0.50</td>
</tr>
<tr>
<td>Credit</td>
<td>3.23</td>
<td>4.92</td>
<td>-0.63</td>
<td>2.99</td>
<td>-12.89</td>
<td>12.52</td>
<td>0.96</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: Canada</strong></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Industrial production</td>
<td>2.65</td>
<td>5.32</td>
<td>-0.52</td>
<td>3.53</td>
<td>-16.80</td>
<td>15.77</td>
<td>0.96</td>
<td>0.18</td>
</tr>
<tr>
<td>Credit</td>
<td>6.66</td>
<td>5.68</td>
<td>0.20</td>
<td>3.28</td>
<td>-8.82</td>
<td>22.28</td>
<td>0.95</td>
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</tr>
<tr>
<td><strong>Panel C: UK</strong></td>
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</tr>
<tr>
<td>Industrial production</td>
<td>0.96</td>
<td>3.98</td>
<td>-0.55</td>
<td>5.31</td>
<td>-12.72</td>
<td>20.40</td>
<td>0.89</td>
<td>0.44</td>
</tr>
<tr>
<td>Credit</td>
<td>5.17</td>
<td>5.67</td>
<td>-0.06</td>
<td>2.69</td>
<td>-8.86</td>
<td>18.30</td>
<td>0.96</td>
<td></td>
</tr>
<tr>
<td><strong>Panel D: Germany</strong></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industrial production</td>
<td>2.28</td>
<td>5.57</td>
<td>-1.27</td>
<td>7.57</td>
<td>-27.67</td>
<td>16.07</td>
<td>0.91</td>
<td>0.30</td>
</tr>
<tr>
<td>Credit</td>
<td>3.67</td>
<td>3.83</td>
<td>0.07</td>
<td>2.13</td>
<td>-3.03</td>
<td>12.24</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td><strong>Panel E: Japan</strong></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Industrial production</td>
<td>2.87</td>
<td>8.07</td>
<td>-1.07</td>
<td>7.14</td>
<td>-40.55</td>
<td>24.15</td>
<td>0.96</td>
<td>0.44</td>
</tr>
<tr>
<td>Credit</td>
<td>3.35</td>
<td>5.12</td>
<td>0.46</td>
<td>2.58</td>
<td>-7.43</td>
<td>17.46</td>
<td>0.96</td>
<td></td>
</tr>
</tbody>
</table>
Table 2.2: Business and Financial Cycles

The table reports the mean of $100 \times \log$-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).

<table>
<thead>
<tr>
<th></th>
<th>USA</th>
<th>Canada</th>
<th>UK</th>
<th>Germany</th>
<th>Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IPI</td>
<td>Credit</td>
<td>IPI</td>
<td>Credit</td>
<td>IPI</td>
</tr>
<tr>
<td>Severe Recession</td>
<td>−0.85</td>
<td>0.06</td>
<td>−0.24</td>
<td>−0.54</td>
<td>−0.29</td>
</tr>
<tr>
<td>Recession</td>
<td>−0.68</td>
<td>0.53</td>
<td>−0.11</td>
<td>0.69</td>
<td>−0.13</td>
</tr>
<tr>
<td>Expansion</td>
<td>0.37</td>
<td>1.01</td>
<td>0.48</td>
<td>1.45</td>
<td>0.25</td>
</tr>
<tr>
<td>Strong Expansion</td>
<td>0.41</td>
<td>1.17</td>
<td>0.57</td>
<td>2.61</td>
<td>0.25</td>
</tr>
</tbody>
</table>
Table 2.3: 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 $\rightarrow$ 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 2.1. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>USA</th>
<th>Canada</th>
<th>UK</th>
<th>Germany</th>
<th>Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Quarterly Frequency</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPI $\rightarrow$ Credit</td>
<td>0.011**</td>
<td>0.001***</td>
<td>0.374</td>
<td>0.116</td>
<td>0.001***</td>
</tr>
<tr>
<td>Credit $\rightarrow$ IPI</td>
<td>0.002***</td>
<td>0.021**</td>
<td>0.001***</td>
<td>0.424</td>
<td>0.014**</td>
</tr>
<tr>
<td><strong>Panel B: Mixed Frequency</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPI $\rightarrow$ Credit</td>
<td>0.015**</td>
<td>0.002***</td>
<td>0.560</td>
<td>0.159</td>
<td>0.004***</td>
</tr>
<tr>
<td>Credit $\rightarrow$ IPI</td>
<td>0.007***</td>
<td>0.009***</td>
<td>0.001***</td>
<td>0.785</td>
<td>0.008***</td>
</tr>
</tbody>
</table>
Table 2.4: 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 significantly caused credit in the USA 88% of the time during severe recessions.

