ESSAYS ON COMMODITY PRICE SHOCKS, BANK RISK, AND MARKET VOLATILITY FORECASTING

by

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Abstract

My dissertation has three main chapters. Chapter 2 develops a structural dynamic factor model that estimates the effects of commodity price shocks on the Canadian macroeconomy, bank lending and bank risk. Unlike most literature treating commodity price changes as exogenous, I identify global structural shocks driving real commodity prices and find that global demand and commodity market–specific shocks are crucial. These two shocks are shown to have quite different implications for bank lending and risk, which confirms the importance of disentangling shocks driving commodity price changes. I also discover that on average, the total loan growth and the noninterest income ratio of large Canadian banks are more responsive to the above two commodity price shocks than those of small Canadian banks.

Chapter 3, coauthored with Tian Xie, studies how to better forecast the daily market volatility (VIX) index. We propose utilizing the ordinary least square post–least absolute shrinkage and selection operator (OLS post–Lasso) from Belloni and Chernozhukov (2013) to select the predictors and estimate the coefficients for a heterogeneous autoregressive (HAR) model (Corsi, 2009). In an out–of–sample analysis with the VIX data, our proposed OLS post–Lasso HAR (OLHAR) model generates a different combination of predictors from those ex ante imposed by the standard HAR model. Moreover, the OLHAR model shows its dominance over the standard
HAR and other competitor models at forecasting the VIX either weekly, biweekly, or monthly ahead.

Chapter 4 develops a tail risk forecasting system tailored to Canada and provides a set of one-quarter ahead forecasts of tail real and financial risk by factor–based conditional quantile projections. My model forecasts the steepest decline in GDP–Oil at 2009Q2, and the peaks of the nonperforming loan (NPL) ratios of Bank of Montreal (BMO) and Canadian Imperial Bank of Commerce (CIBC) at 2010Q2 and 2010Q3, respectively. For BMO and CIBC, the banking factors contribute the most to the peaks of the Value at Risk (VaR) forecasts of the NPL ratios. The commodity price factors also compose a prominent portion of the total contribution from the global factors.
Co-Authorship

I hereby declare that this thesis incorporates material that is result of joint research, as follows: Chapter 3, “Forecasting the CBOE Market Volatility Index with OLS post-Lasso Heterogenous Autoregression”, is co-authored with Tian Xie at Xiamen University in China. In all cases, the key ideas, the literature review, acquisition of data, experimental design, data analysis, interpretation, and writing were performed by author Yue Qiu, and the contribution of co-author Tian Xie was primarily through the provision of computation coding, the statistical proof and tabulating results; Tian Xie also provided feedback on refinement of ideas and editing of the manuscript.
Dedication

I would like to dedicate this thesis to my whole family for their constant encouragement, love and support both spiritually and financially. All these would not have been possible without you.
Firstly, I would like to express my most heartfelt thanks to my Ph.D advisor Prof. Frank Milne for inspiring me with an interesting topic, the valuable support, expertise and guidance on my Ph.D thesis. His mentoring leads me in all the time of research and writing of this thesis. He makes me realize that strong interests shall be the only motivation that keeps you pursuing new knowledge. I am also deeply grateful to Prof. Beverly Lapham and Prof. Allan Gregory for their many helpful insights and suggestions.

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Chapter 1

Introduction

There is growing empirical evidence, see Carvalho and Gabaix (2013) and Crean and Milne (2015), that macroeconomic fluctuations and loan credit risks may originate from shocks generated by certain sectors. By this insight, I study the effects of world commodity price fluctuations on banks and the real economy in the context of a small commodity exporting economy (SCEE), as the commodity sector is a systemically important real sector for SCEEs.

The majority of the literature studies either the macroeconomic effects of commodity price shocks in isolation from banks (Blanchard and Gali, 2007; Kilian, 2009; Cèspedes and Velasco, 2012; Gubler and Hertweck, 2013), or the effects of monetary policy shocks on banks and the macroeconomy (Jimboræan and Mésonnier, 2010; Dave, Dressler, and Zhang, 2013; Buch, Eickmeier, and Prieto, 2014b). Relatively few has evaluated the effects of commodity price shocks on banks. Thus, Chapter 2 contributes to filling the gap in the literature.

Extending the framework in Boivin and Giannoni (2008), I propose a structural dynamic factor model that studies the propagation mechanisms of commodity price shocks on the macroeconomy and banks in a SCEE and allows explicitly for dynamic
interactions with the global economy. For any individual bank, bank risk is measured by the ratios of NPLs and noninterest income, and bank lending is measured by its total loan growth. I construct three median banks from sub-samples of Big Six, foreign subsidiaries and other local banks so as to facilitate comparison. After identifying the commodity price shocks by sign restrictions and a recursive identification scheme, I analyze their respective effects on key macroeconomic variables, bank lending and risk.

After estimation of the model by a Bayesian estimation procedure, I find that real commodity prices are mostly driven by global demand and commodity market-specific shocks rather than global inflation shocks during the sample period (1996Q1-2016Q1). Average bank risk, as measured by the NPL ratio, declines, average bank lending increases and average noninterest income ratio increases after an expansionary global demand shock. However, a negative commodity market-specific shock that raises real commodity prices more than an expansionary global demand shock, produces an opposite result. Moreover, I find that the total loan growth and noninterest income ratio are more responsive for the median Big Six and foreign subsidiary, with higher total assets than the median other local bank. This aligns with the findings of Chen, Damar, Soubra, and Terajima (2012) on Canadian banks but differs from those of Diamond and Rajan (2006) and Kashyap and Stein (2000), that small banks are more responsive to macroeconomic shocks than large banks because small banks have a lower net worth, a lack of diversification and less diversified funding.

Chapter 3 forecasts the daily VIX, a measure of the U.S. equity market risk. The literature suggests forecasting realized volatility measures with the standard HAR model, because it well approximates long memory in volatility series (Corsi, 2009)
and is easy to estimate. Fernandes, Medeiros, and Scharth (2014) prove that the standard HAR better forecasts the VIX. However, few papers statistically validate the choice of predictors of the standard HAR model. There is an exception of Audrino and Knaus (2016).

In Chapter 3, we propose first selecting the set of predictors for the standard HAR model with Lasso method. Then the relevant coefficients are estimated by the OLS. The above procedure is based on the OLS post-Lasso estimator in Belloni and Chernozhukov (2013). We term the HAR type model generated this way as OLHAR. Our method is efficient as it avoids searches over exponentially growing candidate models in model selection.

We find that modeling the VIX with the OLHAR selects different sets of predictors from those initially imposed by the standard HAR model. This is after controlling for the total number of predictors and for other similar exogenous variables as defined in Fernandes et al. (2014). Despite its performance indistinguishable from that of the standard HAR model for the one-day ahead forecasts, the OLHAR model’s performance significantly dominates the standard HAR and other candidate models’ performance when forecasting the VIX either weekly, biweekly, or monthly ahead.

The 2011-2015 commodity price crash has inspired a debate on how the commodity price downturn will affect the financial stability in SCEEs. There are relatively few papers in the literature directly addressing the above question. The most related paper is Crean and Milne (2015), which provides the evidence that the estimated syndicated corporate loan losses concentrate on a small number of systematically important real sectors with some common characteristics. The commodity sector belongs to those systematically important real sectors.
In Chapter 4, I contribute to the debate by providing a framework that allows for assessing the importance of commodity price fluctuations for tail financial risk in Canada. The framework is a tail real and financial risk forecasting system, using factor-based conditional quantile projections (De Nicolò and Lucchetta, 2017), and allows the tail risk measures to be affected by foreign macroeconomic and world commodity price factors. Tail real risks are measured by the VaR of GDP-Oil. Tail financial risks are measured by the VaR of the NPL ratios for individual Big Six banks.

My estimates forecast the steepest decline in GDP-Oil at 2009Q2, and the peaks of the NPL ratios of Bank of Montreal (BMO) and Canadian Imperial Bank of Commerce (CIBC) at 2010Q2 and 2010Q3, respectively. The VaR forecasts of the NPL ratios for other Big Six banks do not have the same accuracy as those for BMO and CIBC. This reflects how closely the NPL ratio of each bank is correlated with the estimated factors.

Most importantly, I show that for BMO and CIBC, the banking factors make the most contribution (i.e., 51.05% for BMO and 70.82% for CIBC) to the large increase in tail financial risk, the peaks of the VaR forecasts for the NPL ratios. The contribution from Canadian macroeconomic factors are second to that of the banking factors (i.e., 31.83% for BMO and 15.86% for CIBC). The direct contribution from real commodity price factors is the lowest (i.e., 13% for BMO and 6.09% for CIBC), compared with other estimated factors. But the magnitudes of the commodity price contribution are not trivial, considering how much they make up the total contribution from the global factors (i.e., 13% out of 17.11% for BMO and 6.09% out of 10.43% for CIBC).
Chapter 2

Commodity Price Shocks and Bank Risk in Small Commodity-Exporting Economies

2.1 Introduction

Booms and busts in commodity prices are proven to be important drivers of macroeconomic fluctuations (Céspedes and Velasco, 2012; Gubler and Hertweck, 2013). Moreover, the slump in base metal and crude oil prices during 2011-2015 has increased concerns about possible loan defaults and the health of financial institutions in SCEEs.¹ For policy regulators in these countries, it is essential to understand and estimate the impacts of world commodity price fluctuations on the macroeconomy and, more importantly, the stability of financial institutions.

However, the previous literature studies either the macroeconomic effects of commodity price shocks in isolation from banks (Blanchard and Gali, 2007; Kilian, 2009; Céspedes and Velasco, 2012; Gubler and Hertweck, 2013), or the effects of monetary

¹On March 8, 2015, Moody’s Investors Service reported that half of the 18 defaults in 2015 were associated with commodity companies. The failure rate is 14% in metals and mining over the following 12 months, while it is 9.1% in oil and gas. Five of the six Gulf Cooperation Council (GCC) nations were also put on review for a rating cut.
2.1. INTRODUCTION

policy shocks on banks in proper empirical models (Jimborean and Mésonnier, 2010; Dave et al., 2013; Buch et al., 2014b).

This chapter aims to contribute to the literature by developing a structural dynamic factor model (SDFM) that studies the propagation mechanisms of commodity price shocks on the macroeconomy and banks in a SCEE. These propagation mechanisms allow explicitly for dynamic interactions with the global economy. My framework can be seen as an extension of Charnavoki and Dolado (2014) with additional information from individual banks. The SDFM is a natural empirical framework to choose in a data-rich environment, since it conveniently analyzes the effect of a small number of structural shocks on a large set of variables (Mumtaz and Surico, 2009).

Because Canada exports many kinds of industrial commodities, it is a very suitable case for us to study the effects of board commodity price changes on bank risk. For example, Figure 2.1 plots the the World Bank Real Commodity Price Index of Energy and the NPL Ratio of Canadian Western Bank during the period 2009Q1-2016Q1, respectively. Canadian Western Bank’s headquarters are located at Edmonton in Alberta, a major oil-producing province in Canada. It can be seen clearly that the NPL ratio of Canadian Western Bank moved against the trend of real energy price index. The NPL ratio rose up sharply to 0.016 at 2010Q2, which followed the bottom of the energy price index at 2009Q1. Subsequently, when the oil price crashed at 2014Q2, I also witness a simultaneous increase of the NPL ratio for Canadian Western Bank. Moreover, the Canadian financial system was relatively immune to the 2007-2009 financial crisis so that the structural breaks of banking series during the sample

\footnote{In Canada, the mining, quarrying, oil, and gas extraction industries contributed 27% to the value of Canadian goods-producing industries in March 2016. Including total exports of basic products and materials from the agriculture and forestry sectors, the commodity sector accounted for about 40% of total merchandise exports in 2016.}
2.1. INTRODUCTION

Figure 2.1: World Bank Real Commodity Price Index of Energy and the NPL Ratio of Canadian Western Bank

Note: This figure shows the World Bank Real Commodity Price Index of Energy and the NPL Ratio of Canadian Western Bank during the period 2009Q1-2016Q1. The World Bank Real Commodity Price Index of Energy is presented by a blue line in the left panel. The NPL ratio of Canadian Western Bank is presented by a red line in the right panel.

period (1996Q1-2016Q1) are not that serious.\(^3\)

From various sources, I collect three large groups of panel datasets ranging from 1996Q1 to 2016Q1: global, Canadian macroeconomic and individual Canadian banks.\(^4\) The global datasets contain global real activities, global inflation levels, and real world commodity price indices categorized by various commodity types. The Canadian macroeconomic datasets include those variables considered in the literature as important for bank performance. I also collect the bank-level information from the financial statements of twenty-seven individual Canadian banks, which make up over 90% of the total assets in the Canadian banking industry in 2006Q1, the middle of

\(^3\) Interested readers may want to refer to Calmès and Théoret (2013) and Calmès and Théoret (2014) for a comparison of U.S. and Canadian banking systems. Calmès and Théoret (2013) also provide explanations why the Canadian banking system seems relatively robust.

\(^4\) The sources of datasets are described in Appendix A.2.
my sample. The collected bank-level information is then used to construct the total loan growth, the equity capital ratio, and the return on total assets as important bank-level variables. To measure bank risk, the share of NPLs and noninterest income ratio for each bank are computed and included as well. For the convenience of comparing results among individual banks, I create three hypothetical median banks from subsamples of banks with similar portfolio compositions, degrees of internationalization, and total asset sizes (i.e., the Big Six Canadian Bank, other local bank and foreign subsidiary).

Because I assume in a measurement equation that there exist certain comovements among observables within each group of panel datasets, the information in each group can be summarized by three individual blocks of factors: global, Canadian macroeconomic and banking factors. These blocks of factors are related to each other by a structural vector autoregression (SVAR). To feature a small open economy, I impose the block exogeneity restriction in the SVAR equation following Cushman and Zha (1997). Other restrictions in my framework are outlined in Section 2.3.

Following Kilian (2009) and Kilian and Murphy (2012), I treat commodity price changes as endogenously decided by the global factors, and thus disentangle the underlying structural shocks driving real commodity prices. Utilizing sign restrictions combined with bounds on the impact matrix as my benchmark identification scheme (Kilian and Murphy, 2012), I assume three global shocks driving real commodity prices: (i) an unexpected increase/decrease in demand from an expansionary/recessionary global economic growth, (ii) a sudden increase/decrease in global price levels not due to commodity price changes, and (iii) a commodity market-specific shock possibly due to supply disruptions or an expected shortfall of future supplies. To robustness
check the results of sign restrictions, I also include a more conventional recursive identification.

To estimate the equations in my framework, I adopt a two-step principal component analysis (PCA) and a Bayesian estimation procedure (Bernanke, Boivin, and Eliasz, 2005; Koop, Poirier, and Tobias, 2007; Boivin and Giannoni, 2008; Mumtaz and Surico, 2009).

My main findings can be summarized as follows. First, the estimated global factors explain roughly the same portions of variances of the bank-level variables as the factors that represent domestic macroeconomic fluctuations. Also during my sample period, real commodity prices are mostly driven by global demand and commodity-market-specific shocks rather than global inflation shocks, which confirms the recent findings of Kilian and Murphy (2012) and Baumeister and Kilian (2016).

Second, I find that the sources of commodity price changes can not be ignored, because they have heterogeneous implications for the macroeconomy, bank lending, and bank risk. After an expansionary (i.e., positive) global demand shock, the real economy and average bank lending within Canada strengthen significantly, whereas the bank risk gauged by NPL ratios is decreased to different extents for all of the median banks. In contrast, after a recessionary (i.e., negative) commodity market-specific shock, the increase in average bank lending for all of the median banks is insignificant and diminishes as real GDP growth slows down. Except the median foreign subsidiary, NPL ratios for all of the median banks (including Big Six and other local banks) deteriorate. My findings support the theoretical prediction in Zhang (2009) that an expansionary economic shock not only increases credit demand but also increases banks’ credit supply through a healthy balance sheet channel.
Third, if bank risk is measured by the noninterest income ratio, bank responses can be quite diverse depending on the type of commodity price shocks. When facing an expansionary global demand shock, only the median Big Six and foreign subsidiary banks would increase their share of noninterest income, whereas the median other local bank would reduce their share of noninterest income, though insignificantly. In contrast, a negative commodity market-specific shock causes all of the median banks to reduce their share of noninterest income. My results support the conclusions of Calmès and Théoret (2014) that banks take more homogeneous strategies to reduce their holdings of risky assets during slow growth episodes, and they take more heterogeneous strategies to hold risky assets when economic prospects are favorable.