<table>
<thead>
<tr>
<th></th>
<th>USA</th>
<th>Canada</th>
<th>UK</th>
<th>Germany</th>
<th>Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: IPI → Credit</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Severe Recession</td>
<td>0.88</td>
<td>0.45</td>
<td>0.67</td>
<td>0.73</td>
<td>0.71</td>
</tr>
<tr>
<td>Recession</td>
<td>0.70</td>
<td>0.56</td>
<td>0.58</td>
<td>0.58</td>
<td>0.78</td>
</tr>
<tr>
<td>Expansion</td>
<td>0.93</td>
<td>0.53</td>
<td>0.49</td>
<td>0.58</td>
<td>0.72</td>
</tr>
<tr>
<td>Strong Expansion</td>
<td>0.93</td>
<td>0.51</td>
<td>0.47</td>
<td>0.50</td>
<td>0.63</td>
</tr>
<tr>
<td><strong>Panel B: Credit → IPI</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Severe Recession</td>
<td>0.75</td>
<td>0.90</td>
<td>0.67</td>
<td>0.63</td>
<td>0.45</td>
</tr>
<tr>
<td>Recession</td>
<td>0.70</td>
<td>0.92</td>
<td>0.60</td>
<td>0.53</td>
<td>0.43</td>
</tr>
<tr>
<td>Expansion</td>
<td>0.41</td>
<td>0.91</td>
<td>0.86</td>
<td>0.46</td>
<td>0.37</td>
</tr>
<tr>
<td>Strong Expansion</td>
<td>0.42</td>
<td>0.87</td>
<td>0.81</td>
<td>0.36</td>
<td>0.29</td>
</tr>
</tbody>
</table>
The table presents evidence on the relation between causality and the nominal interest rate. The table shows the estimates from the probit model: \( P_{i,t} = \alpha_i + \beta_i r_{i,t} + \epsilon_{i,t} \), 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 \( t \). The numbers in parentheses are the p-values of the coefficients \( \beta_i \).

<table>
<thead>
<tr>
<th></th>
<th>Individual Countries</th>
<th></th>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>USA</td>
<td>Canada</td>
<td>UK</td>
<td>Germany</td>
<td>Japan</td>
</tr>
<tr>
<td>IPI → Credit</td>
<td>−0.25</td>
<td>0.34</td>
<td>−0.10</td>
<td>−0.13</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.01)</td>
<td>(&lt;0.01)</td>
<td>(&lt;0.01)</td>
<td>(&lt;0.01)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Credit → IPI</td>
<td>0.08</td>
<td>0.42</td>
<td>0.03</td>
<td>−0.07</td>
<td>−0.02</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.01)</td>
<td>(&lt;0.01)</td>
<td>(0.38)</td>
<td>(0.05)</td>
<td>(0.71)</td>
</tr>
</tbody>
</table>
Table 2.6: Descriptive Statistics for Housing and Equity Price

The table reports descriptive statistics for $100 \times$ 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.