In the case of Canadian banks, I also find that the median Big Six bank and foreign subsidiary banks, which hold greater quantities of total assets, are more responsive in the total loan growth and the noninterest income ratio than the median other local bank, which is smaller by the size of total assets. This conclusion is true for both types of commodity price shocks. My finding supports what Chen et al. (2012) conclude about the Canadian banks. However, it differs from the theoretical implications of Diamond and Rajan (2006) and Kashyap and Stein (2000) that small banks are more vulnerable to macroeconomic shocks than large banks, in terms of their lending and noninterest income generating activities. Kashyap and Stein (2000) further argue that this could happen because small banks have a lower net worth, a lack of diversification, and less diversified funding.

This chapter is organized as follows. Section 2.2 briefly reviews the relevant literature and discusses my contributions. Section 2.3 formulates the empirical model framework, including model specifications and restrictions, the estimation procedure,
2.2 RELATED LITERATURE

and the identification schemes of the structural global shocks driving real commodity price changes. Section 2.4 describes the data and how I prepare them for a factor analysis. My empirical results are presented and discussed in Section 2.5. I particularly focus on the dynamic responses of bank lending and bank risk to a positive global demand shock and a negative commodity market-specific shock. Section 2.6 provides a robustness analysis of the results. Section 2.7 summarizes my main findings and indicates some potential extensions. More details on the Bayesian estimation procedure, data sources and construction process, and additional results are contained in Appendix A.

2.2 Related Literature

This chapter is related to two strands of the literature. The first strand discusses the link between macroeconomic developments and bank risk. Empirical studies, for example Nkusu (2011) and Klein (2013), among others, use panel VARs to study the dynamic interaction of major macroeconomic indicators and bank risk measured by the amount of NPLs. Using data from advanced economies and developing economies, they argue that NPLs are indeed affected by both macroeconomic and bank-level factors, whereas a sharp increase in NPLs also triggers a harmful effect that cripples the macroeconomic performance.

Other empirical papers in this line mostly study the effects of monetary policy shocks on bank lending and risk, utilizing the recently developed factor-augmented VAR (FAVAR) model in Bernanke et al. (2005). Papers such as Jimborean and Mésonnier (2010), Dave et al. (2013), Buch, Eickmeier, and Prieto (2014a) and Buch et al. (2014b) empirically assess how an expansionary monetary policy shock influences the
2.2. RELATED LITERATURE

amount of U.S. bank lending, loan composition changes and bank risk taking. They find that expansionary monetary policy shocks unequivocally raise bank lending, but their impacts on bank risk are less clear cut and depend on the measure of risk used. In addition, substantial heterogeneity of individual bank responses are also discovered after the same policy shock. However, as stated by Buch et al. (2014b), this research strand restricts its attention to the impact on bank risk of monetary policy shocks. The impact of other real shocks has not yet been subject to careful empirical examinations. Hence, Chapter 2 adds to this literature by providing an analysis of the effects of commodity price shocks on bank risk in the context of SCEEs.

Chapter 2 is also related to the second strand of the literature that investigates the connection between commodity price fluctuations and key macroeconomic aggregates. Céspedes and Velasco (2012) formulate a open economy model with nominal rigidities and financial frictions, to examine different channels through which commodity price shocks are transmitted to commodity-producing economies. Their model implies that commodity price shocks play a significant role in determining output and investment dynamics, where the magnitude of responses depends on the structural characteristics of the economy and the policy framework in place. Gubler and Hertweck (2013) empirically assess the relative importance of commodity price shocks in the U.S. business cycle between 1955Q3 and 2007Q4. They employ a SVAR which identifies several other shocks along with the commodity price shocks. Their analysis shows that commodity price shocks are very important driving forces of macroeconomic fluctuations, second only to investment-specific technology shocks.

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5 As discussed in Buch et al. (2014b), such heterogeneity is mainly due to variations in bank size, capitalization, liquidity, risk, and the exposure to real estate and consumer loans.

6 An exception is Buch et al. (2014a), which reveal that an expansionary house price shock increases additional risk-taking by commercial banks.
2.2. RELATED LITERATURE

A common approach in the above literature is to treat commodity price shocks as exogenous. In other words, as one varies commodity prices, he holds all other macroeconomic variables constant (see, e.g., Hamilton, 1985, 1988, 2000; Rotemberg and Woodford, 1996). Barsky and Kilian (2001) and Kilian (2009) have criticized this ignorance of reverse causality from macro aggregates to commodity prices and suggest identifying common underlying sources driving commodity price changes and other macroeconomic variables. Subsequently, Kilian (2009), Kilian and Murphy (2012), and Lippi and Nobili (2012), study the global crude oil market and find that the oil price and other macroeconomic aggregates respond heterogeneously to underlying shocks from different sources. For instance, temporary oil production disruptions increase the oil price quickly and temporarily, which depresses real activities at other sectors, whereas an expansionary worldwide GDP growth generates a delayed but sustained rise in the oil price and also stimulates outputs from other sectors. Jacks and Stuermer (2015) and Alquist and Coibion (2014) perform their analyses on other non-energy primary commodity markets in a similar manner as Kilian (2009).

Although the above strand of the literature has concentrated on macroeconomic impacts of commodity price shocks, these impacts are studied without an explicit role of banks. This may lead to problems, as banks in SCEEs have both direct and indirect exposure to this sector. Moreover, empirical evidence provided by Crean and Milne (2015) indicates that loans made to the commodity sector are particularly vulnerable to insolvency problems, as firms at this sector are often run on high leverage and earn fairly volatile revenues, depending on aggregate demands worldwide. Thus Chapter 2 contributes to the second strand of the literature by developing an empirical model to estimate the impacts of commodity price shocks on both the macroeconomy and
individual banks in a small commodity-exporting nation.

To my best knowledge, few papers in the previous literature deal directly with the explicit effects of commodity price downturns on the financial sector fragility. An exception is Kinda, Mlachila, and Ouedraogo (2016). In their paper, they look at the effects of commodity price shocks on the financial sector of 71 commodity-exporters among emerging and developing economies. The experiments are conducted through running logit and probit regressions on several financial fragility indicators. Their results confirm that the negative shocks to commodity prices are correlated with higher financial sector fragility. Another paper closely relevant to my study is Alodayni (2015), in which they confirm the significant negative effect of recent oil price slumps on the responses of NPLs of banks at six oil exporting countries in the GCC.

2.3 Empirical Model-Structural Dynamic Factor Model

The key objective of Chapter 2 is to study how various global shocks driving real commodity prices are transmitted to Canadian macroeconomic aggregates, and affect individual Canadian banks heterogeneously.

To achieve this objective, the proposed model draws from a growing literature of the dynamic factor model (Stock and Watson, 2002; Stock and Watson, 2005; Forni, Giannone, Lippi, and Reichlin, 2009) and the FAVAR (Bernanke and Boivin, 2003; Bernanke et al., 2005; Boivin and Giannoni, 2008; Mumtaz and Surico, 2009). The dynamic factor model (DFM) allows systematic information in large data sets to be summarized by relatively few estimated factors so that forecast accuracy of the variables of interest may be improved. Furthermore, Stock and Watson (2005) and
Forni et al. (2009) show that factor models can go beyond forecasting and are capable of analyzing macroeconomic shocks and their propagation mechanisms with the usual SVAR identification techniques. Mumtaz and Surico (2009) extend the FAVAR model in Bernanke et al. (2005) to estimate the dynamic responses of a large number of U.K. macroeconomic variables to foreign shocks.\(^7\)

The proposed SDFM is an extension of Boivin and Giannoni (2008) and Charnavoki and Dolado (2014) in the direction of including individual banks and featuring the dynamic interactions of commodity price shocks and banks. In terms of modeling commodity price shocks, I follow Kilian (2009) and treat them as endogenously determined within the global block of factors. Also in line with the literature on banking studies (Jimborean and Mésonnier, 2010; Buch et al., 2014b; Buch et al., 2014a), the proposed DFM separately extracts a vector of banking factors over time from a large panel of individual bank-level series, so as to exploit the linkages among individual banks through the interbank market or through the exposure to common shocks. In the subsequent subsections, I will explain the details of the model and relevant assumptions.

### 2.3.1 Model Setup

I partition the observable indicators into three distinct blocks: the global economy \(X^G_t\), the Canadian economy \(X^C_t\) and the individual Canadian bank-level variables.

\(^7\)Noticeably, the global VAR is an interesting alternative to the FAVAR approach and is introduced by Mauro, Smith, Dees, and Pesaran (2007). However, it is not easy to implement in my case since Mumtaz and Surico (2009) stress that it is more suitable to examine the impact of shocks originating in a specific foreign country rather than the rest of the world.
2.3. EMPIRICAL MODEL-STRUCTURAL DYNAMIC FACTOR MODEL

I assume that the state of three blocks at any time $t$, which is possibly unobserved, can be adequately summarized by a $K \times 1$ vector of factors $F_t$ such that

$$F_t \equiv \left[ F_t^{G^\top}, F_t^{C^\top}, F_t^{B^\top} \right]^\top.$$

Vectors $F_t^G$ with superscript $G$ denote three crucial global factors: $F_t^G = \left[ F_{Y,t}^G, F_{\pi,t}^G, F_{P,t}^G \right]^\top$. The first factor, $F_{Y,t}^G$, summarizes dynamic information about global real economic activity and is measured by large vectors of global and regional output, industrial production and trade indicators $X_{Y,t}^G$ of dimension $N_y^G \times 1$. The second factor, $F_{\pi,t}^G$, measures the comovement of the global inflation series and is extracted from vectors of global and regional consumer prices, producer prices and GDP deflators $X_{\pi,t}^G$ of dimension $N_{\pi}^G \times 1$. The last factor, $F_{P,t}^G$, captures the comovement of the real industrial commodity prices and is extracted from vectors of categorized primary commodity price indices $X_{P,t}^G$ of dimension $N_P^G \times 1$. The vector of the global economy series $X_t^G$ is $N^G \times 1$ and consists of three subsets of panel data

$$X_t^G = \left[ X_{Y,t}^G, X_{\pi,t}^G, X_{P,t}^G \right]^\top,$$

where $N^G = N_Y^G + N_{\pi}^G + N_P^G$. I assume that there exists only one factor for each subset of global panel data.\(^8\)

I collect large vectors of macroeconomic and financial series for Canada, $X_t^C$ of dimension $N^C \times 1$, from which a $J \times 1$ vector of domestic factors $F_t^C$ is extracted. Similar to Charnavoki and Dolado (2014), I do not impose any prior restriction on the number of factors within $F_t^C$. Linear combinations of components within $F_t^C$ can be regarded as describing various aspects of the business cycle fluctuations in the large

\(^8\)As argued by Mumtaz and Surico (2009), global factors are required to have an explicit economic meaning. For the convenience of identifying different global structural shocks, I assume that each variable in $F_t^G$ is measured by each set of global panel data of the same concept ($Y$, $\pi$, and $P$, respectively). Similar restrictions on the factor loadings are also used in Kose, Otrok, and Whiteman (2003), Stock and Watson (2005) and Boivin and Giannoni (2006).
Finally, I extract a $(K - J - 3) \times 1$ vector of banking factors $F^B_t$ from large panel data-sets of individual bank-level variables $X^B_t$ of dimension $N^B \times 1$. Factors $F^B_t$ are assumed to drive part of the common dynamics of five banking variables for twenty-seven individual banks. Details about the sources of raw data and how to build these individual bank-level variables are laid out in Section 2.4.2.

The three sets of factors are assumed to relate to the indicators in each block according to the following measurement equation:

$$
\begin{bmatrix}
X^G_{Y,t} \\
X^G_{\pi,t} \\
X^G_{P,t} \\
X^C_t \\
X^B_t
\end{bmatrix} =
\begin{bmatrix}
\Lambda^G_Y & 0 & 0 & 0 \\
0 & \Lambda^G_\pi & 0 & 0 \\
0 & 0 & \Lambda^G_P & 0 \\
\Lambda^C_Y & \Lambda^C_\pi & \Lambda^C_P & \Lambda^C_H \\
\Lambda^B_Y & \Lambda^B_\pi & \Lambda^B_P & \Lambda^B_H & \Lambda^B_U
\end{bmatrix}
\begin{bmatrix}
F^G_{Y,t} \\
F^G_{\pi,t} \\
F^G_{P,t} \\
F^C_t \\
F^B_t
\end{bmatrix} +
\begin{bmatrix}
e^G_{Y,t} \\
e^G_{\pi,t} \\
e^G_{P,t} \\
e^C_t \\
e^B_t
\end{bmatrix},
$$

where $\Lambda^i_{j}$s for $i = G, C, B$ and $j = Y, \pi, P, H, U$ are matrices of the factor loadings of appropriate dimensions. The $N^G \times 1$ error vectors $e^G_t = \left[ e^G_{Y,t} \top, e^G_{\pi,t} \top, e^G_{P,t} \top \right] \top$, $e^C_t$ ($N^C \times 1$), and $e^B_t$ ($N^B \times 1$) are assumed to be mean-zero i.i.d and include series-specific components that are uncorrelated with the corresponding factors. I assume that the number of common factors is small relative to the total number of indicators, i.e. $(N^G + N^C + N^B) \gg K$. I do not impose lags on $\Lambda^i_{j}$, because the $F_t$ values here can be interpreted as containing arbitrary lags of the fundamental factors (Bernanke

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9Specifically, I assume that there exists certain comovements among individual banks in Canada, which are collectively driven by worldwide economic activities, domestic economic conditions, and some common bank-specific conditions. This assumption is inspired by the findings of Nkusu (2011) and Klein (2013) that both macroeconomic factors and bank-level factors determine the levels of NPLs. Moreover, considering that the Big Six banks in Canada have many foreign affiliates (Chapman and Damar, 2015), the force of foreign economic factors definitely plays a role.
et al. 2005). I also impose a block-diagonal restriction on the matrices of the factor loadings of the global block, which implies that each variable in $F^G_t$ is measured by the corresponding set of global indicators of the same concept. A lower triangular structure is assumed for the blocks of the domestic economy and banking variables so that three global factors are included explicitly into the Canadian economy and banking blocks.

Following the previous literature (Jimborean and Mésonnier, 2010; Buch et al., 2014b), the vector of banking factors $F^B_t$ does not enter the Canadian economy block, as I hypothesize that the current state of the banking sector does not have a contemporaneous effect on the current state of the Canadian economy. Instead, $F^B_t$ influences the state of Canadian economy with lagged effects, which is shown in the SVAR Equation (2.2). Note that $F^G_t$ and $F^C_t$ are included explicitly into the block of the banking sector, because I assume that the state of Canadian banks depends on both domestic factors and international factors concurrently. This is intuitive since banks usually make investment decisions based on the current state of the economy and ahead of the results of investment projects, which can affect the state of the next-period economy. Also because the Big Six banks have a lot of international exposure through their foreign branches or subsidiaries, the role of international economic fluctuations on their performance cannot be ignored.

The dynamics of the common factors are modeled by a restricted SVAR:

$$
\begin{bmatrix}
F^G_t \\
F^C_t \\
F^B_t
\end{bmatrix} =
\begin{bmatrix}
\Phi_{11}(L) & 0 & 0 \\
\Phi_{21}(L) & \Phi_{22}(L) & \Phi_{23}(L) \\
\Phi_{31}(L) & \Phi_{32}(L) & \Phi_{33}(L)
\end{bmatrix}
\begin{bmatrix}
F^G_{t-1} \\
F^C_{t-1} \\
F^B_{t-1}
\end{bmatrix} + u_t,
$$

(2.2)
2.3. EMPIRICAL MODEL-STRUCTURAL DYNAMIC FACTOR MODEL

where $\Phi(L)$ values are conformable lag polynomials of the finite order $p$ and $u_t \sim N(0, \Omega)$ denotes reduced-form residuals that are related to structural disturbance $\epsilon_t$ by the impact matrix $A$ and $u_t = A \epsilon_t$, where $\epsilon_t \sim N(0, I)$ and $\Omega = AA^\top$. Considering Canada as a typical example of a small open economy, I impose block exogeneity restrictions $\Phi_{12}(L) = 0$ and $\Phi_{13}(L) = 0$ on the global factors, akin to Cushman and Zha (1997). To put it another way, I allow domestic factors to respond to global factors with lags, but restrict the dynamics of global factors to be self-contained and not influenced by the dynamics of the Canadian macro-economy and banking factors. Hence, the right upper $3 \times (K - 3)$ block of $A$ is constrained to be zeros. To formally test this restriction, I follow Cushman and Zha (1997) and conduct a joint likelihood ratio test. First I set the lags of the SVAR at $L = 2$, the optimal number of lags selected by the AIC criterion, which results in 48 restrictions. The joint likelihood ratio test statistics is 57.01 with a $p$-value of 0.1749, which means that I cannot reject the null hypothesis that block exogeneity exists at 5% level of significance. Therefore, my block exogeneity assumption is statistically sustained.