<table>
<thead>
<tr>
<th>Sample Period</th>
<th>Begin</th>
<th>End</th>
<th>Mean</th>
<th>SDev</th>
<th>Skew</th>
<th>Kurt</th>
<th>Min</th>
<th>Max</th>
<th>AR(1)</th>
<th>Corr with Credit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<tr>
<td><strong>Panel A: USA</strong></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Housing price</td>
<td>1984M1</td>
<td>2016M6</td>
<td>0.57</td>
<td>1.35</td>
<td>0.03</td>
<td>3.42</td>
<td>−3.04</td>
<td>4.78</td>
<td>0.96</td>
<td>0.33</td>
</tr>
<tr>
<td>Equity price</td>
<td>1971M1</td>
<td>2016M6</td>
<td>5.78</td>
<td>17.08</td>
<td>−0.90</td>
<td>4.13</td>
<td>−62.32</td>
<td>44.20</td>
<td>0.94</td>
<td>0.06</td>
</tr>
<tr>
<td><strong>Panel B: Canada</strong></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Housing price</td>
<td>1970M1</td>
<td>2016M6</td>
<td>−0.16</td>
<td>1.70</td>
<td>0.14</td>
<td>3.38</td>
<td>−4.87</td>
<td>4.87</td>
<td>0.96</td>
<td>0.17</td>
</tr>
<tr>
<td>Equity price</td>
<td>1971M1</td>
<td>2016M6</td>
<td>5.28</td>
<td>18.45</td>
<td>−0.55</td>
<td>3.81</td>
<td>−60.83</td>
<td>56.12</td>
<td>0.94</td>
<td>0.19</td>
</tr>
<tr>
<td><strong>Panel C: UK</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Housing price</td>
<td>1984M1</td>
<td>2016M6</td>
<td>3.00</td>
<td>9.12</td>
<td>−0.11</td>
<td>3.22</td>
<td>−23.75</td>
<td>25.31</td>
<td>0.98</td>
<td>0.61</td>
</tr>
<tr>
<td>Equity price</td>
<td>1971M1</td>
<td>2016M6</td>
<td>5.38</td>
<td>19.52</td>
<td>−1.41</td>
<td>7.83</td>
<td>−94.51</td>
<td>69.66</td>
<td>0.93</td>
<td>0.15</td>
</tr>
<tr>
<td><strong>Panel D: Germany</strong></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Housing price</td>
<td>1970M1</td>
<td>2016M6</td>
<td>0.47</td>
<td>1.54</td>
<td>1.46</td>
<td>6.42</td>
<td>−2.42</td>
<td>6.66</td>
<td>0.95</td>
<td>0.53</td>
</tr>
<tr>
<td>Equity price</td>
<td>1971M1</td>
<td>2016M6</td>
<td>5.33</td>
<td>21.99</td>
<td>−0.54</td>
<td>3.60</td>
<td>−78.56</td>
<td>61.65</td>
<td>0.94</td>
<td>0.12</td>
</tr>
<tr>
<td><strong>Panel E: Japan</strong></td>
<td></td>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Housing price</td>
<td>1971M1</td>
<td>2016M6</td>
<td>0.38</td>
<td>1.88</td>
<td>−1.58</td>
<td>9.74</td>
<td>−9.49</td>
<td>6.05</td>
<td>0.96</td>
<td>0.36</td>
</tr>
<tr>
<td>Equity price</td>
<td>1971M1</td>
<td>2016M6</td>
<td>4.00</td>
<td>23.17</td>
<td>−0.17</td>
<td>3.25</td>
<td>−64.37</td>
<td>72.12</td>
<td>0.95</td>
<td>0.30</td>
</tr>
</tbody>
</table>
Table 2.7: 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 $\rightarrow$ 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 2.1 and 2.6. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>USA</th>
<th>Canada</th>
<th>UK</th>
<th>Germany</th>
<th>Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Quarterly Frequency</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HPI $\rightarrow$ Credit</td>
<td>0.010***</td>
<td>0.110</td>
<td>0.003***</td>
<td>0.145</td>
<td>0.093*</td>
</tr>
<tr>
<td>Credit $\rightarrow$ HPI</td>
<td>0.003***</td>
<td>0.320</td>
<td>0.004***</td>
<td>0.889</td>
<td>0.001***</td>
</tr>
<tr>
<td>EPI $\rightarrow$ Credit</td>
<td>0.009***</td>
<td>0.459</td>
<td>0.622</td>
<td>0.071*</td>
<td>0.267</td>
</tr>
<tr>
<td>Credit $\rightarrow$ EPI</td>
<td>0.677</td>
<td>0.251</td>
<td>0.069*</td>
<td>0.965</td>
<td>0.009***</td>
</tr>
<tr>
<td><strong>Panel B: Mixed Frequency</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HPI $\rightarrow$ Credit</td>
<td>0.001***</td>
<td>0.206</td>
<td>0.024**</td>
<td>0.205</td>
<td>0.003***</td>
</tr>
<tr>
<td>Credit $\rightarrow$ HPI</td>
<td>0.129</td>
<td>0.200</td>
<td>0.023**</td>
<td>0.531</td>
<td>0.001***</td>
</tr>
<tr>
<td>EPI $\rightarrow$ Credit</td>
<td>0.004***</td>
<td>0.306</td>
<td>0.891</td>
<td>0.124</td>
<td>0.090*</td>
</tr>
<tr>
<td>Credit $\rightarrow$ EPI</td>
<td>0.297</td>
<td>0.494</td>
<td>0.069*</td>
<td>0.774</td>
<td>0.010***</td>
</tr>
</tbody>
</table>
Table 2.8: 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 $\rightarrow$ 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 2.1 and 2.6. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>USA</th>
<th>Canada</th>
<th>UK</th>
<th>Germany</th>
<th>Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPI $\rightarrow$ Credit</td>
<td>0.152</td>
<td>0.008***</td>
<td>0.826</td>
<td>0.197</td>
<td>0.057*</td>
</tr>
<tr>
<td>Credit $\rightarrow$ IPI</td>
<td>0.001***</td>
<td>0.206</td>
<td>0.002***</td>
<td>0.387</td>
<td>0.030**</td>
</tr>
<tr>
<td>HPI $\rightarrow$ Credit</td>
<td>0.012**</td>
<td>0.198</td>
<td>0.079*</td>
<td>0.086*</td>
<td>0.074</td>
</tr>
<tr>
<td>Credit $\rightarrow$ HPI</td>
<td>0.002***</td>
<td>0.017**</td>
<td>0.033**</td>
<td>0.477</td>
<td>0.001***</td>
</tr>
<tr>
<td>EPI $\rightarrow$ Credit</td>
<td>0.020**</td>
<td>0.264</td>
<td>0.468</td>
<td>0.067*</td>
<td>0.659</td>
</tr>
<tr>
<td>Credit $\rightarrow$ EPI</td>
<td>0.334</td>
<td>0.244</td>
<td>0.228</td>
<td>0.798</td>
<td>0.011**</td>
</tr>
</tbody>
</table>
Figure 2.1: 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.
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 2.3: Industrial Production Causing Credit - Quarterly Frequency

The figure plots the $p$-value for the quarterly frequency Wald test used to assess the causality from the aggregated quarterly industrial production index to quarterly credit. The $p$-value is estimated using a 20-year rolling window.
The figure plots the $p$-value for the quarterly frequency Wald test used to assess the causality from quarterly credit to the aggregated quarterly industrial production index. The $p$-value is estimated using a 20-year rolling window.
Figure 2.5: Industrial Production → Credit: Max Test

The figure plots the $p$-value for the mixed frequency MAX 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 2.6: Credit Causing Industrial Production - MAX Test

The figure plots the $p$-value for the mixed frequency MAX 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.
CHAPTER 3
ON THE DIRECTION OF CAUSALITY BETWEEN BUSINESS
AND FINANCIAL CYCLES: EVIDENCE ON THE US AS A
GLOBAL LEADER