I leave other portions of the lag polynomials unrestricted. Following the financial accelerator theory literature (see Bernanke, Gertler, and Gilchrist, 1999), I permit Canadian economy factors to respond to the states of banking factors in previous periods, because the financial intermediaries can decide on the amount of loans that will be issued for investment and production. Similarly, banking conditions are also assumed to be affected by the states of the Canadian economy in previous periods.

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10 Cushman and Zha (1997) make a similar assumption when they study the impacts of monetary policy shocks for a small open economy, i.e. Canada. They postulate that block exogeneity on U.S. variables may not be a strong hypothesis for small open economies like Canada, since shocks from Canada probably have little effect on other countries. Moreover, I test the results by removing the block exogeneity restriction and the results remain basically unaffected.
2.3. EMPIRICAL MODEL-STRUCTURAL DYNAMIC FACTOR MODEL

2.3.2 Estimation Procedure

To estimate my framework, I choose a two-step approach employed by Bernanke et al. (2005), Boivin and Giannoni (2008) and Muntaz and Surico (2009) for its computational simplicity. Muntaz and Surico (2009) demonstrate that a one-step procedure that simultaneously estimates the unobserved factors, the factor loadings, and the SVAR coefficients in a large cross-sectional dimension of data set, as in my case, entails excessive computational costs. Moreover, Bernanke et al. (2005) show that both approaches lead to similar results in their experiment. Another clear advantage of a two-step procedure is that it allows the use of the expectation-maximization (EM) algorithm of Stock and Watson (2002) to deal systematically with data irregularities such as series of mixed frequencies and missing values.

As shown by the PCA, the first step consists of extracting the largest principal components (PCs) from each block of the panel data sets, $X_{G,t}^G$, $X_{π,t}^G$, $X_{P,t}^G$, $X_t^C$, and $X_t^B$ to consistently recover the space spanned by the factors. In practice, arbitrarily selecting the number of factors may lead to inefficient results (Boivin, Giannoni, and Mojon, 2009). Therefore, I rely on several information criteria proposed in Bai and

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11 Muntaz and Surico (2009) argue that a one-step approach requires a full Bayesian estimation of the model that requires the Kalman filter to derive the mean and the variance of the conditional distribution of the factors. The computation of the Kalman gain is computationally burdensome, since it involves a very large dimensional factor loading matrix, which is repeated for each time period.

12 Stock and Watson (2002) prove that the principal components remain consistent when there is some time variation in factor loading matrices $Λ$ and a small number of data irregularities, as long as the number of indicators is very large relative to the time length of each indicator, i.e., $N^k \gg T$ and $k = G, C, B$. 
Ng (2002) to determine the optimal value of $J$ and $K - J - 3$.\footnote{Bai and Ng (2002) propose several criteria to determine the number of factors extracted from large data series. All of these criteria are constructed so as to minimize the mean squared errors of the model. For instance, their panel information criteria $IC_{p1}$ and $IC_{p2}$ suggest the presence respectively for 4 and 3 in the panel for Canadian economy, and respectively for 4 and 5 in the panel for Canadian banks. However, these criteria do not necessarily answer the question of how many factors should be included in the VAR.} I end up with four Canadian macroeconomic factors ($J = 4$) and four banking factors ($K - J - 3 = 4$). It should be mentioned that I do try including additional domestic factors and banking factors, which barely changes the estimated impulse responses.

Following Boivin and Giannoni (2008), in the first step, I impose the constraint that the global factors are included in the PCs of the domestic block in Equation (2.1). To recover dimensions of the common dynamics not captured by the global factors, I follow the iterative procedure employed by Boivin and Giannoni (2008):

i. Estimate the three global factors $\hat{F}^G_t = [\hat{F}^G_{Y,t}, \hat{F}^G_{\pi,t}, \hat{F}^G_{P,t}]^\top$ and the initial estimates of $\hat{F}^C_{t,(0)}$ by extracting PCs from $X^G_t$ and $X^C_t$, respectively;

ii. Regress $X^C_t$ on $\hat{F}^C_{t,(0)}$ and the three estimated global factors $\hat{F}^G_{Y,t}, \hat{F}^G_{\pi,t}$, and $\hat{F}^G_{P,t}$ to obtain the associated factor loading matrices $\hat{\Lambda}^C_{Y,(0)}, \hat{\Lambda}^C_{\pi,(0)}, \hat{\Lambda}^C_{P,(0)}$, and $\hat{\Lambda}^C_{H,(0)}$;

iii. Compute $\tilde{X}^C_{t,(0)} = X^C_t - \hat{\Lambda}^C_{Y,(0)} \hat{F}^G_{Y,t} - \hat{\Lambda}^C_{\pi,(0)} \hat{F}^G_{\pi,t} - \hat{\Lambda}^C_{P,(0)} \hat{F}^G_{P,t}$;

iv. Estimate $\hat{F}^C_{t,(1)}$ as the first $J$ principal components of $\tilde{X}^C_{t,(0)}$;

v. Repeat Steps (ii) to (iv) until convergence in $\hat{F}^C_{t,(s)}$ is achieved.

I denote the converged $J$ factors as $\hat{F}^C_t$. In a similar manner, I obtain the $K - J - 3$ banking sector factors $\hat{F}^B_t$.

In the second step, the estimated factors from the first step are utilized as eleven endogenous variables to estimate the restricted SVAR. As discussed above, I choose
2.3. EMPIRICAL MODEL-STRUCTURAL DYNAMIC FACTOR
MODEL

two lags to capture the dynamics in the SVAR model. In my restricted SVAR equa-
tion, a large number of free parameters (the total number is 194) have to be estimated
using 81 observations for each variable. Hence I follow Sims and Zha (1998) which
suggest using a Bayesian estimation procedure in this situation. More details about
the estimation process are given in Appendix A.1.

2.3.3 Identification of Global Structural Shocks Driving Commodity Prices

In this section, I discuss the economic meanings of three global structural shocks
driving a wide range of real commodity prices: (i) an unexpected shock to global
demand $\epsilon_{D,t}$, (ii) a global inflation shock $\epsilon_{\pi,t}$, changing global price levels and not
originated from commodity markets, and (iii) a commodity market-specific shock $\epsilon_{C,t}$, for
example a commodity production disruption raising the commodity price. The
identification of the above three shocks utilizes two different schemes: sign restrictions
and a recursive identification (Kilian, 2009; Kilian and Murphy, 2012; Charnavoki and
Dolado, 2014).

As postulated by Kilian (2009), an expansionary global demand shock $\epsilon_{D,t}$ repres-
sents shocks to the global demand for industrial commodities resulting from global
economic growth. A typical example for a positive global demand shock is the early
2000s, when the rising global GDP growth, mostly attributed to emerging economies,
caused sharp increases in major commodity prices. Moreover, a positive global de-
mand shock also raises the demand for other nonresource tradable goods produced
by Canada.

A global inflation shock $\epsilon_{\pi,t}$ mainly reflects changes in the global price levels,
which is not caused by commodity price variations. An example of a positive global
inflation shock raising real commodity prices is provided by Rogoff (2003), which
dокументы the world CPI dropping from 14.5% in early the 1980s to 3.9% in 2003.
He argues that the greater competition from international trade leads to sharp drops
in monopoly rents for domestic firms and also in the price levels. This thus reduces
the price deflators used to deflate nominal commodity prices, which leads to higher
real commodity prices. An example of a negative global inflation shock reducing real
commodity prices is a natural disaster affecting noncommodity exporting countries
such as the 2011 Japan earthquake. The disaster abruptly increases the cost of
memory chips, display panels and hence the levels of relevant price deflators, which
lowers real commodity prices.

A commodity market-specific shock $\epsilon_{C,t}$ accounts for both supply and inventory
demand shocks in commodity markets. A commodity supply shock is defined as
any unanticipated shift in the commodity supply curve that results in an opposite
movement in the commodity production and the real price of the commodity. A
commodity inventory demand shock arises from the possibility of a sudden shortage
in future production or an expectation of higher demand in the future, which increases
the contemporaneous demand for inventories and leads to an increase in the real price
of the commodity. I do not disentangle these two commodity market specific shocks
not only due to a lack of relevant production and inventories data for most non-energy
commodities, but also because of their qualitatively similar effects on the global real
activity factor and the global real commodity price factor. In the case of a sudden
supply disruption and booming inventory demand, they both increase real commodity
prices and hinder real GDP growth worldwide.\textsuperscript{14}

My benchmark identification scheme for these shocks is based on sign restrictions combined with restrictions on some elements of impact matrix $A$ (Kilian and Murphy, 2012). More specifically, I constrain the signs of accumulated IRFs over the first four quarters to comply with those reported in Table 2.1. I employ the rotation procedure given by Rubio-Ramírez, Waggoner, and Zha (2010) to impose the sign restrictions. The details of the rotation procedure are explained in Appendix A.1.2.

<table>
<thead>
<tr>
<th></th>
<th>GD Shock, $\epsilon_{D,t}$</th>
<th>GI Shock, $\epsilon_{\pi,t}$</th>
<th>GC, $\epsilon_{P,t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global real activity</td>
<td>$+$</td>
<td>$-$</td>
<td>$-$</td>
</tr>
<tr>
<td>Global inflation</td>
<td>$+$</td>
<td>$+$</td>
<td>$+$</td>
</tr>
<tr>
<td>Real commodity price</td>
<td>$+$</td>
<td>$-$</td>
<td>$+$</td>
</tr>
</tbody>
</table>

Note that a GD shock corresponds to a positive global demand shock, a GI shock corresponds to a negative global inflation shock, and a GC shock refers to a negative commodity market-specific shock.

I postulate that a positive global demand shock will tend to raise inflation, stimulate real activity and increase real prices of primary commodities. A negative global inflation shock will, on impact, raise general price levels, but lower real activity and real commodity prices. A negative commodity market-specific shock, such as a commodity supply disruption, will lower commodity production and increase real commodity prices. It will also inhibit real activity, while increasing global inflation levels.

\textsuperscript{14} Note that I do not separately identify commodity supply shocks and commodity inventory demand shocks like Kilian (2009) and Kilian and Murphy (2012), because quarterly supply and inventory data sets for some of the primary commodities are not readily accessible. I can only find the quarterly world production data for crude oil, natural gas and coal from the Datastream. Yet, this is unlikely to be restrictive, since the literature find that the relative contribution of the commodity supply shock to real commodity price fluctuations is small and transitory (Kilian, 2009; Kilian and Murphy, 2012; Jacks and Stuermer, 2015; Baumeister and Kilian, 2016). Moreover, I do not consider a commodity market speculation shock here, since the macroeconomic effects of these types of shocks are usually transitory and ambiguous. The recent paper by Juvenal and Petrella (2015) identify an oil market speculation shock, which does not have a determined sign effect on the real economic activity.
As argued by Kilian and Murphy (2012), the major issue of sign restriction-based VAR identification is that possible structural models are not exactly identified but only set identified. This implies that there does not exist a unique structural model characterized by a single impact matrix $A$. Instead, there may be a set of impact matrices ($A$s) that are equally consistent with the identifying assumptions. In this case, reporting the medians or specific quantiles of the impulse respond functions (IRFs) may provide misleading results, since IRFs for various time horizons can correspond to different structural models, some of which do not make economic sense.

To alleviate this issue, I follow Kilian and Murphy (2012) to impose bounds on some elements of impact matrix $A$ to narrow the set of admissible structural models. In line with Charnavoki and Dolado (2014), I assume that the short-run elasticity of global real economy activities to a commodity market-specific shock is small. The corresponding element of impact matrix $A(1,3)$ is constrained to fall in the interval $[-0.1, 0.05]$, which approximately accords with the estimates of the short-run elasticity of the U.S. GDP to real oil price.\footnote{In Section 2.6, I test my results by alternative choices of this interval, from other empirical estimates of the short-run impact on U.S GDP of an oil price increase (Cashin, Mohaddes, Raissi, and Raissi, 2014; Baffes, Kose, Ohnsorge, and Stocker, 2015).} In Section 2.5, the area between the 16% and 84% quantiles of the posterior distribution will be reported; these contain only those structural models that satisfy both the sign restrictions and the bound constraint on $A(1,3)$.

To provide an alternative scheme and robustness test, I also conduct a recursive ordering identification and impose the impact matrix restriction in Table 2.2. More specifically, it is imposed on the foreign $3 \times 3$ block and is assumed to be lower triangular.

Three global factors are ordered by decreasing order of exogeneity. The global
Table 2.2: Recursive Identification Restrictions on the Impact Matrix

<table>
<thead>
<tr>
<th></th>
<th>GD Shock, $\epsilon_{D,t}$</th>
<th>GI Shock, $\epsilon_{\pi,t}$</th>
<th>GC Shock, $\epsilon_{P,t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global real activity, $u_{G,Y,t}^G$</td>
<td>x</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Global inflation, $u_{G,\pi,t}^G$</td>
<td>x</td>
<td>x</td>
<td>0</td>
</tr>
<tr>
<td>Real commodity price, $u_{G,P,t}^G$</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

Note that a GD shock corresponds to a positive global demand shock, a GI shock corresponds to a negative global inflation shock, and a GC shock refers to a negative commodity market-specific shock.

Demand shocks are defined as unpredictable innovations to the global real activity factor. Both the global inflation factor and the real commodity price factor are assumed to respond to innovations to the global demand shock within the same quarter. Innovations to the global inflation factor are assumed to have no contemporaneous effects on global real activity, while the commodity market-specific shocks are assumed to only influence the real commodity price factor concurrently. Kilian (2009) confirms that the above restriction is consistent with the sluggish adjustment of global real economic activity after each of the major oil price increases in their sample.

2.4 Data Description and Bank Risk Measures

My empirical model focuses on the joint analysis of macroeconomic data and individual bank-level data, both over the period 1996:Q1 to 2016:Q1, with quarterly frequency.

2.4.1 Macroeconomic Data

The macroeconomic data set comprises 280 series - 48 for the foreign block and 232 for the Canadian block. The list of macroeconomic series and their sources can be found in Appendix A.2.2 and Appendix A.2.3. As in Bernanke et al. (2005), I first difference the nonstationary variables and then demean and standardize all variables.
before extracting the factors by principal component analysis.

The foreign block includes data for the world economy, as well as for large regional groups (i.e., Organization for Economic Co-operation and Development, G7, European Union and BRIC countries) and the United States. These groups cover Canada’s main trading partners and the major industrialized countries across the world. Following convention in the international business cycles literature and Kilian (2009), I collect data on real activities, inflation levels, and real commodity price indices. For real activities, I consider 16 series on real GDP, industrial production, exports and imports volumes and the global real economic activity index of Kilian (2009). Note that I include these real variables for several regional groups, because I want to identify shocks that are large enough. Meanwhile, these shocks should be relevant to global trade demand for industrial commodities and simultaneously drive the common dynamics of real GDP, industrial production and the world trade indices. Foreign inflation consists of 23 series on implicit deflators of GDP, consumer price indices and producer price indices. The real commodity prices are measured by five sub-categories of commodity price indices for energy, food, agricultural raw

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16 For more details, refer to the “Imports, exports and trade balance of goods on a balance-of-payments basis, by country or country grouping” table found in Canadian Socioeconomic Information Management (CANSIM) at Statistics Canada http://www.statcan.gc.ca/tables-tableaux/sum-som/l01/cst01/gblec02a-eng.htm. The trading partner countries included are United States, European Union, Mexico, Japan, South Korea, Norway, Switzerland, Turkey, Australia, Brazil, Russia, India and China. The sum of the exports and imports values between Canada and these country groups exceeds 97% of the total value of exports and imports for Canada in 2015. Those countries excluded by my regional data sets have only a small impact on bilateral trade with Canada and are instead captured by the indices of world exports and world imports from the CPB World Trade Monitor.

17 Unfortunately, consistent quarterly real GDP values for BRIC countries are not available for my sample period. However, quarterly industrial production and inflation series for these countries are collected to reflect the effects from major developing economies.

18 As stressed by Kilian (2009), the index of global real economic activity is not a measure to obtain a proxy for global real value added, but rather a measure of those parts of worldwide real economic activity that drive demand for industrial commodities in international markets.
2.4. DATA DESCRIPTION AND BANK RISK MEASURES

materials, base metals, and fertilizers reported by the World Bank.\textsuperscript{19}

As in Charnavoki and Dolado (2014) and the literature on modelling macroeconomic VAR with bank-level data,\textsuperscript{20} the data for Canada includes many different real activity indicators, inflation series, exchange rates, narrow and broad money, and financial variables such as various interest rates, the S&P/TSX composite stock index and real house prices.\textsuperscript{21} I consider house prices not only because they may be relevant for the macroeconomy but also because house prices affect the value of assets that serve as collateral for mortgage lending.\textsuperscript{22} In addition to these macroeconomic variables, a large number of disaggregated deflators and volume series for household expenditure are drawn from CANSIM. I also consider data for industry-level GDP, as I expect heterogeneous impulse responses of industry-level GDP to different commodity price shocks.

\textsuperscript{19} I am also aware of other nominal commodity price indices constructed by the Bank of Canada and the IMF. However, real commodity prices are not directly available from these two sources. Hence, I first deflate those nominal values by the Manufactures Unit Value Index (MUV), corresponding to how the World Bank deflates its commodity prices. The MUV is a composite index of the prices of manufactured exports from the fifteen major developed and emerging economies to low- and middle-income economies, valued in U.S. dollars; it is often regarded as more appropriate price deflators than the U.S. GDP deflators for commodity prices. Then, the estimation of equations is run with alternative commodity price indices and the results are basically unaffected.

\textsuperscript{20} For example, Buch et al. (2014b), Jimborean and Mésonnier (2010) and Dave et al. (2013) all consider real GDP growth, central bank policy rates, inflation rates and housing-related variables in their analyses.

\textsuperscript{21} Real house prices are measured by the New Housing Price Index (NHPI) constructed by Statistics Canada. As suggested by its name, NHPI only captures the prices of new houses available from 1981. The benefit of using NHPI is its full string of series over my sample period with details down to the provincial level. Another index taking into account the prices of existing houses is the Royal LePage Housing Price Index, which is available only until 2015Q2 and is missing data at the provincial level.

\textsuperscript{22} In the case of small open economies, Tomura (2010) uses Canadian data to show a positive correlation of uncertainty in terms of trade improvements with increases in real house prices, indirectly working though increased household income. The effect is more pronounced for western Canada. Wang and Tumbarello (2010) and Ng and Feng (2016) find similar patterns in Australia and Hong Kong.
2.4.2 Bank Level Data and Measuring Bank Risk

I collect raw bank-level data from monthly balance sheet statements, quarterly income statements and statements of impaired assets made available on the Office of the Superintendent of Financial Institutions (henceforth, OSFI) website. The OSFI website data are submitted by individual banks in each month or each quarter and have been audited by a major accounting firm.

Following Buch et al. (2014b), I consider that the following bank-level variables capture balance-sheet strength, profitability, loan growth and risk: (i) the ratio of NPL to total loans, (ii) the ratio of equity capital to total assets, (iii) the ratio of net income to total assets, (iv) the growth of total loans, and (v) the ratio of noninterest income to net operating income. Details on variable definitions and where to locate the information from accounting statements are in Appendix A.2.1.

I choose the ratio of NPLs to capture changes in the overall quality about the stock of credit at banks, as it measures the share of outstanding loans that are past due 90 days or longer. Thus Buch et al. (2014b) define it as a measure of backward looking risk. This measure has the advantage of being available over a large number of banks for a long period of time, which is particularly convenient for those banks not publicly listed. Another benefit of this measure is that it is little affected by changes in accounting standards and bank management decisions. Moreover, it matches up with theoretical models that describes banks as intermediaries that take deposits and issue loans and that consider loan defaults as the main source of banking system risk.

\[ \text{The data is available from http://www.osfi-bsif.gc.ca/Eng/wt-ow/Pages/FINDAT.aspx.} \]

\[ \text{Other items closely related to default loans are the provision for credit losses and the allowance for credit losses, both of which are subject to the discretion of the bank management board. Interested readers may want to refer to McKeown (2015).} \]
While the ratio of NPLs tracks the traditional credit business risk for banks, the noninterest income ratio is more recently proposed as a measure of nontraditional business risk (DeYoung and Roland, 2001; Brunnermeier, Dong, and Palia, 2012; Buch et al., 2014b; and Calmès and Théoret, 2014). A noninterest income ratio captures the proportion of revenues from trading, capital market fees and securitization, which is regarded as a flow measure of risk and is thus more forward-looking. Empirically, Brunnermeier et al. (2012) prove that banks with higher shares of noninterest income are more systemically risky than banks with a more traditional business model. Furthermore, Calmès and Théoret (2014) prove that the cross-sectional dispersion of the noninterest income ratio comoves more with the uncertainty of economic growth than the ratio of gross impaired loans to total assets; so Canadian banks with a larger product-mix of trading and capital market fees are more sensitive to business conditions than their U.S. peers. As shown in McKeown (2015), although the noninterest income ratio for Canadian banks has shrunk by 6.7% since 2006, it still makes up

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25 Boyd and De Nicoló (2005) propose that banks can become more risky as their market shares become more concentrated. They base their argument on the contracting theory with a moral hazard, where banks with higher market powers tend to charge higher loan rates, which could cause higher loans’ probability of defaults. Zhang (2009) models the propagation mechanism of unexpected aggregate shocks to banks, mainly through the deviation of loan default rates from what is expected. Martinez-Miera and Repullo (2010) investigate the effects of increased competition on the risk of bank failure, and show that a U-shaped relationship exist between probabilities of loan defaults and competition.

26 An early study by DeYoung and Roland (2001) on 472 U.S. commercial banks, adopts a degree of total leverage framework and concludes that banks tilting towards more fee-based activities raise their revenue and earning volatilities. Brunnermeier et al. (2012) extend the question into investigating whether and how 538 U.S. commercial banks with higher non-interest income ratios can have higher contribution to the systemic risk, as measured by $\Delta \text{CoVaR}$ and the Systemic Expected Shortfall (SES) from 1986 to 2008. Total non-interest income is further decomposed into two components: trading income, and investment banking and venture capital income, so as to evaluate their individual impact on the systemic risk. Their empirical results find that a one standard deviation increase to bank’s non-interest income to interest income ratio increases its systemic risk contribution by 11.6% in $\Delta \text{CoVaR}$ and 5.4% in SES. Two components of non-interest income are basically equally related to ex ante systemic risk.
44.3% of aggregate revenues in 2015.

I am also aware of alternative measures of bank risk used in the literature (Beck, 2008; Buch et al., 2014b; Calmès and Théoret, 2014; and Berger, Ghoul, Guedhami, and Roman, 2016). They are either computed from figures of accounting statements or from market data.\textsuperscript{27} However, data are not always available for the full sample period or for all of the considered banks.\textsuperscript{28}

Screening Bank-Level Data and Preparing for Factor Analysis

First, I omit 72 life insurance companies, 13 fraternal benefit societies and 160 property and casualty insurance companies from my sample data sets since their main business lines are quite different from my definition of a financial intermediary. Cooperative credit associations and cooperative retail associations are also excluded since their disclosure of financial data does not contain the statement of impaired assets that I need. Note that I also exclude 31 foreign branches since they are not required to hold equity, which is necessary to calculate the ratio of equity capital.\textsuperscript{29} At this stage of preliminary screening, my initial data set consists of 30 domestic banks, 24 foreign banks, 45 trust companies and 18 loan companies, as classified by the OSFI.

Following previous studies on micro-level bank data, I implement a data cleaning procedure to exclude banks with implausible observations or with more than 8 quarters of missing observations. In other words, the process is mainly targeted at

\textsuperscript{27} As in Esty (1998), total bank risk is calculated as the standard deviation of the daily stock returns over the previous 12 months of values computed at the end of each calendar quarter.

\textsuperscript{28} Since not all the institutions in my sample are publicly traded companies, I only have market data for 8 domestic banks out of 27 institutions. For foreign subsidiaries, their market data are more reflective of the economic situations in countries where the parent companies are located.

\textsuperscript{29} Instead, they hold a capital equivalency deposit with an approved financial institution in Canada.
observations for the above five bank-level variables with negative or missing values, ratio variables with values greater than one and those values falling into either the top or into bottom percentile at any point in time. For those banks with fewer than 8 quarters of missing observations, I implement the EM algorithm in Stock and Watson (2002) to estimate the missing observations, as long as those missing observations are not due to banks ceasing to exist or being not yet established. In Table A1, I list 27 chartered financial institutions consist of (i) twelve domestic banks; (ii) ten foreign bank subsidiaries; and (iii) five loan and trust companies (two and three respectively).

To prepare the bank-level data for factor analysis, I test all five bank-level series for stationarity and seasonally adjust them. The financial statement ratios are usually regarded as stationary, while regulatory changes possibly cause structural breaks.\footnote{Chen et al. (2012) provide a chronological list of important legislative amendments and regulatory changes in the Canadian financial system through until 2010.} By means of Bai and Perron (2003) multiple breakpoint test, I detect two structural break dates in the time series: the first threshold point is 2008Q2, or the pre-financial crisis period, and the second structural break date is in 2000Q4, when the OSFI officially increased the minimum requirements to 7% and 10% for the Tier 1 capital and total capital ratios, respectively. To tackle the structural breaks, series are demeaned and structural breaks are corrected by subtracting the shifted means. See Buch et al. (2014b) and Jimborean and Mésonnier (2010) for a similar treatment in the case of a factor model. Furthermore, series are standardized and outliers are replaced by the median value of the preceding five observations (Stock and Watson, 2005 and Buch et al., 2014b). For a detailed description of the data cleaning procedure and preparation for factor analysis, refer to Appendix A.2.1.

Since it is hard to track the impulse responses of 27 institutions in the same figure,
I create three hypothetical banks to represent individual banks for the following three categories: (i) The Big Six,\textsuperscript{31} (ii) other local banks,\textsuperscript{32} and (iii) foreign subsidiaries.\textsuperscript{33} The representative bank in each category adopts the medians of the five banking variables within each of these three sub-samples. I then include these three representative banks in the data set of banking variables $X^B_t$, which then consists of three representative banks and 27 real chartered banks.

Note that my categorization of banks roughly follows the organization of data by the OSFI. This is in contrast to the way that Buch et al. (2014b) discuss their results for U.S. banks, where they focus on the responses of one median bank representing all U.S. banks in their sample. Considering the disparate asset composition among bank groups, focusing on the median bank of all banks is insufficiently representative. Compared with other domestic banks, the Big Six and foreign subsidiaries hold relatively larger shares of risky assets, such as non-mortgage loans and private securities (Chen et al., 2012). Among those banks with risky assets, the Big Six banks have the highest exposure to capital market risks through possessing the highest proportion of trading securities.\textsuperscript{34} When studying international shock transmissions, isolating the Big Six banks from other chartered banks may also be meaningful as the Big Six banks are more internationalized and usually have foreign affiliates, while other domestically owned institutions only have cross-border claims (Chapman and Damar, 2009).

\textsuperscript{31} The Big Six banks are Bank of Montreal (BMO), Bank of Nova Scotia (BNS), Canadian Imperial Bank of Commerce (CIBC), National Bank of Canada (NB), Royal Bank of Canada (RBC), and Toronto-Dominion Bank (TD).

\textsuperscript{32} This category includes six domestic banks, five trust and loan companies and excludes the Big Six banks.

\textsuperscript{33} I exclude foreign bank branches, since they are not required to hold equity, which is necessary to calculate the ratio of equity capital to total assets. Instead, foreign bank branches are required by the OSFI to hold a capital equivalency deposit with an approved financial institution in Canada.

\textsuperscript{34} Figure 3 in Chen et al. (2012) presents the balance sheet compositions of different types of banks by size, charter type and wholesale funding ratio.
2.5. EMPIRICAL RESULTS

Table 2.3 presents some descriptive statistics of the five banking variables for my sample at 2016Q1. Note that the sample, although relatively small, is still quite diverse along the share of noninterest income, equity capital ratio and growth of total loans. Among these five banking variables, the distribution of noninterest income share is the most dispersed across banks, having the highest standard deviation value of 0.2417. Regarding the share of NPLs and return on assets, the sample banks are more homogeneous as they have relatively small standard deviations (0.0547 and 0.0001, respectively). After a careful examination of data between bank groups, I find that the Big Six and foreign subsidiaries are riskier than other local banks in terms of having higher median values on the ratio of NPLs, share of noninterest income and growth rate of total loans. In contrast, the Big Six is dominated by foreign subsidiaries and other local banks on the equity-capital ratio and return on assets.

Table 2.3: Descriptive Statistics for Five Bank-Level Variables (2016:Q1)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>SD</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonperforming Loans Share</td>
<td>0.0185</td>
<td>0.0041</td>
<td>0.0547</td>
<td>0.0000</td>
<td>0.3128</td>
</tr>
<tr>
<td>Equity Capital Ratio</td>
<td>0.1155</td>
<td>0.0774</td>
<td>0.1292</td>
<td>0.0412</td>
<td>0.7963</td>
</tr>
<tr>
<td>Return on Assets</td>
<td>0.0014</td>
<td>0.0013</td>
<td>0.0010</td>
<td>-0.0016</td>
<td>0.0045</td>
</tr>
<tr>
<td>Change in Total Loans</td>
<td>0.0091</td>
<td>0.0196</td>
<td>0.1118</td>
<td>-0.2432</td>
<td>0.4983</td>
</tr>
<tr>
<td>Noninterest Income Share</td>
<td>0.3272</td>
<td>0.2867</td>
<td>0.2417</td>
<td>-0.0184</td>
<td>0.9558</td>
</tr>
</tbody>
</table>

Note that each figure in Columns 2-6 represents the cross-sectional value at 2016Q1.

2.5 Empirical Results

In this section, I first start by determining to what extent variables of different blocks are correlated with the estimated factors. Furthermore, I investigate the average explanatory powers of global, domestic and banking factors on each of the five banking
variables. I then plot the estimates of the three global factors, present the historical decomposition of these factors in terms of the shocks identified by sign restrictions and recursive identification schemes, and illustrate their dynamic responses to global shocks. I see that positive global demand and negative commodity market-specific shocks are more important in explaining the volatility of real commodity price factors. Thus I restrict my attention to the role of the above two shocks in the remainder of Chapter 2.

Next, I demonstrate how the two commodity price shocks are transmitted to the selected Canadian macroeconomic variables and the five banking variables of each median bank. The impulse responses of each of the Big Six banks are also investigated in Appendix A.3. Finally, I revisit Calmès and Théoret (2014) and report the cross-sectional dispersions of the noninterest income ratio under a positive global demand shock and a negative commodity market-specific shock, respectively.

2.5.1 Explanatory Power of Estimated Factors on Variables

I examine to what extent the observables are correlated with the estimated factors, as specified in Equation (2.1). Table 2.4 reports the different quantiles (1%, 10%, 50%, 90%, and 99%) of the adjusted $R^2$ values for regressions of each observable on the appropriate set of factors for the whole sample period. I report distributions for four blocks of data: global economic activity $X_t^G$, Canadian economy $X_t^C$, banking sector $X_t^B$, and overall data $X_t$ (all series pooled together). To complement the results, I also plot the corresponding four histograms of the adjusted $R^2$ values in Figure 2.2.