3.1 Introduction

This chapter extends the analysis of the previous chapter by assessing the role of the US as a global leader in causing the business and financial cycles of other countries. There is a growing literature on the impact of the US on global real production and financial conditions. Borio, McCauley, and McGuire (2011) note that the US is exporting its credit boom to the global credit markets through the international role played by US dollar credit. The US dollar credit to borrowers outside the United States amounted to $11.5 trillion in 2018, or 14% of global GDP.¹ Laeven and Tong (2012), Georgiadis (2016), and Nitschka (2018) find that global risk factors are affected by US monetary policy, which is the global financial system’s central country. In addition to US monetary policy, Miniane and Rogers (2007), Feldkircher and Huber (2016), and Du and Rousse (2018) find that shocks from US real production spread to the global real output market through the interest rate.

In this context, the empirical questions this chapter addresses are the following: (i) do US business and financial cycles cause the business and financial cycles of other countries?; (ii) if a causal relation exists, does it change over time? To be more specific, is the causal relation more likely to appear in recession or expansion periods?; and (iii) are there spillover effects from US real production shocks and aggregate credit shocks to the business and financial cycles of other countries? To address these questions, we implement the

¹Data for US dollar credit to borrowers outside the US is obtained from Bank for International Settlement. The data of global GDP is obtained from the World Bank.
mixed frequency vector autoregression (MF-VAR) model developed by Ghysels, Hill, and Motegi (2016, 2018). The data on business cycles is based on monthly industrial production, which is observed at a higher frequency than data on financial cycles that is based on quarterly aggregate credit. The advantage of using the MF-VAR model has been discussed in Chapter 2.

Our empirical investigation focuses on five industrialized countries: USA, Canada, UK, Germany and Japan. We test the Granger causality with both mixed frequency (monthly industrial production and quarterly credit) and aggregated quarterly data over the sample period from 1960 to 2016. To examine whether US industrial production (or credit) causes the industrial production (or credit) of each of the other four countries, we pair the US with one other country and test the Granger causality using full data sample. We then assess whether causality is related to the phase of the cycles, e.g., whether the causal relationship between the US business cycle and the UK financial cycle is stronger in recessions or expansions.

In addition, we examine whether shocks from US real production (or credit) have an impact on the industrial production (or credit) of each of the other four countries by implementing the impulse response analysis from the MF-VAR model. Finally, we employ the standard quarterly frequency vector autoregression (LF-VAR) model for robustness check.

Our main finding is that the US business cycle strongly causes the business cycle of Canada, UK and Germany. This causal relation is strong at all times but is stronger during bad times. The US financial cycle is causing the financial cycles of UK and Japan. There is little evidence that the US business cycle is causing other countries’ financial cycles, nor the US financial cycle is causing other countries’ business cycles. Furthermore, we find that there exist spillover effects from the shocks in the US real production to the global business cycles. We typically find that shocks from the second and third months of a US quarter have stronger impacts on the foreign business cycles than the first month of the US quarter. That further justifies the use of mixed frequency data.
Our empirical analysis is mainly motivated by Claessens, Kose, and Terrones (2012), and Rapach, Strauss, and Zhou (2013). Claessens, Kose, and Terrones (2012) primary contribution is to show that 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. Rapach, Strauss, and Zhou (2013) perform an analysis for equity markets and find that the US is a global leader because it causes the movements of other international equity markets.

The main motivation for this chapter’s focus on the spillover effects from the US industrial production and credit shocks stems from Borio, McCauley, and McGuire (2011), Nitschka (2018), and Ghysels (2016). Nitschka (2018), and Borio, McCauley, and McGuire (2011) investigate the spillover effects from the US real production (or credit) shocks to the other countries’ real production (or credit), but not a causal relation between the US real production (or credit) and the foreign countries’ real production (or credit). Meanwhile, their results are based on the same frequency data analysis, e.g., impacts from monthly shocks on monthly variables. Ghysels (2016) points out that policy analysis usually requires mixed frequency data. For example, some high frequency vectors (i.e. monthly industrial production) that contain real production shocks, will have different impulse responses to the low frequency vectors (i.e. quarterly aggregate credit). The MF-VAR model is able to investigate the impulse response functions of the quarterly credit from each monthly production shocks. Thus, it is more appropriate for policy analysis.

Finally, motivated by Miniane and Rogers (2007), Feldkircher and Huber (2016), and Du and Rousse (2018), which indicate the role of interest rate in spreading the shocks from the US to the rest of the world. We examine whether the interest rate will change the significance of the Granger causality in our empirical work. The result shows that causality is high when the US interest rate is higher compared to other countries.

The remainder of the chapter 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 quarterly frequency and mixed frequency data is set out in Section 3. In Section 4, we report the empirical results. Finally, we conclude in Section 5.

3.2 Business and Financial Cycles

3.2.1 Data

We assess the role of the US as a global leader in causing the business and financial cycles for four countries: Canada, UK, Germany and Japan. We use the same data as in Chapter 2. See section 2.2.1 for a detailed description. In brief, the main variables of our analysis are monthly industrial production index which is a standard measure of real economic activity used to determine the business cycle, and quarterly aggregate credit, which is the link between savings and investment used to determine the financial cycle. Table 2.1 reports descriptive statistics on the real annual growth rates of the two variables.

3.2.2 Defining Business and Financial Cycles

The business and financial cycles are defined exactly the same as in Chapter 2. See Section 2.2.3 for a detailed description.

3.2.3 Interaction of Business and Financial Cycles

The growth rates for monthly industrial production and quarterly aggregate credit during the four phases are presented in Table 2.2. For all countries, growth rates of IPI and credit are monotonically increasing when we move from a severe recession to strong expansion. This finding indicates that the credit growth and real output growth are correlated globally, which is consistent with previous literature (e.g., Georgiadis (2016); Du and Rousse (2018)).

In addition to the global interaction between business and financial cycles, emerging literature (e.g., Borio, McCauley, and McGuire (2011); Feldkircher and Huber (2016); Laeven and Tong (2012)) indicates the global financial markets are strongly affected by
the US real economic activities and financial markets. Having thus established this international leadership of the US, the natural question to consider next is whether the US is a global leader in causing the domestic cycles of other countries.

3.3 Causality Tests

Our empirical set up is similar to that described in Chapter 2. The main difference is that we focus on the role of the US as a global leader in causing the business and financial cycles of another country. Specifically, we assess the Granger causality between US monthly industrial production or US quarterly aggregate credit and the monthly industrial production or quarterly aggregate credit of an other country. To do this, we pair the US with one of the other country and test whether US industrial production (or credit) causes the industrial production (or credit) of another country. For example, pairing US with UK, the Granger causality tests include: (1) US IPI causing UK IPI; (2) US IPI causing UK credit; (3) US credit causing UK IPI; (4) US credit causing UK financial cycle; (5) UK IPI causing US IPI; (6) UK IPI causing US credit; (7) UK credit causing US IPI; (8) UK credit causing US financial cycle. Since we want to investigate the role of the US as a global leader, our empirical analysis will focus on the causality tests (1), (2), (3), and (4).

Our empirical analysis uses mixed frequency vector autoregression (MF-VAR) model for Granger causality test, because the industrial production is monthly and aggregated credit is quarterly. In addition to the MF-VAR model, a benchmark model using quarterly frequency is applied to our empirical analysis. By aggregating the monthly industrial production to the quarterly frequency, the benchmark model uses quarterly frequency vector autoregression (LF-VAR) for Granger causality test. Our empirical analysis relies primarily on mixed frequency causality tests since existing literature (e.g., Breitung and Swanson (2002) and Ghysels (2016) shows temporal aggregation might exhibit spurious causality.

In what follows, we describe the two sets of causality test models, MF-VAR and LF-VAR. 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.

3.3.1 MF-VAR

In the context of the MF-VAR model, 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 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:

$$
\begin{bmatrix}
\tilde{x}_M^U(\tau) \\
\tilde{x}_M^D(\tau) \\
\tilde{x}_Q^U(\tau) \\
\tilde{x}_Q^D(\tau)
\end{bmatrix} = \sum_{p=1}^{P} A_p
\begin{bmatrix}
\tilde{x}_M^U(\tau - p) \\
\tilde{x}_M^D(\tau - p) \\
\tilde{x}_Q^U(\tau - p) \\
\tilde{x}_Q^D(\tau - p)
\end{bmatrix}
+ \begin{bmatrix}
\tilde{\epsilon}_M^U(\tau) \\
\tilde{\epsilon}_M^D(\tau) \\
\tilde{\epsilon}_Q^U(\tau) \\
\tilde{\epsilon}_Q^D(\tau)
\end{bmatrix}, \quad (3.1)
$$

where $\tilde{x}_M^U(\tau) = [x_M^U(\tau, 1), x_M^U(\tau, 2), x_M^U(\tau, 3)]'$ 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; $x_Q^U(\tau)$ and $x_Q^D(\tau)$ are the quarterly US and domestic variables respectively; $\tilde{\epsilon}_M^U(\tau) = [\epsilon_M^U(\tau, 1), \epsilon_M^U(\tau, 2), \epsilon_M^U(\tau, 3)]'$ and $\tilde{\epsilon}_M^D(\tau) = [\epsilon_M^D(\tau, 1), \epsilon_M^D(\tau, 2), \epsilon_M^D(\tau, 3)]'$ are the monthly error terms respectively; and $\tilde{\epsilon}_Q^U(\tau)$ and $\tilde{\epsilon}_Q^D(\tau)$ 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.\(^2\) 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. Note that the Wald test follows Ghysels, Hill, and Motegi (2016) and is based on a bootstrap method with a heteroskedasticity-robust covariance matrix.