At first glance, the volatilities of all $X_t$ have been explained to a great extent, with a median adjusted $R^2$ value of 0.5968. I see that for $X_t^G$, the adjusted $R^2$ values
2.5. EMPIRICAL RESULTS

Table 2.4: Quantiles of Adjusted $R^2$ Values for Regressions of Each Variable within Each Data Block on the Corresponding Set of Factors

<table>
<thead>
<tr>
<th>Data Series</th>
<th>Quantiles of Adjusted $R^2$</th>
<th># of Series</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1%</td>
<td>10%</td>
</tr>
<tr>
<td>Global Data, $X_G^t$</td>
<td>0.0842</td>
<td>0.2616</td>
</tr>
<tr>
<td>Canadian Macroeconomic Data, $X_C^t$</td>
<td>0.1885</td>
<td>0.3273</td>
</tr>
<tr>
<td>Banking Sector Data, $X_B^t$</td>
<td>0.2594</td>
<td>0.3837</td>
</tr>
<tr>
<td>Overall Data, $X_t$</td>
<td>0.1639</td>
<td>0.3465</td>
</tr>
</tbody>
</table>

Note: The adjusted $R^2$'s are computed from regressions of each observed variable (Column 1) on the appropriate set of factors defined in the measurement equation. Each figure in this table indicates various quantiles of the adjusted $R^2$ values obtained from regressions within each data block.

Figure 2.2: Histogram of Adjusted $R^2$ Values for Regressions of Each Variable within Each Data Block on the Corresponding Set of Factors

are skewed to the right. After a careful examination of the adjusted $R^2$ values within subsets of $X_G^t$, it is found out that the median adjusted $R^2$ values of $X_{Y,t}$ and $X_{P,t}$
can be as large as 0.8617 and 0.7495, respectively. Although the volatilities of global inflation indicators $X^G_{\pi,t}$ are somewhat poorly captured by the global inflation factor $F^G_{\pi,t}$, the median (50% quantile) adjusted $R^2$ value is still higher than 74.95%, indicating that half of the global price indicators are well captured.\footnote{After a careful inspection of those poorly explained price level indicators, I find that eight of them are GDP deflators and consumer price indices of developing nations (Brazil, India, China and Russia), and so reflects that some other force than $F^G_{\pi,t}$ guides the price dynamics for BRIC countries.} In summary, the estimated global factors have strong explanation power for the global block of variables. The explanatory powers of the estimated factors on the series of the Canadian macroeconomic block and the banking sector block are a bit lower, but still within fair ranges of $[0.1885, 0.9204]$ and $[0.2594, 0.9549]$. As demonstrated in Figure 2.2, the distribution of the adjusted $R^2$ values for these two blocks of series are centered around 0.5553 and 0.6176, respectively.

To better understand the contribution of each set of factors (global, domestic and banking) to the fluctuations of the five banking variables, I present, in Table 2.5, the median adjusted $R^2$ across regressions of each bank-level variable on various sets of factors. There is reasonably strong comovement of the banking series and the estimated factors, which on average explains 61.76% of the variation of these bank-level variables. The explanatory power of all the estimated factors for the total loan growth and the equity capital ratio is slightly lower, where all the factors, on average, explain 45.32% and 60.16% of the variation, respectively.

Consistent with the evidence for U.S. banks in Buch et al. (2014b), banking factors, on average, contribute most to the variation of each banking variable, where they have a relatively higher explanatory power for the variation in the return on assets and the share of NPLs (63.61% and 46.59%, respectively). This pattern is
Table 2.5: Median Adjusted $R^2$s Across Banks for Regressions of Each Bank-Level Variable on Various Sets of Factors

<table>
<thead>
<tr>
<th>Banking Data Series</th>
<th>Global ($F^G_t$)</th>
<th>Canadian ($F^C_t$)</th>
<th>Banking ($F^B_t$)</th>
<th>All Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Banking Data Series</td>
<td>0.1527</td>
<td>0.1424</td>
<td>0.4470</td>
<td>0.6176</td>
</tr>
<tr>
<td>(i) Nonperforming Loans Share</td>
<td>0.1433</td>
<td>0.1796</td>
<td>0.4659</td>
<td>0.6216</td>
</tr>
<tr>
<td>(ii) Equity Capital Ratio</td>
<td>0.1142</td>
<td>0.1392</td>
<td>0.4276</td>
<td>0.6016</td>
</tr>
<tr>
<td>(iii) Return on Assets</td>
<td>0.3456</td>
<td>0.1554</td>
<td>0.6361</td>
<td>0.7424</td>
</tr>
<tr>
<td>(iv) Growth of Total Loans</td>
<td>0.1442</td>
<td>0.1107</td>
<td>0.2619</td>
<td>0.4532</td>
</tr>
<tr>
<td>(v) Noninterest Income Share</td>
<td>0.1975</td>
<td>0.1838</td>
<td>0.4433</td>
<td>0.6469</td>
</tr>
</tbody>
</table>

Note: The adjusted $R^2$s are computed from regressions of each individual bank-level variable (Column 1) on various sets of factors defined in Column 2-5. Each figure in this table indicates the median of those adjusted $R^2$ values across all sampled banks.

This is not surprising as Buch et al. (2014b) show that the banking factors may capture linkages between individual banks, running through the interbank market or through exposure to common shocks not modeled explicitly in my DFM such as shocks to the balance sheets of the nonfinancial private sector or shocks to the international financial markets propagated through the banking system.

On average, I attribute 15.27% of the variation in the banking variables to global factors, which is comparable with the contribution of Canadian macroeconomic factors (14.24%). Noticeably, the average explanatory power of global factors for the volatilities of the return on assets (34.56%), growth of total loans (14.42%) and share of noninterest income (19.75%) are larger than those of Canadian macroeconomic factors. In contrast, Canadian factors, on average, play a relatively important role in determining the fluctuations of the share of NPLs (17.96%) and the equity capital ratio (13.92%). These results are consistent with the findings of Chapman and Damar (2015) that the Big Six banks are very globally active, with 27.5% of foreign claims out of total assets and with those claims spread over 58 countries by 2012Q4.
2.5.2 Historical Decompositions of Global Factors

Figure 2.3 illustrates the development of estimated global factors for real activities, inflation levels and real commodity prices, respectively. These factors represent empirical facts about international business cycles reported by Mumtaz and Surico (2009) and Monnet and Puy (2016), as well as the main dynamics in the world commodity markets summarized by Stuermer (2014) and Baumeister and Kilian (2016) in their analysis of the oil and major mineral markets.

The global real activity factor captures the main global recessions between 1996Q1-2016Q1 such as the East Asia crisis in 1997-1998, the bust of the early 2000s Dot-com bubble, the recessions after the 2008 financial crisis and the uncertainty caused by the public debt crisis in Europe starting from 2010Q2. Similarly, it also captures the expansion during the great moderation period and the temporary recovery from 2009Q2 to 2010Q2 due to the reaction of monetary and fiscal policies of most nations to the 2007-2009 financial crisis.

The real commodity price factor fluctuation captures crucial events in the commodity markets: declining commodity prices during the East Asian crisis from 1997 to 1998, rising commodity prices from the demand side in the early 2000s, the retreat in commodity prices during the 2008 financial crisis, rising base metal prices in 2009-2010 due to a strong stimulus from Chinese government policies, the bust of booming metal prices from early 2011 and falling oil prices from June 2014. Lastly, the global inflation factor includes rising food and energy prices in the early 2000s, the deflation of the late 2000s, and long-lasting deflation from 2012 onwards.

Figure 2.3 also plots historical decompositions of the three global factors based on sign restriction-identified and recursive-identified structural models. The shaded
2.5. EMPIRICAL RESULTS

Figure 2.3: Historical Decompositions of Global Factors: 1996:Q1 – 2016:Q1

Panel A: Identification by Sign Restrictions

Panel B: Recursive Identification

Note: Solid lines represent the three global factors. The shaded areas represent the portion of global factors explained by each global structural shock, identified by sign restrictions in Panel A and by recursive identification in Panel B.
2.5. EMPIRICAL RESULTS

areas measure the portion of dynamics of the three global factors explained by each of the three global shocks during the sample period. First, both schemes suggest that most of the volatility in the global real activity factor during this period is explained by global demand shocks. Second, both identification schemes show that the development of the global inflation factor is mostly attributed to global inflation shocks, although sign restrictions demonstrate that falling real commodity prices seem to have made some contributions to the deflation after mid-2014.

I am very interested in how much each global structural shock contributes to the volatility in the real commodity price factor during this period, as this determines which structural shock to focus on in subsequent analysis. The last row of Figure 2.3 implies that a large part of the volatility in real commodity prices is attributed to a commodity market-specific shock and, to a lesser extent, to a global demand shock under both sign restrictions and recursive identification, which corresponds with the conclusions of Charnavoki and Dolado (2014) for their sample period from 1975Q1 to 2010Q1. The global demand shock implies that the waning global economic demand was behind the falling commodity prices during 2008-2009. My findings also support the conclusions of Baumeister and Kilian (2016) that the declining crude oil price since June 2014 is attributed to the oil market-specific shocks and, to a lesser extent, caused by a global economic demand shock. Hence, I concentrate on these two shocks (a positive global demand shock and a negative commodity market-specific shock) in studying their effects on the Canadian economy and banks.

\footnote{Baumeister and Kilian (2016) estimate that, as of June 2014, $11 of this decline in the oil price is attributed to a slowing global economy with the remaining $16 due to the cumulative effects of positive oil supply shocks and shocks to expected oil production, both captured by the commodity market-specific shock in my case.}
2.5. EMPIRICAL RESULTS

2.5.3 Impulse Responses of Global Factors to Key Commodity Price Shocks

I now examine how three global factors react to identified global demand and commodity market-specific shocks. Figure 2.4 respectively plots the IRFs of global factors to the above two shocks, based on the sign restriction scheme and the recursive identification scheme. The shaded areas cover the conventional 68% credible set of results produced by sign restrictions. The solid lines stand for the median impulse responses identified by the recursive identification and their 68% credible interval are marked by dashed lines.

Results are generally similar under the two identified commodity price shocks, with the exception of the effects on the global real activity factor. A one standard deviation increase of a positive global demand shock on impact pushes up the global real activity factor and the real commodity price factor by 0.5 and 0.23, respectively. The effects are persistent, significant and separately reach their maximum at 1.3 and 0.44 within one year. In contrast to a positive global demand shock, a one standard deviation increase of a negative commodity market-specific shock gives rise to a temporary and stronger spike of 0.47 in the real commodity price factor and the effect becomes insignificant after one year. The negative commodity market-specific shock, however, has an adverse effect on the global real activity factor after two quarters and the effect peaks at -0.72 within six quarters. As for the global inflation factor, it gradually increases after a positive global demand shock and peaks at 0.43 after six quarters, whereas a negative commodity market-specific shock generates a short-lived and stronger increase (0.58) in global inflation.
2.5. EMPIRICAL RESULTS

Figure 2.4: Impulse Responses of Global Factors to a Positive Global Demand and a Negative Commodity Market Shocks

Note: This figure shows the impulse responses of the three global factors to a one standard deviation increase of a positive global demand shock and a negative commodity market-specific shock under sign restrictions and recursive identifications. The shaded areas represent the equally-tailed 68% credible set under sign restrictions. The solid lines denote the median impulse responses and the dashed lines represent the equally-tailed 68% credible set under the recursive identification. Error bands are estimated based on 100 Gibbs sampling draws from the posterior distribution.

2.5.4 How Are Commodity Price Shocks Transmitted to the Domestic Economy?

Before exploring how commodity price shocks are transmitted to the Canadian banks, I am curious about how they are transmitted to those macroeconomic variables, empirically proven to play an important role in determining the levels of NPLs (Nkusu, 2011; Klein, 2013). In particular, I am interested in real GDP growth, the inflation rate, the monetary policy rate, the total employment rate, share prices and real house prices. Real GDP growth determines the future prospects of banks’ loans and
is strongly correlated with the default rates on loans. The monetary policy rate is a major consideration in the cost of funds for banks and a return benchmark on investments. Houses, as modeled by Kiyotaki and Moore (1997), are usually used as debt collateral for residential mortgages and other types of individual loans. Their values are crucial to assess of the health of the banking industry and are closely monitored by banking regulators. Since commodity prices directly affect the tradable goods sector, I also examine exports, imports, terms of trade, and the real effective exchange rate. I also include personal and government consumption and investment, total credit from the household sector and the business sector. Moreover, disaggregated GDP values by industry are also presented to see how commodity price shocks impact various industries heterogeneously. Note that I convert the IRFs of the macroeconomic variables to the original units of the data by multiplying standard deviations computed in the first stage of the estimation procedure.

A Positive Global Demand Shock

Figure 2.5 illustrates the impulse responses of considered macroeconomic variables to a one standard deviation increase in global demand shock $\epsilon_{D,t}$, which roughly corresponds to a 4% increase in the real energy price index. Table 2.6 shows the estimates of median impulse responses under a recursive identification scheme, over three time horizons (0 quarter, the 4th quarter and the 8th quarter). In line with the evidence from Vasishtha and Maier (2013) and Charnavoki and Dolado (2014),

37 As shown by the Bank of International Settlements (BIS), a nominal effective exchange rate (NEER) is an index of some weighted average of bilateral exchange rates. A real effective exchange rate (REER) is the NEER adjusted by some measure of relative prices or costs; changes in the REER thus take into account both nominal exchange rate developments and the inflation differential vis-à-vis trading partners. Thus, an appreciation of the real (nominal) exchange rate in Canada indicates an increase in the REER of Canada.
the impulse responses show that a positive global demand shock, caused by booming foreign demand for Canadian tradable goods, leads to persistent and significant increases in important aggregate variables, such as real GDP, inflation, total employment, consumption, investment, exports and imports, and that the effects reach their maximum after approximately four quarters. Household consumption increases much more than government consumption. Real private investment responds quickly and strongly by 1.23% on impact, while real government investment insignificantly increases by 0.25% and then gradually declines after one year, consistent with the counter-cyclical properties of government expenditure in most business cycle studies.

The GDP of disaggregated industries all rise, albeit to different degrees. While the GDP of services benefits to a less degree than other industries, mining industry production grows significantly by 0.49% on impact in response to rising commodity prices. Inflation measured by the GDP deflator jumps by 0.26%, triggering an increase in the Canadian monetary policy rate (1.35%) to dampen the inflation. The terms of trade also improves by 0.93% on impact, and for approximately six quarters after the initial shock. Within four quarters, the peak effect of real house price increase reaches 1.67% in response to rising incomes, and the S&P TSX index also reaches its maximum at 5.1%. Moreover, I also find an appreciation of the real effective exchange rate (1.77%) due to an increase in real commodity prices, similar to that documented by Chen and Rogoff (2003). From Figure 2.5, I see that a positive global demand shock is generally expansionary, because consumers, firms of non-resource and resource industries, and the government all share the windfall income gains from strong commodity exports. Households and firms, on average, borrow more and invest more than how much they spend before the shock, because total liquidity becomes
2.5. EMPIRICAL RESULTS

Figure 2.5: Impulse Responses of Canadian Macroeconomic Variables to a Positive Global Demand Shock

Note: This figure contains the impulse responses of key Canadian macroeconomic variables to a one standard deviation increase of a positive global demand shock. The shaded areas represent the equally-tailed 68% credible set under sign restrictions. The solid lines denote the median impulse responses and the dashed lines represent the equally-tailed 68% credible set under the recursive identification. Error bands are estimated based on 100 Gibbs sampling draws from the posterior distribution.
2.5. EMPIRICAL RESULTS

more abundant for banks due to increased total income. However the increase in the policy rate may partially offset the benefits.

Table 2.6: Impulse Responses: Key Macroeconomic Variables

<table>
<thead>
<tr>
<th>Key Macroeconomic Variables</th>
<th>Positive demand shock</th>
<th>Negative commodity shock</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.0000</td>
</tr>
<tr>
<td>Total Employment</td>
<td>0.0011*</td>
<td>0.0038*</td>
</tr>
<tr>
<td>Real GDP</td>
<td>0.0026*</td>
<td>0.0074*</td>
</tr>
<tr>
<td>GDP Deflator</td>
<td>0.0442*</td>
<td>0.0510*</td>
</tr>
<tr>
<td>S&amp;P TSX Index</td>
<td>0.0026*</td>
<td>0.0067*</td>
</tr>
<tr>
<td>Terms of Trade</td>
<td>0.0093*</td>
<td>0.0164*</td>
</tr>
<tr>
<td>Exports of Goods</td>
<td>0.0120*</td>
<td>0.0241*</td>
</tr>
<tr>
<td>Imports of Goods</td>
<td>0.0129*</td>
<td>0.0305*</td>
</tr>
<tr>
<td>Real Effective Exchange Rate</td>
<td>0.0177*</td>
<td>0.0183*</td>
</tr>
<tr>
<td>Policy Rate</td>
<td>0.0135*</td>
<td>0.0339*</td>
</tr>
<tr>
<td>House Price (Canada)</td>
<td>0.0048*</td>
<td>0.0167*</td>
</tr>
<tr>
<td>Real Personal Consumption</td>
<td>0.0022*</td>
<td>0.0044*</td>
</tr>
<tr>
<td>Real Private Investment</td>
<td>0.0123*</td>
<td>0.0285*</td>
</tr>
<tr>
<td>Real Government Consumption</td>
<td>0.0005</td>
<td>0.0000</td>
</tr>
<tr>
<td>Real Government Investment</td>
<td>0.0025</td>
<td>0.0000</td>
</tr>
<tr>
<td>Total Household Credit</td>
<td>0.0011*</td>
<td>0.0042*</td>
</tr>
<tr>
<td>Total Business Credit</td>
<td>0.0008*</td>
<td>0.0026*</td>
</tr>
<tr>
<td>GDP (Manufacturing)</td>
<td>0.0097*</td>
<td>0.0210*</td>
</tr>
<tr>
<td>GDP (Mining)</td>
<td>0.0049*</td>
<td>0.0152*</td>
</tr>
<tr>
<td>GDP (Construction)</td>
<td>0.0055*</td>
<td>0.0125*</td>
</tr>
<tr>
<td>GDP (Services)</td>
<td>0.0019*</td>
<td>0.0039*</td>
</tr>
</tbody>
</table>

Note: Identified by a recursive scheme, the left panel implies the median impulse responses of key macroeconomic variables to a one standard deviation increase of a positive global demand shock, while the right panel contains the median impulse responses to a one standard deviation increase of a negative commodity market-specific shock. I round my results to four decimal places. * denotes significance at the 68 percent level of confidence.

A Negative Commodity Market-Specific Shock

As shown in Figure 2.6, the impulse responses of most macroeconomic aggregates to a negative commodity market-specific shock differ from those to a positive global demand shock. The increase in the real energy price index is 6%, actually higher than the 4% increase after a positive global demand shock. However, as shown in Table 2.6, the impacts of a commodity market-specific shock are mostly insignificant. The booming commodity prices only significantly strengthen the terms of trade by 0.67% for two quarters and then start to fade afterwards, which corresponds to the falling
2.5. EMPIRICAL RESULTS

exports of goods. Imports slightly increase for one quarter, though the effects are insignificant.

Among the major macroeconomic indicators, real GDP, government investment and consumption barely increase. Although real consumption and investment by households and private sectors rise up significantly on impact, the effects soon diminish and become insignificant after four quarters. Government investment initially falls and then rebounds by 0.04%. The disaggregated GDP values vary to different extents. I find a delayed decline in the GDP of mining industries due to higher commodity prices. Manufacturing GDP declines by 0.88% within two years, while servicing GDP and construction GDP respectively ramp up by 0.15% and 0.07% on impact, which is much weaker than their increase after a positive global demand shock. The GDP deflator significantly increases for four quarters, which is understandable since a negative commodity market-specific shock increases commodity prices, an element used to calculate the inflation index. The policy rate declines by 0.18% within eight quarters, and the house price increases slightly for four quarters after the initial shock and then declines. The above results show that the economy initially gains from expansionary exports of primary commodities. However, slowing foreign real activities due to the higher real commodity prices depress manufactured goods exports and abate real GDP growth in the long run. The economy only benefits for a short period from the increased value of commodity exports and relatively cheap imported products due to an appreciating real effective exchange rate.
2.5. EMPIRICAL RESULTS

Figure 2.6: Impulse Responses of Canadian Macroeconomic Variables to a Negative Commodity Market-Specific Shock

Note: This figure contains the impulse responses of key Canadian macroeconomic variables to a one standard deviation increase of a negative commodity market-specific shock. The shaded areas represent the equally-tailed 68% credible set under sign restrictions. The solid lines denote the median impulse responses and the dashed lines represent the equally-tailed 68% credible set under the recursive identification. Error bands are estimated based on 100 Gibbs sampling draws from the posterior distribution.
2.5. EMPIRICAL RESULTS

2.5.5 Impulse Responses of Important Bank-Level Variables

In this section, I assess the dynamic transmission of two global shocks to individual Canadian banks by respectively estimating the IRFs of three median banks: Big Six, foreign subsidiaries and other local bank. The estimated IRF values of the median banking variables are presented in Figure 2.7 and Figure 2.8, respectively. To make the results more understandable, I convert them to the original units of the data by multiplying corresponding standard deviations. I will focus on the impacts of shocks on the total loan growth, the share of NPLs and the noninterest income ratio, since I am mainly interested in the impact on bank risk of commodity price shocks, and also want to compare my results with those for U.S. banks in Buch et al. (2014b).

Table 2.7: Impulse Responses: Five Bank-Level Variables of Three Median Banks

<table>
<thead>
<tr>
<th>Five Banking Variables</th>
<th>Positive Global Demand Shock</th>
<th>Negative Commodity Market-Specific Shock</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td><strong>Panel A: Big 6 Banks</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(i) Nonperforming Loan Share</td>
<td>5.33*</td>
<td>-2.67*</td>
</tr>
<tr>
<td>(ii) Equity Capital Ratio</td>
<td>2.00*</td>
<td>2.33*</td>
</tr>
<tr>
<td>(iii) Return on Assets</td>
<td>4.67*</td>
<td>1.00</td>
</tr>
<tr>
<td>(iv) Total Loan Growth</td>
<td>-46.40*</td>
<td>22.86*</td>
</tr>
<tr>
<td>(v) Noninterest Income Ratio</td>
<td>0.00</td>
<td>60.11*</td>
</tr>
<tr>
<td><strong>Panel B: Foreign Subsidiaries</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(i) Nonperforming Loan Share</td>
<td>-2.50*</td>
<td>-6.50*</td>
</tr>
<tr>
<td>(ii) Equity Capital Ratio</td>
<td>83.30*</td>
<td>33.30*</td>
</tr>
<tr>
<td>(iii) Return on Assets</td>
<td>21.67*</td>
<td>5.00*</td>
</tr>
<tr>
<td>(iv) Total Loan Growth</td>
<td>-71.40*</td>
<td>41.43*</td>
</tr>
<tr>
<td>(v) Noninterest Income Ratio</td>
<td>216.67*</td>
<td>57.14*</td>
</tr>
<tr>
<td><strong>Panel C: Other Local Banks</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(i) Nonperforming Loan Share</td>
<td>5.00*</td>
<td>0.00</td>
</tr>
<tr>
<td>(ii) Equity Capital Ratio</td>
<td>4.38</td>
<td>3.13</td>
</tr>
<tr>
<td>(iii) Return on Assets</td>
<td>4.00*</td>
<td>1.20</td>
</tr>
<tr>
<td>(iv) Total Loan Growth</td>
<td>36.00*</td>
<td>16.00*</td>
</tr>
<tr>
<td>(v) Noninterest Income Ratio</td>
<td>-14.30</td>
<td>-17.70</td>
</tr>
</tbody>
</table>

Note: All identified by a recursive scheme, panel A indicates the median impulse responses of five banking variables for a representative Big 6 bank, to a one standard deviation increase of a positive global demand shock and a negative commodity market-specific shock respectively. Panel B and C contains the median impulse responses for a representative foreign subsidiary and a representative local bank. * denotes significance at the 68 percent level of confidence. I express my figures in basis points (1 basis point = 0.0001).
2.5. EMPIRICAL RESULTS

Figure 2.7: Impulse Responses of Median Banking Variables to a Positive Global Demand Shock

*Note:* This figure contains the impulse responses of five banking variables for three median banks to a one standard deviation increase of a positive global demand shock. The shaded areas represent the equally-tailed 68% credible set under sign restrictions. The solid lines denote the median impulse responses and the dashed lines represent the equally-tailed 68% credible set under the recursive identification. Error bands are estimated based on 100 Gibbs sampling draws from the posterior distribution.
Figure 2.8: Impulse Responses of Median Banking Variables to a Negative Commodity Market-Specific Shock

Note: This figure contains the impulse responses of five banking variables for three median banks to a one standard deviation increase of a negative commodity market-specific shock. The shaded areas represent the equally-tailed 68% credible set under sign restrictions. The solid lines denote the median impulse responses and the dashed lines represent the equally-tailed 68% credible set under the recursive identification. Error bands are estimated based on 100 Gibbs sampling draws from the posterior distribution.
2.5. EMPIRICAL RESULTS

Impulse Response Functions of Growth of Total Loans

Consistent with theoretical implications in Angeloni and Faia (2009), Zhang (2009), Dib (2010), Gerali, Neri, Sessa, and Signoretti (2010) and Meh and Moran (2010), Table 2.7 demonstrates a delayed increase in bank lending for all of the median banks, after both a positive global demand shock and a negative commodity market-specific shock.

After a positive global demand shock, I record a strong and significant effect on the total loan growth for all of the median banks, peaking at 35.71 basis points, 41.43 basis points and 60 basis points respectively for the median Big Six, foreign subsidiary and other local bank. In contrast, these numbers insignificantly reach their maximum at 14.29 basis points, 31.67 basis points and 12 basis points, respectively, after a negative commodity market-specific shock. The effects last between four quarters and approximately two years. The results comply with Buch et al. (2014b) findings for U.S. banks after an expansionary demand shock. The intuition behind this is suggested by the DSGE model in Zhang (2009) showing that as long as macroeconomic shocks improve the economic growth, the return prospects for investment projects improve, which motivates banks to increase their credit supply. However, the monetary policy reacts to a positive global demand shock by raising interest rates (Figure 2.5) and thus increasing funding costs for banks, which can explain the subsequent decrease in total loan growth. In the case of a negative commodity market-specific shock, the benefits from rising commodity prices to economic growth is limited and temporary, as high commodity price, not due to a global economic expansion, only

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38 Angeloni and Faia (2009), Zhang (2009), Dib (2010), Gerali et al. (2010) and Meh and Moran (2010) propose dynamic stochastic general equilibrium (DSGE) models with an explicit role for banks that account for the amplification effects of good/bad bank balance sheets on economic fluctuations. These models imply an unequivocally positive effect on lending following an expansionary shock.
benefits commodity-relevant sectors. The consequent appreciating exchange rates cause a slowdown of real GDP growth by depressing the exports of other noncommodity industries. The central bank reacts by lowering the policy rate, which causes a reduction in the cost of funds for banks (Figure 2.6). Hence, I may witness weaker but more persistent increases in total loan growth for all the median banks.

Noticeably for the median foreign subsidiary bank, the magnitudes of responses are larger than those of the other two median banks under both types of commodity price shocks. Chen et al. (2012) state that this may be attributed to the fact that these entities also have better access to foreign market-based funding, so foreign subsidiaries are less constrained by the cost of domestic sources of funds fluctuating with Canadian policy rates.

**Impulse Response Functions of the Nonperforming Loan Ratio**

The NPL ratio captures the banks’ risk as liquidity providers (Zhang, 2009). Theoretical models such as Zhang (2009) predict a reduction of the NPL ratio after a shock expands real economic activities. Because banks sign loan contracts with entrepreneurs based on expectations of future capital returns and expected loan default rates, an expansionary shock like a positive global demand shock helps entrepreneurs to realize unexpected profits which, in turn, leads to a lower loan default ratio than that anticipated by banks.

For all the median banks, the NPL ratios decline after a positive global demand shock. The peak effects are significant for the Big Six (-3.35 basis points) and foreign subsidiary (-7.50 basis points) median banks, while they are insignificant for other local banks (-2.50 basis points), which supports the theoretical results of Zhang (2009).
2.5. EMPIRICAL RESULTS

Note that as the monetary policy rate subsequently tightens after a positive global demand shock, the decrease in NPL ratios becomes weaker. After a negative commodity market-specific shock, the real GDP and total employment do not increase and eventually plunge. Therefore, I also witness that the NPL ratios for the median Big Six and other local banks increase to some extent, though insignificantly (3.25 basis points and 2.29 basis points, respectively). For the median foreign subsidiary bank, the NPL ratio initially declines by 8.2 basis points within two quarters, and it starts to elevate after that.

Impulse Response Functions of the Noninterest Income Ratio

As argued by Brunnermeier et al. (2012), an increase in the noninterest income ratio usually implies that banks increase their activities at trading, securitization and investment banking. Thus this ratio is more reflective of banks’ expectations about future business conditions.

As for the noninterest income ratio, I find out that banks respond heterogeneously under different types of commodity price shocks. A positive global demand shock has significant and positive impacts on this ratio for the median Big Six and foreign subsidiary banks. The peak effect reaches 62.86 basis points for the median Big Six bank, and 216.67 basis points for the median foreign subsidiary. In contrast, the noninterest income ratio declines sharply for the median other local bank (-28.6 basis points). After a negative commodity market-specific shock, the ratio of noninterest income for the median Big Six bank declines on impact (-28 basis points), then the effect becomes insignificant and trivial afterwards. For the median other local and foreign subsidiary banks, the noninterest income ratio increases on impact (50 basis
points for the median other local bank and 70 basis points for the median foreign subsidiary), and starts to decline subsequently.

The banking literature predicts that small banks are more affected by macroeconomic shocks than large banks because of their lower net worth, lack of diversification, and less diversified funding (Kashyap and Stein, 2000 and Diamond and Rajan, 2006). For Canadian banks, I observe the opposite situation. Total loans issued by large banks (the Big Six and foreign subsidiaries) generally increase more than total loans made by small other local banks after a positive global demand shock. Similar patterns can be found for the noninterest income ratio. The magnitudes of impulse responses of the noninterest income ratio for the median Big Six and foreign subsidiary are larger than those for other local banks after a positive global demand shock. After a negative commodity-market specific shock, we can find a similar but less obvious pattern between large and small banks. This may lead to a conclusion that risk tends to concentrates on large Canadian banks in terms of their more volatile noninterest income and aggressive total loan growth, which is particularly encouraged by an expansionary global demand shock driving up real commodity prices. My findings are in line with the conclusions in Chen et al. (2012), Calmès and Théoret (2013), and

39 As measured by Chen et al. (2012), the Big Six banks are the largest with an average asset size of $512.7 billion U.S., foreign subsidiaries are second to the Big Six banks with an average size of $8.7 billion U.S., while other local banks are the smallest with an average size of $4.9 billions U.S.
2.5. EMPIRICAL RESULTS

are comparable with the results for U.S. banks in Buch et al. (2014b).\footnote{In contrast to my conclusions, Buch et al. (2014b) find out that the size of banks is negatively correlated with the responses of bank lending and noninterest income, after an expansionary monetary policy shock and house price shocks. Moreover, financial regulations in U.S. and Canada differ substantially, which may partially explain why bank risk measured by the noninterest income ratio is concentrated on large Canadian banks in my sample. According to Chen et al. (2012), regulatory approaches in Canada, like asset-to-capital limits, are individually tailored for Canadian banks and are more stringent for small institutions. The results of differential regulatory approaches are an increasing number of non-Big Six banks in Canada with lower leverage ratios (higher equity-capital ratios). On the contrary, minimum capital requirements in the United States are uniformly applied across financial institutions ever since 1985. So small U.S. banks show more vulnerability than their larger competitors in terms of having higher leverage ratios.}

Figure 2.7 and Figure 2.8 also reveal that the return on total assets declines after a negative commodity market-specific shock and increases after a positive global demand shock for all the median banks. The equity capital ratio of all the median banks increases much more after a negative commodity market-specific shock than that after a positive global demand shock.