\(^2\)The set up of causality tests for individual countries in isolation is described in Chapter 2.
3.3.2 LF-VAR

In the context of the LF-VAR model, we test whether US industrial production (or credit) causes the industrial production (or credit) of another country at quarterly frequency. Similar as the MF-VAR model, the MF-VAR model is specified as follows:

\[
\begin{bmatrix}
\bar{x}^U_M(\tau) \\
\bar{x}^D_M(\tau) \\
x^U_Q(\tau) \\
x^D_Q(\tau)
\end{bmatrix}
= \sum_{p=1}^{P} A_p
\begin{bmatrix}
\bar{x}^U_M(\tau - p) \\
\bar{x}^D_M(\tau - p) \\
x^U_Q(\tau - p) \\
x^D_Q(\tau - p)
\end{bmatrix}
+ \begin{bmatrix}
\varepsilon^U_M(\tau) \\
\varepsilon^D_M(\tau) \\
\varepsilon^U_Q(\tau) \\
\varepsilon^D_Q(\tau)
\end{bmatrix},
\tag{3.2}
\]

where \(\bar{x}^U_M = x^U_M(\tau, 1) + x^U_M(\tau, 2) + x^U_M(\tau, 3)\), and \(\bar{x}^D_M = x^D_M(\tau, 1) + x^D_M(\tau, 2) + x^D_M(\tau, 3)\) are the quarterly aggregated US and domestic industrial production respectively; \(x^U_Q(\tau)\) and \(x^D_Q(\tau)\) are the quarterly US and domestic credit respectively. We set \(P = 2\) quarterly lags which is consistent with the MF-VAR model.

3.4 Results

3.4.1 Is the US a Global Leader?

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. Both the mixed frequency and quarterly frequency results are reported in Table 3.1.

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. For the causality direction from US credit to the credit of other countries, the \(p\)-value is significant for UK and Japan in both mixed frequency and quarterly frequency models.
The other causal relations are predominantly insignificant, the results indicate 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. The US financial cycle causes the business cycle of UK and Japan. Compared to the impact from financial market, the role of the US as a global leadership is stronger and more common in terms of real economic activities.

## 3.4.2 Is Causality Cyclical?

Having established 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 3.2, Figure 3.1 and 3.2 have the mixed frequency results. Figure 3.3 and 3.4 have the quarterly frequency results.

Comparing Figure 3.1 (Figure 3.2) with Figure 3.3 (Figure 3.4), both mixed frequency and low frequency models present the similar results. The results are 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.
3.4.3 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. 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 3.3.

We find 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.

3.4.4 The Impacts from the US Shocks

In order to investigate the impact of shocks from US monthly IPI (or quarterly credit) on the monthly IPI (or quarterly credit) of each of the other four countries, we implement the impulse response analysis from the MF-VAR model.

Figures 3.5 to 3.8 display the mixed frequency impulse response curves. Each of the figures shows the impacts from US monthly industrial production (or quarterly credit) shocks to the industrial production (or credit) of one of the other four countries. Among these figures, the first three rows are the impulse responses of the foreign country’s monthly industrial production, and the last row is the impulse response of the foreign country’s quarterly credit. The first three columns are the impacts of the US monthly industrial production shocks, and the last column is the impact of the US quarterly credit shock. For example, the sub-figure on the upper left in Figure 3.5 shows the impulse response curve of industrial
production of Canada in January (or April, July, October), with respect to a shock from US industrial production in January (or April, July, October). Take the sub-figure on the upper right in Figure 3.5 as another example, this sub-figure shows the impulse response curve in terms of industrial production of Canada in January (or April, July, October), with respect to a shock from US aggregate quarterly credit.

For the monthly shocks from the US industrial production, the impulse responses of the foreign countries’ industrial production are significant. Specifically, from column 1 to 3 in figure 3.5 to 3.8, most of the impulse response curves are significantly different than zero for at least 4 quarters. In addition, we find that shocks from the second and third months of a US quarter have stronger impacts on the foreign business cycles than the first month of the US quarter. This is reflected by the fact that almost all sub-figures in the second and third columns present impulse response curves with the inverted-U shape, and the curves are significantly above zero. On the other hand, most of the sub-figures in the 1st column have a flat impulse response curve which is close to zero.

For the quarterly shocks from the US credit, almost all the impulse response curves of the foreign industrial production are flat and close to zero. This indicates that, compared to the US industrial production shocks, US credit shocks have less impact on the global industrial production. On the other hand, the impulse response curves of the foreign credit, are only significant in UK and Japan. This is similar to the result as we discussed in Section 3.4.1, the US credit shocks have significant impacts only on UK and Japan.

In conclusion, we find that there exist spillover effects from US real production shocks to the business cycles in each of the other four countries. Shocks from the second and third months of a US quarter have stronger impacts on the foreign business cycles than the first month of the US quarter. This result further justifies the use of mixed frequency data. The significance of impacts from US credit shocks are different across countries.
3.5 Conclusion

Motivated by historically prominent the role of the US in global economic and financial activity, this chapter quantifies the leadership of the US in causing the business and financial cycles of other countries. In addition, we assess whether causality is related to the phase of the US and foreign business and financial cycles, e.g., whether the causal relation between the US and one other country is stronger in recessions or expansions.

Our analysis is based on both mixed frequency vector autoregression and standard low frequency vector autoregression models. We find that the US is a global leader in that the US business cycle causes the business cycles of all other countries. This relation is true at all times but is especially strong during recessions. On the other hand, the causality between the US and the other countries’ financial cycles varies over different countries. There is a significant causal relation between financial cycles in some cases (e.g., US and UK, US and Japan), but insignificant in other cases (e.g., US and Canada, US and Germany). Overall, these findings indicate that the US business cycle is causing the global business cycles, and the causal relation between the US and global financial cycles is more determined by the characteristics of the receiving country.
Table 3.1: 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, “IPI\textsubscript{USA} → Credit\textsubscript{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.