2.5.6 Forecast Error Variance Decompositions: Bank-Level Variables

Table 2.8 shows the forecast error variance decomposition (FEVD) and allows assessment of the relative importance of each identified commodity price shock for banking sector developments. I distinguish the short run (the one-year forecast horizon) from the medium run (the five-year horizon). In addition, I report the results on the median Big Six bank as a representative case.\footnote{The results of other median banks are very similar to those of the median Big Six bank and are available upon request.}

Following Bernanke et al. (2005), I consider a more appropriate FEVD to be that the relative importance of a structural shock is assessed to the extent of an observable variable explained by the common factors. For any variable $X_{it} \in X_t$, the modified
2.5. EMPIRICAL RESULTS

Table 2.8: Forecast Error Variance Decomposition: Bank-Level Variables

<table>
<thead>
<tr>
<th>Banking Data Series</th>
<th>1-year Horizon</th>
<th>5-year Horizon</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\epsilon_{D,t}$</td>
<td>$\epsilon_{\pi,t}$</td>
</tr>
<tr>
<td>Median Big Six Bank</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(i) Nonperforming Loan Share</td>
<td>6.4012</td>
<td>4.0933</td>
</tr>
<tr>
<td>(ii) Equity Capital Ratio</td>
<td>8.5573</td>
<td>4.2119</td>
</tr>
<tr>
<td>(iii) Return on Assets</td>
<td>13.7880</td>
<td>5.7377</td>
</tr>
<tr>
<td>(iv) Total Loan Growth</td>
<td>20.3370</td>
<td>7.0008</td>
</tr>
<tr>
<td>(v) Noninterest Income Ratio</td>
<td>8.8965</td>
<td>4.9128</td>
</tr>
</tbody>
</table>

Note: The above table illustrates the forecast error variance decomposition of five bank-level variables for the median Big Six bank. Each number reports the percentage of the forecast error variance explained by various commodity price shocks.

FEVD under $h$ forecast horizon can be expressed as

$$\frac{\Lambda_i \hat{\text{Var}}(F_{t+h} - \hat{F}_{t+h} | v_t^j) \Lambda_i^\top}{\Lambda_i \hat{\text{Var}}(F_{t+h} - \hat{F}_{t+h}) \Lambda_i^\top}$$

for specific shock $j$ imposed on error term $v_t$, where $\Lambda_i$ is the $i$th row of the factor loading matrix $\Lambda$ defined in Equation (2.1). The term $\frac{\hat{\text{Var}}(F_{t+h} - \hat{F}_{t+h} | v_t^j)}{\hat{\text{Var}}(F_{t+h} - \hat{F}_{t+h})}$ is usually regarded as the standard FEVD, where $\hat{\text{Var}}(F_{t+h} - \hat{F}_{t+h} | v_t^j)$ is the variance matrix conditional on specific shock $j$ imposed on the error term $v_t$ and $\hat{\text{Var}}(F_{t+h} - \hat{F}_{t+h})$ is the unconditional forecasting variance for $\hat{F}_{t+h}$.

For the median Big Six bank, all three global structural shocks together explain 16.99% of the NPL ratio, 25.98% of the equity capital ratio, 24.23% of the return on assets, 35.55% of the total loan growth, and 22.46% of the noninterest income ratio in the short run. For all the bank-level variables, these numbers increase by 1.39 to 5.96 percentage points in the medium run.

Next, the importance of each commodity price shocks is examined. In the short run, commodity market-specific shocks and global demand shocks are equivalently important for the ratio of NPLs, while global demand shocks obviously dominate
commodity market-specific shocks on explaining this ratio in the medium run. Similar conclusions can also be drawn for the total loan growth and the noninterest income ratio. To explain the variation in the return on total assets, global demand shocks strictly dominate other two commodity price shocks in the short run as well as in the medium run. As for the equity capital ratio, commodity market-specific shocks distinguish in the short run, while global demand shocks contribute equally as commodity market-specific shocks in the medium run. In a summary, both commodity market-specific shocks and global demand shocks are important for bank lending and bank risk in the short run. In the medium run, global demand shocks seem to play a more important role in explaining the variance of most bank-level variables.

Figure 2.9: Dispersion of Noninterest Income Ratio across All Banks under Two Commodity Price Shocks
2.5.7 Dispersion of Noninterest Income Ratio across All Banks

Inspired by Calmès and Théoret (2014), I investigate if the cross-sectional dispersion of the noninterest income ratio differs under either a positive global demand shock or a negative commodity market-specific shock, since a positive global demand shock accelerates real GDP growth and a negative commodity market-specific shock depresses real GDP growth. Figure 2.9 shows the cross-sectional standard deviations of the median impulse responses of the noninterest income ratio, as forecasting horizons increase. It is apparent that the cross-sectional standard deviation of the noninterest income ratio after a negative commodity market-specific shock always stay below its counterpart after a positive global demand shock. This discrepancy turns largest at the second quarter after the initial shocks, where it equals 0.06. The gap then gradually decreases as the impact of both commodity price shocks fades away. The result of this analysis clearly indicates that banks adopt more similar strategies such as slowly increasing or even decreasing their share of volatile noninterest income during slow growth episodes (i.e., after a negative commodity market-specific shock). In contrast, banks behave more heterogeneously in terms of their choices for the noninterest income ratio during fast growth episodes (i.e., after a positive global demand shock), which supports the findings by Calmès and Théoret (2014).

2.6 Robustness Analysis

In this section, I am going to implement some robustness check on the sensitivities of the estimated IRFs to sub-sample analyses and prior parameter changes.
2.6. ROBUSTNESS ANALYSIS

Figure 2.10: Robustness Check: Subsample 1996Q1 to 2014Q2

Panel A: Impulse Responses of Banking Variables to a Positive Global Demand Shock

Panel B: Impulse Responses of Banking Variables to a Negative Commodity Market-Specific Shock

Note: This figure shows the estimated IRFs of five banking variables for three median banks to one standard deviation increase of a positive global demand shock and a negative commodity market-specific shock, corresponding to the subsample period of 1996:Q1 -2014:Q2. The shaded areas represent the equally-tailed 68% credible set under sign restrictions. The solid lines denote the median impulse responses and the dashed lines represent the equally-tailed 68% credible set under recursive identification. Error bands are estimated based on 100 Gibbs sampling draws from the posterior distribution.
2.6.1 Subsample Analysis of the Big Oil Price Crash in 2014

During my sample period, primary commodity prices have undergone several large movements, which has been discussed in Section 2.5.2. This might motivate a need for testing the time invariance of factor loadings, a standard assumption made in the analysis of large factor models.\(^{42}\) I apply the time invariance test of the factor loadings, suggested by Chen et al. (2014), to the Canadian macroeconomic and banking blocks of the SDFM model.\(^{43}\) The \(p\)-values of the time invariance test are 0.15 and 0.22 for the Canadian macroeconomic and banking blocks respectively, which indicates that the null hypothesis of no big structural breaks can not be rejected during my sample period.

As argued by Baumeister and Kilian (2016), the price of crude oil experienced one of its largest declines in modern history since June 2014. The monthly average price of Brent crude oil fell by $49 U.S. between June 2014 and December 2014, which equals approximately 44% of its original value.

For the sake of caution, I still implement a subsample analysis ranging from 1996Q1 to 2014Q2, since the crude oil production now constitutes almost 50% of values of Canadian commodity output in 2016. Specifically, I compare the estimated IRFs for the full sample of 1996Q1-2016Q1 and for a subsample of 1996Q1-2014Q2.

\(^{42}\) As argued by Chen, Dolado, and Gonzalo (2014), unless parameter shifts are mild, the factor space estimated by the PCA is inconsistent, the number of factors tends to be overestimated under big breaks. Negligence of these breaks can have serious forecasting problems in later analyses.

\(^{43}\) This test is really straightforward to implement in empirical applications. In the first step, the number of factors is still chosen by Bai and Ng (2002) information criteria and factors are estimated by the PCA. Then the second step consists of applying Chow tests (for known breaking date) or sub-type tests (for unknown breaking date) towards regressions of the first factor on the remaining ones. If a structural break is detected, then I reject the null hypothesis of no big breaks. Otherwise, I can not reject the null of no big breaks, which leave me no worries about the stability of factor loadings over time. In my case, since no prior break date is assumed to be known, the Sup-Wald test is applied with the trimming \(\Pi = [0.3, 0.7]\). It corresponds to the time period ranging from 2002Q2 to 2010Q2.
The results for the subsample are provided in Figure 2.10. Generally speaking, the results are qualitatively similar to those for the full sample. The most noticeable difference is the impulse responses of the noninterest income ratio after a negative commodity market-specific shock, as I can see that the effect of all the median banks reducing their noninterest income becomes stronger for the subsample than that for the full sample. This is particularly pronounced for the median Big Six bank, which significantly decreasing its noninterest income ratio by 38 basis points on impact. Additionally, the effect of raising the NPL ratio for all the median banks also gets stronger for the subsample than those for the whole sample. Take the median other local bank as an example, I record a significant increase in the NPL ratio by 7.2 basis points after a negative commodity market-specific shock, much higher than the result for the whole sample.

2.6.2 The Effects of Varying the Short-Run Elasticity Bounds

Following Kilian and Murphy (2012), I also test the robustness of my results by varying the short-run elasticities of the global real economic factor to a commodity market-specific shock. Drawn from estimates in the empirical literature on the short-run impact of an oil price increase on U.S. output (Cashin et al., 2014 and Baffes et al., 2015), I consider two alternative scenarios: (i) \(-0.12 \leq A(1,3) \leq 0.05\) and (ii) \(-0.3 \leq A(1,3) \leq 0.05\). In other words, the global real economic activity is permitted to be more negatively influenced by an increase in real commodity prices.

The results of scenario (i) are provided in Panel A of Figure 2.11 and the results of scenario (ii) are plotted in Panel B of the same figure. The shapes of the IRFs remain basically unaffected by this change on the lower bound of \(A(1,3)\). I only witness some
2.6. ROBUSTNESS ANALYSIS

Figure 2.11: Robustness Check: Different Short-Run Elasticity Bounds After a Negative Commodity Market-Specific Shock

Panel A: $-0.12 \leq A(1,3) \leq 0.05$, Cashin et al. (2014)

Panel B: $-0.3 \leq A(1,3) \leq 0.05$, Baffes et al. (2015)

Note: This figure shows the estimated IRFs of five banking variables for three median banks to one standard deviation increase of a negative GC shock. The shaded areas represent the equally-tailed 68% credible set under sign restrictions. The solid lines denote the median impulse responses and the dashed lines represent the equally-tailed 68% credible set under the recursive identification. Error bands are estimated based on 100 Gibbs sampling draws from the posterior distribution.
widening of 68% credit sets for the IRFs identified by sign restrictions, as the lower bound of $A(1, 3)$ decreases from -0.1 to -0.12 and -0.3, respectively.\footnote{Note that here I only report the IRFs after a negative commodity market-specific shock, since the results after a positive global demand shock remain unaffected by this new parameter set-up.}
2.7 Conclusions

To my best knowledge, the empirical literature that models the effects of macroeconomic shocks on banks, generally focuses on monetary policy shock and the financial market shock (Dave et al., 2013; Buch et al., 2014b; and Abbate, Eickmeier, Lemke, and Marcellino, 2016). Few papers explicitly address the dynamic impacts of commodity price-relevant shocks on bank lending and bank risk, with the exception of Alodayni (2015).

This paper contributes to the literature by proposing a SDFM model to decompose the underlying forces that drive real commodity price changes and analyzing their dynamic effects on banks and pertinent macroeconomic indicators in an SCEE like Canada. Due to the availability of large-panel micro-level banking datasets from the OSFI, I exploit the linkages between individual banks through the extracted banking factors from a principal component analysis and include them in my framework.

Utilizing the sign restrictions that Kilian and Murphy (2012) propose and a conventional recursive identification scheme, I identify global demand, commodity market-specific and global inflation shocks underlying real commodity price changes. The first two shocks explain most of the volatilities in real commodity prices. I then analyze how the above two key commodity price shocks transmit into the macroeconomy and three median banks. The hypothetical median banks are created by taking the median values of bank-level variables within subsamples categorized as Big Six banks, other local banks and foreign subsidiaries. Commodity price shocks play a nontrivial role in explaining the dynamics of Canadian bank-level variables, especially return on assets, the growth of total loans, and the noninterest income ratio.
The various underlying shocks that drive real commodity price changes cannot be ignored, because they can have heterogeneous impacts on bank risk, lending, and other bank-level variables. Only a real commodity price increase following an expansionary global demand shock can bring about a significant increase in bank lending for all of the median banks, which is consistent with the explanation of an increased demand for investment during boom periods (e.g., Zhang, 2009). The response of bank risk provides mixed answers that depend on which measure of bank risk is taken. NPL ratios of all of the median banks decline after an expansionary global demand shock; they deteriorate after a negative commodity market-specific shock that increases real commodity prices and is caused by supply disruptions or inventory demands. If bank risk is measured by the noninterest income ratio, the large median banks (i.e., Big Six and foreign subsidiaries) significantly increase their risk-taking by increasing shares of noninterest income following an expansionary global demand shock. In contrast, noninterest income ratios of all the median banks decline after a negative commodity market-specific shock.

I also discover substantial heterogeneity across bank responses to a common commodity price shock. The magnitudes of responses of the median Big Six bank and foreign subsidiary are larger than those of the median other local bank, especially in terms of the total loan growth and the noninterest income ratio. This is in contrast with the evidence of U.S. banks that Buch et al. (2014b) provide and theoretical predictions in Diamond and Rajan (2006), which posit that small banks are usually more responsive to macroeconomic shocks than large banks. However, my results support previous findings by Calmès and Théoret (2013), which compare U.S. and Canadian banks and suggest that most of the risk indicated by these balance-sheet ratios are
concentrated among large banks such as the Big Six and foreign subsidiaries. My findings are interesting from bank regulators’ perspective. The increase in volatile noninterest revenues and loan growth of large Canadian banks after commodity price shocks raise the question of whether the Canadian banking system would be that robust, had it confronted a comparable shock like the subprime mortgage crisis.

Sensitivity checks, including a subsample analysis and adjustments of the elasticity bounds of the impact matrix, confirm my results to some extent. In an analysis of the subsample period before the 2014 oil price crash (1996Q1-2014Q2), I find some evidence that before the 2014 oil price crash, banks are more risk averse and are more willing to reduce their proportions of noninterest income when facing headwinds like a negative commodity market-specific shock.

Overall, my analysis can be seen as a first step in the direction of jointly modeling dynamics of foreign economic shocks and the banking sector in a small commodity-exporting country. Note that in my framework, I solely focus on the impacts of commodity price shocks because it is to my best knowledge that few structural models can identify the multiple foreign shocks affecting banks in an SCEE, along with commodity price shocks. In future work, it will be meaningful to extend my analysis in the direction of identifying the multiple foreign shocks crucial for domestic banks in an SCEE.
Chapter 3

Forecasting the Market Volatility Index with OLS post-Lasso Heterogeneous Autoregression

3.1 Introduction

Modeling volatility of financial assets is of great interest to many practitioners of risk management and asset allocation. The distinct features of its clustering, slowly decaying auto-correlation function and nonlinear responses to previous market information other than volatility itself is constantly stressed in predicting financial market volatility.\footnote{This phenomenon has been uncovered by Dacorogna, M"uller, Nagler, Olsen, and Pictet (1993), Andersen, Bollerslev, Diebold, and Labys (2001b) for the foreign exchange market, and Andersen, Bollerslev, Diebold, and Ebens (2001a) for the stock market return.} To capture main characteristics of this variance series, various models are suggested; the most renowned fractionally integrated autoregressive moving average (ARFIMA) models for the realized volatility are developed in Andersen et al. (2001b) and the standard HAR model is proposed by Corsi (2009). The standard HAR model essentially claims that the conditional variance of the discretely sampled returns is a linear function of the lagged squared return over the identical return horizon in combination with the lagged squared returns over longer and/or shorter return
horizons. Compared with the ARFIMA, the standard HAR model has been widely regarded as a more parsimonious model that accurately approximates the property of long memory and permits more convenient estimation (e.g., OLS). In addition, the standard HAR model carries a straightforward economic interpretation that agents with different frequencies of trading perceive and respond to, which causes different types of volatility components. This is termed as the Heterogeneous Market Hypothesis in Müller, Dacorogna, Davé, Pictet, Olsen, and Ward (1993). Other empirical works reveal that the volatility over longer time horizons has a stronger impact on the volatility over shorter time horizons than vice versa (Müller, Dacorogna, Davé, Olsen, Pictet, and von Weizsäcker, 1997; Arneodo, Muzy, and Sornette, 1998).

In this chapter, we concentrate exclusively on forecasting the VIX published by the Chicago Board Options Exchange (CBOE), because the VIX is a popular barometer for market sentiment. Many trading practitioners of hedging and speculation monitor it closely. Moreover, the VIX index hinges on the S&P 500 index options with a wide array of strike prices and enjoys the convenience of being a model-free estimator of the implied volatility (Jiang and Tian, 2005). Recent work by Fernandes et al. (2014) uncovers an intrinsically long-range dependence of the VIX and demonstrates that the standard HAR model fares well in forecasting the VIX index.