<table>
<thead>
<tr>
<th></th>
<th>Canada</th>
<th>UK</th>
<th>Germany</th>
<th>Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Quarterly Frequency</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPI\textsubscript{USA} → IPI\textsubscript{Other}</td>
<td>0.001***</td>
<td>0.001***</td>
<td>0.004***</td>
<td>0.023**</td>
</tr>
<tr>
<td>IPI\textsubscript{USA} → Credit\textsubscript{Other}</td>
<td>0.194</td>
<td>0.636</td>
<td>0.582</td>
<td>0.142</td>
</tr>
<tr>
<td>Credit\textsubscript{USA} → IPI\textsubscript{Other}</td>
<td>0.681</td>
<td>0.962</td>
<td>0.424</td>
<td>0.162</td>
</tr>
<tr>
<td>Credit\textsubscript{USA} → Credit\textsubscript{Other}</td>
<td>0.997</td>
<td>0.058*</td>
<td>0.899</td>
<td>0.104</td>
</tr>
<tr>
<td><strong>Panel B: Mixed Frequency</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPI\textsubscript{USA} → IPI\textsubscript{Other}</td>
<td>0.003***</td>
<td>0.046**</td>
<td>0.055*</td>
<td>0.155</td>
</tr>
<tr>
<td>IPI\textsubscript{USA} → Credit\textsubscript{Other}</td>
<td>0.194</td>
<td>0.706</td>
<td>0.174</td>
<td>0.058*</td>
</tr>
<tr>
<td>Credit\textsubscript{USA} → IPI\textsubscript{Other}</td>
<td>0.768</td>
<td>0.677</td>
<td>0.141</td>
<td>0.275</td>
</tr>
<tr>
<td>Credit\textsubscript{USA} → Credit\textsubscript{Other}</td>
<td>0.322</td>
<td>0.100*</td>
<td>0.911</td>
<td>0.021**</td>
</tr>
</tbody>
</table>
Table 3.2: 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 significantly caused IPI Canada 71% of the time during severe recessions according to the US cycle.

<table>
<thead>
<tr>
<th>Panel A: USA causing Canada</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{IPI}<em>{\text{USA}} \rightarrow \text{IPI}</em>{\text{Canada}}$</td>
<td>$\text{Credit}<em>{\text{USA}} \rightarrow \text{Credit}</em>{\text{Canada}}$</td>
</tr>
<tr>
<td>Severe Recession</td>
<td>0.71</td>
</tr>
<tr>
<td>Recession</td>
<td>0.74</td>
</tr>
<tr>
<td>Expansion</td>
<td>0.57</td>
</tr>
<tr>
<td>Strong Expansion</td>
<td>0.57</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: USA causing UK</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{IPI}<em>{\text{USA}} \rightarrow \text{IPI}</em>{\text{UK}}$</td>
<td>$\text{Credit}<em>{\text{USA}} \rightarrow \text{Credit}</em>{\text{UK}}$</td>
</tr>
<tr>
<td>US Cycle</td>
<td>UK Cycle</td>
</tr>
<tr>
<td>Severe Recession</td>
<td>0.57</td>
</tr>
<tr>
<td>Recession</td>
<td>0.43</td>
</tr>
<tr>
<td>Expansion</td>
<td>0.29</td>
</tr>
<tr>
<td>Strong Expansion</td>
<td>0.21</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: USA causing Germany</th>
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</thead>
<tbody>
<tr>
<td>$\text{IPI}<em>{\text{USA}} \rightarrow \text{IPI}</em>{\text{Germany}}$</td>
<td>$\text{Credit}<em>{\text{USA}} \rightarrow \text{Credit}</em>{\text{Germany}}$</td>
</tr>
<tr>
<td>US Cycle</td>
<td>Germany Cycle</td>
</tr>
<tr>
<td>Severe Recession</td>
<td>0.88</td>
</tr>
<tr>
<td>Recession</td>
<td>0.85</td>
</tr>
<tr>
<td>Expansion</td>
<td>0.74</td>
</tr>
<tr>
<td>Strong Expansion</td>
<td>0.71</td>
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</table>

<table>
<thead>
<tr>
<th>Panel D: USA causing Japan</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{IPI}<em>{\text{USA}} \rightarrow \text{IPI}</em>{\text{Japan}}$</td>
<td>$\text{Credit}<em>{\text{USA}} \rightarrow \text{Credit}</em>{\text{Japan}}$</td>
</tr>
<tr>
<td>US Cycle</td>
<td>Japan Cycle</td>
</tr>
<tr>
<td>Severe Recession</td>
<td>0.00</td>
</tr>
<tr>
<td>Recession</td>
<td>0.21</td>
</tr>
<tr>
<td>Expansion</td>
<td>0.52</td>
</tr>
<tr>
<td>Strong Expansion</td>
<td>0.47</td>
</tr>
</tbody>
</table>
Table 3.3: Causality Tests: The Role of Interest Rates

The table presents evidence on the relation between causality and the nominal interest rate. The table 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 $\beta_i$.

<table>
<thead>
<tr>
<th>The US as a Global Leader</th>
<th>The US as a Global Leader</th>
<th>The US as a Global Leader</th>
<th>The US as a Global Leader</th>
<th>The US as a Global Leader</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPI$<em>{USA}$ $\rightarrow$ IPI$</em>{Other}$</td>
<td>IPI$<em>{USA}$ $\rightarrow$ Credit$</em>{Other}$</td>
<td>Credit$<em>{USA}$ $\rightarrow$ IPI$</em>{Other}$</td>
<td>Credit$<em>{USA}$ $\rightarrow$ Credit$</em>{Other}$</td>
<td></td>
</tr>
<tr>
<td>Canada</td>
<td>UK</td>
<td>Germany</td>
<td>Japan</td>
<td></td>
</tr>
<tr>
<td>$-8.25$</td>
<td>$-19.44$</td>
<td>$0.22$</td>
<td>$2.34$</td>
<td></td>
</tr>
<tr>
<td>$(0.13)$</td>
<td>$(&lt;0.01)$</td>
<td>$(0.91)$</td>
<td>$(0.49)$</td>
<td></td>
</tr>
<tr>
<td>$-34.37$</td>
<td>$-15.82$</td>
<td>$1.27$</td>
<td>$-1.30$</td>
<td></td>
</tr>
<tr>
<td>$(&lt;0.01)$</td>
<td>$(&lt;0.01)$</td>
<td>$(0.50)$</td>
<td>$(0.70)$</td>
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</tr>
<tr>
<td>$1.21$</td>
<td>$5.91$</td>
<td>$0.30$</td>
<td>$-5.35$</td>
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</tr>
<tr>
<td>$(0.86)$</td>
<td>$(0.15)$</td>
<td>$(0.88)$</td>
<td>$(0.15)$</td>
<td></td>
</tr>
<tr>
<td>$11.91$</td>
<td>$-10.25$</td>
<td>$1.02$</td>
<td>$-42.20$</td>
<td></td>
</tr>
<tr>
<td>$(0.04)$</td>
<td>$(0.04)$</td>
<td>$(0.66)$</td>
<td>$(&lt;0.01)$</td>
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</tr>
</tbody>
</table>
Figure 3.1: 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 3.2: 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.
Figure 3.3: US Industrial Production as a Global Leader - Quarterly Frequency

The figure plots the p-value for the quarterly frequency Wald test used to assess the causality from the US aggregate quarterly 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 3.4: US Credit as a Global Leader - Quarterly Frequency

The figure plots the p-value for the quarterly frequency Wald test used to assess the causality from the US quarterly credit to another country’s aggregated quarterly industrial production index or quarterly credit. The p-value is estimated using a 20-year rolling window.
Figure 3.5: Impulse Response: US and Canada

The figure plots the impulse response curves from the MF-VAR model. In each sub-figures, the x-axis represents the quarters after the shock, the y-axis represents the impulse response of Canada. The shocks in the first three columns are from the US industrial production in the 1st, 2nd and 3rd month of each quarter respectively. The shock in the last column is from the US quarterly aggregate credit. The first three rows are the impulse response curves of industrial production for Canada in the 1st, 2nd and 3rd month of each quarter respectively. The last row is the impulse response curve of quarterly aggregated credit in Canada. The red lines display the 90% statistical inference.
Figure 3.6: Impulse Response: US and UK

The figure plots the impulse response curves from the MF-VAR model. In each sub-figure, the x-axis represents the quarters after the shock, the y-axis represents the impulse response of UK. The shocks in the first three columns are from the US industrial production in the 1st, 2nd and 3rd month of each quarter respectively. The shock in the last column is from the US quarterly aggregate credit. The first three rows are the impulse response curves of industrial production for UK in the 1st, 2nd and 3rd month of each quarter respectively. The last row is the impulse response curve of quarterly aggregated credit in UK. The red lines display the 90% statistical inference.
Figure 3.7: Impulse Response: US and Germany

The figure plots the impulse response curves from the MF-VAR model. In each sub-figure, the x-axis represents the quarters after the shock, the y-axis represents the impulse response of Germany. The shocks in the first three columns are from the US industrial production in the 1st, 2nd and 3rd month of each quarter respectively. The shock in the last column is from the US quarterly aggregate credit. The first three rows are the impulse response curves of industrial production for Germany in the 1st, 2nd and 3rd month of each quarter respectively. The last row is the impulse response curve of quarterly aggregated credit in Germany. The red lines display the 90% statistical inference.
Figure 3.8: Impulse Response: US and Japan

The figure plots the impulse response curves from the MF-VAR model. In each sub-figure, the x-axis represents the quarters after the shock, the y-axis represents the impulse response of Japan. The shocks in the first three columns are from the US industrial production in the 1st, 2nd and 3rd month of each quarter respectively. The shock in the last column is from the US quarterly aggregate credit. The first three rows are the impulse response curves of industrial production for Japan in the 1st, 2nd and 3rd month of each quarter respectively. The last row is the impulse response curve of quarterly aggregated credit in Japan. The red lines display the 90% statistical inference.