Inspired by the success achieved by the HAR-like models, most papers that follow Corsi (2009) have extended the standard HAR model in the direction of generalizing the univariate HAR model with jumps, leverage effects, and other nonlinear behaviors
to the multivariate context. However, few papers validate the choice of predictors, as priorly imposed by the univariate HAR model. There is an exception: Audrino and Knaus (2016) theoretically prove that the Lasso could recover the choice of predictors for the standard HAR model, provided that the standard HAR model was the true model of the underlying data generating process (DGP). Nevertheless, Audrino and Knaus (2016) also agree with Corsi (2009) that, in reality, the standard HAR model is only a simple approximation to the realized volatility and its predefined choice of predictors does not fully conform to that recovered from the Lasso. Finally, the standard HAR model performs as well as the Lasso HAR model in the out-of-sample analysis that Audrino and Knaus (2016) implement.

We are motivated by the fact that the original set of predictors imposed by the standard HAR model could be suboptimal, depending on the underlying series and its level of contained noise at different frequencies. This chapter contributes to the literature by embedding a model selection procedure into the standard HAR model, namely OLHAR, which is flexible at picking the set of important predictors of the standard HAR model as the forecasting horizons vary. Model selection is significant

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2 Corsi, Pirino, and Renó (2010) use the C-Tz test for jumps detection and threshold bipower variation to estimate relevant parameters. The jumps are also included in the HAR model in a volatility cascade way. Bollerslev, Litvinova, and Tauchen (2006) also stress the importance of allowing for the asymmetric leverage effects when modeling the volatility process. More complicated nonlinear effects, including structural breaks and regime-switches, are modeled by McAleer and Medeiros (2008) and Scharth and Medeiros (2009). Corsi, Audrino, and Renó (2012) provide a comprehensive survey on the development of HAR-type models and their possible extensions.

3 The Lasso and its related methods have received enormous attention in the past few decades since the seminal work of Tibshirani (1996) because this estimator can be applied when the number of regressors exceeds the number of observations. This estimator minimizes the sum of squared errors subject to a penalty term.

4 This phenomena is quite remarkable when Corsi (2009) applies the univariate HAR model to three different types of daily series, USD/CHF exchange data, S&P500 futures, and T-BOND futures. The coefficient of lagged daily realized volatility is insignificant for the T-Bond future, which may be due to the fact that daily realized volatility of the T-Bond future shows a higher level of noise than the exchange rate and stock index future at same frequency, as Corsi (2009) claims.
3.1. INTRODUCTION

to decide model predictors for forecasting; however, its benefits are often compro-
mised by high-computational, costly search over exponentially growing models. To
mitigate this problem, we resort to the OLS post-Lasso method suggested by Belloni
and Chernozhukov (2013) to first prescreen potential predictors of models so as to
construct a shrunk potential model. Then we can estimate the selected predictors
using the conventional OLS method. Note that the selected predictors may change
as the forecasting horizon expands. Our analysis differs from that of Audrino and
Knaus (2016) in two aspects. We explore the multistep ahead forecast performance
of the Lasso-type estimators, whereas only the 1-day ahead forecasts are analyzed
in Audrino and Knaus (2016). Our analysis considers an application to the implied
volatility, the VIX, whereas Audrino and Knaus (2016) limit their analysis to realized
volatilities of individual stocks.

Our main findings are listed as follows. First, we show that applying the OLHAR
model to the VIX index produces different combinations of predictors from what
is assumed in the standard HAR model, as a prior setup (Fernandes et al., 2014).
We reach this conclusion, after controlling for the same total number of predictors
and other exogenous variables as Fernandes et al. (2014). This further sustains the
findings of Audrino and Knaus (2016) that the predictors of a standard HAR may
not be fully recovered by a model selection device in some cases.

Second, we find substantial superiority of the OLHAR model when it comes to
the multistep ahead forecasting of the VIX index. Despite being indistinguishable
from the performance of the standard HAR model at one-day horizon, the OLHAR
significantly dominates the standard HAR model and the Lasso HAR model at fore-
casting the VIX five days, ten days, and twenty-two days ahead. Noticeably, our
robustness check verifies that the good performance of the OLHAR is insensitive to the total number of predictors. Moreover, we also provide a discussion based on Theorem 5 (Performance of OLS post-Lasso) in Belloni and Chernozhukov (2013). The arguments explain why the OLHAR statistically outperforms the conventional Lasso HAR.

The outline for the rest of this chapter is as follows. Section 3.2 introduces the HAR model and shows how the OLS post-Lasso can be integrated in this context. We provide an intuitive discussion on the advantages of the OLHAR over the conventional Lasso HAR in Section 3.3. Section 3.4 features an out-of-sample comparison of the OLHAR versus the standard HAR and other popular HAR-type models, in the case of an application to the VIX index. Section 3.5 designs a robustness check on adjusting the total number of predictors within the OLHAR and explores its impact on the out-of-sample performance of the OLHAR model. We conclude the chapter in Section 3.6.

3.2 OLS post-Lasso Heterogeneous Autoregression

In this section, we are primarily interested in modeling and forecasting the VIX, the implied option volatility of the S&P500 index for contracts with a maturity of one month. Suppose $y_t$ is the dependent variable, for example the logarithm of the VIX index at time $t$. We define $\bar{y}_t^{(d)} = \frac{1}{d} \sum_{s=1}^{d} y_{t-s+1}$ as the average of previous $d$-periods of $y_t$, where the upper script indicates the aggregation period and thus the $d$-period aggregation is denoted by $\bar{y}_t^{(d)}$. Denote $x_t = [1, \bar{y}_t^{(l_1)}, \ldots, \bar{y}_t^{(l_p)}] \in \mathbb{R}^{p+1}$ for some vector of indexes $l = [l_1, \ldots, l_p] \in \mathbb{Z}^+_p$, where $p$ represents the maximum positive order of lags. In line with Corsi (2009), the series $y_t, \{y_t, 1 \leq t \leq T\}$, are presumably approximated
by the standard HAR model with a $h$-period-ahead forecast horizons if $y_t$ satisfies

$$y_t = x_{t-h} \beta + \epsilon_t \quad \text{for any } h \in \mathbb{Z}_+, \quad (3.1)$$

where $\beta$ is the $(p + 1) \times 1$ coefficient vector including constants and $\epsilon_t$ is a generic (weak) white noise.\(^5\)

As argued by Corsi et al. (2012), a common choice in the literature for the index vector $l$ is $[1, 5, 22]$ so as to reflect the daily, weekly and monthly component contributions to the volatility process. In Fernandes et al. (2014), $l$ is arbitrarily fixed at $l^0 \equiv [1, 5, 10, 22, 66]$ in all the exercises for various forecasting horizons. We argue that such setup may not be robust for two reasons: (i) although $l^0$ is frequently chosen to mirror intuitive concepts like daily, weekly, biweekly, monthly and quarterly components of volatility process, such decision lacks solid statistical proofs (Audrino and Knaus, 2016); and (ii) as illustrated in Corsi (2009), the out-of-sample performance of the standard HAR model with fixed $l^0$ is sometimes unstable and depends on the level of noise contained in the underlying pricing series of the considered asset, which could further rely on the arrival frequency of new information that changes the asset volatility. Yet, fixing $l^0$ at $[1, 5, 10, 22, 66]$ may not be the best way to accommodate the altering time horizons of new information.

Thus we contribute to the literature by considering the forecast implication of a flexible choice on the set of predictors under the HAR specification. In other words, instead of restricting the index vector $l$ at $l^0$ for each forecasting horizon,

---

\(^5\) Generally white noise is a strong assumption as most financial time series display heteroskedasticity, which does not bias the OLS regression. Corsi, Mittnik, Pigorsch, and Pigorsch (2008) consider a more sophisticated estimation procedure that are able to account for this generalized autoregressive conditional heteroskedasticity (GARCH) effect.
3.2. OLS POST-LASSO HETEROGENEOUS AUTOREGRESSION

we allow \( l \) to be driven by data of the VIX index. Then it is natural to think about all possible combination of \( 2^p \) HAR models and compare their performance altogether. Nevertheless, as argued by Craioveanu and Hillebrand (2012) and Audrino and Knaus (2016), the model selection in this conventional manner can be extremely computationally costly, since it requires an exhaustive \( 2^p \) model comparisons and the number of potential models grows exponentially with \( p \), especially for large values of maximum lag order \( p \). In order to circumvent such issue, we utilize the data-driven model selection estimator in Belloni and Chernozhukov (2013) that can shrink the number of parameters to a manageable extent. For convenience purposes, we denote our proposed estimator as OLHAR.

The OLHAR works as follows. First we impose some prior restrictions to control the computational cost and to ease the comparison with the HAR type models in Fernandes et al. (2014): (i) the maximum \( p \) within the index vector \( l \) is fixed at 66 (ii) the total number of predictors for each forecasting horizon is restricted to be five.\(^6\)

Second, we utilize the conventional Lasso estimator to select important predictors, which is the constrained least-squares estimator \( \hat{\beta} \) for Model (3.1) subject to the constraint \( \beta_1 = \beta_2 = \ldots = 0 \). Following Tibshirani (1996), the conventional Lasso estimator shrinks \( \hat{\beta} \) towards \( \tilde{\beta} \) by solving

\[
\hat{\beta}^{\text{Lasso}} = \arg \min_{\beta} \frac{1}{2T} \sum_{t=1}^{T} (y_t - x_{t-h}^T \beta)^2 + \lambda \sum_{j=1}^{p+1} |\beta_j|, \tag{3.2}
\]

\(^6\) We also release this restriction and test its implication in Section 3.5. We set the alternative total number of predictors to be three and ten, respectively. Our main conclusions remain basically unaffected.
where $\lambda$ is the tuning parameter that controls the penalty term.\footnote{In practice, researchers either assign $\lambda$ a specific value or use the $k$-fold cross-validation to determine the optimal $\lambda$. A common choice is to pick $\lambda$ to minimize the $k$-fold cross-validation. In the benchmark case, we follow the previous literature to adopt the five-fold cross-validation.} Here, $\lambda$ is chosen by the $k$-fold cross-validation ($k = 5$) and fixed at $\lambda = \sqrt{\frac{\log p \log p}{T}}$.\footnote{Note that the Lasso estimator chooses five predictors according to the relevant penalty term $\lambda$ chosen by five-fold cross validation. In Section 3.5, we tune the penalty term $\lambda$ so that the Lasso estimator chooses three and ten predictors respectively in the robustness analysis.} In general, the benefits of applying the conventional Lasso other than the OLS estimator exist in some cases, where the number of regressors exceeds the number of observations, which involves shrinkage, or in other cases, where the number of parameters is not small relative to the sample size and some form of regularization is necessary.

Last, we use the OLS method to estimate the coefficients of those significant predictors selected by the conventional Lasso. As suggested by Belloni and Chernozhukov (2013), the OLS estimation of the selected predictors reduces the bias and the possibly asymptotic risk caused by the conventional Lasso. According to Belloni and Chernozhukov (2013), updated information may change the selected predictors. Thus we redo the OLHAR whenever the forecasting horizon $h$ changes. Our OLHAR procedure is robust to the time variance in parameter estimates, because it is dynamically driven by the actual data $[y_t, x_t]$.

### 3.3 Discussions on the Advantages of OLS post-Lasso

Belloni and Chernozhukov (2013) shows that the OLS post-Lasso estimator performs at least as well as the conventional Lasso in terms of the rate of convergence, and has the advantage of a smaller bias. Remarkably, the superiority of the OLS post-Lasso remains even if the Lasso-based model selection “fails” in the sense of missing some components of the “true” regression model. This is exactly the case implied
3.3. DISCUSSIONS ON THE ADVANTAGES OF OLS POST-LASSO

by the empirical exercise in Audrino and Knaus (2016). Belloni and Chernozhukov (2013) also prove that the OLS post-Lasso estimator can achieve sufficient sparsity and perform “strictly better” than the Lasso, if the Lasso model selection correctly includes all components of the “true” model as a subset of candidate models.

We demonstrate that the theoretical results in Belloni and Chernozhukov (2013) can be applied to the context of the proposed OLHAR model. Given that \( \{y_i\} \) is stationary, the standard HAR model defined in (3.1) satisfies Conditions M, V, RE, and RSE in Belloni and Chernozhukov (2013). Therefore, their Theorem 5 (Performance of the OLS post-Lasso) is viable. The required conditions for the validity of Theorem 5 are:

**Condition M.** We have data \( \{(y_i, z_i), i = 1, ..., n\} \) such that for each \( n \)

\[
y_i = f(z_i) + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \sigma^2), \quad i = 1, ..., n,
\]

where \( y_i \) are the outcomes, \( z_i \) are vectors of fixed (true) regressors, and \( \epsilon_i \) are i.i.d. errors. \( f \) is the nonparametric regression function to be estimated at the design points such that \( f_i = f(z_i) \), for \( i = 1, ..., n \). Let \( P(z_i) \) be a given \( p \)-dimensional dictionary of technical regressors with respect to \( z_i \). \( P(z_i) \) can also be interpreted as a \( p \)-vector transformation of \( z_i \), with components \( x_i = P(z_i) \). Variables \( x_i \) are what we observed and used in the estimation.\(^9\) We assume that \( n \rightarrow \infty \) and \( p = p_n \rightarrow \infty \).

Condition M formalizes the true DGP, and imposes asymptotic assumptions on \( n \) and \( p \). This condition is quite general and can be easily satisfied by the HAR process discussed here. The asymptotic assumption on \( p \rightarrow \infty \) is not common in the HAR

\(^9\)For convenience, Belloni and Chernozhukov (2013) assumes that \( x_i \) is normalized so that \( \mathbb{E}_n(x_j^2) = 1 \) for \( j = 1, ..., p \). Such normalization is not crucial in their proof.
literature, since the maximum lag index in the HAR model is usually fixed at 22 or 66, so as to mirror monthly or quarterly averaged volatilities. However, this can't be restrictive, since we can easily increase the maximum lag index to mimic a longer time span, for example, 250 for yearly averages.

**Condition V.** The estimated standard deviation of \( y_i \), \( \hat{\sigma} \) obeys

\[
b \leq \hat{\sigma}/\sigma \leq u \quad \text{with probability of } 1 - \tau \text{ at least,}
\]

where \( 0 < b \leq 1, u \geq 1, \) and \( 0 \leq \tau < 1 \) are constants.

Condition V imposes boundary constraints on the estimated \( \hat{\sigma} \). In line with Belloni and Chernozhukov (2013), we can construct \( \hat{\sigma} \) that satisfies this condition under mild assumptions. In other words, we can use the sample standard deviation of \( y_i \), say \( \hat{\sigma}_0 \), as a starting value to compute the OLS post-Lasso estimates. We then use the fitted \( \hat{\sigma} \) from the equation estimated by the OLS post-Lasso, as a new starting value for the next round of iteration. We perform this procedure by a limited number of times. Belloni and Chernozhukov (2013) provides a detailed description of the above iteration process.

Before we proceed to the remaining conditions, we first introduce some notations consistent with Belloni and Chernozhukov (2013). We denote \( \| \cdot \|_0 \) as the number of non-zero components of a vector, \( \| \cdot \|_1 \) as \( l_1 \)-norm, and \( \| \cdot \|_2 \) as \( l_2 \)-norm. Given a vector \( \delta \in \mathbb{R}^p \) and an index set \( T \subset \{1, \ldots, p\} \), we define \( \delta_T \) to be the vector in \( \mathbb{R}^p \), in which \( \delta_{Tj} = \delta_j \) if \( j \in T \) and \( \delta_{Tj} = 0 \), otherwise. Given covariate values \( x_1, \ldots, x_n \), we define the prediction norm of a vector \( \delta \in \mathbb{R}^p \) as \( \| \delta \|_{2,n} = \left\{ \mathbb{E}_n(x'\delta)^2 \right\}^{1/2} \). Let \( s \) be the smallest integer among the optimal values of the oracle risk minimization program of

\[
\min_{0 \leq k \leq \min(p,n)} c_k^2 + \sigma^2 k/n \quad \text{with} \quad c_k^2 = \min_{\|\beta\|_0 \leq k} \mathbb{E}_n(f - x'\beta)^2.
\]
3.3. DISCUSSIONS ON THE ADVANTAGES OF OLS POST-LASSO

**Condition RE.** Then, for a given positive number $\bar{c} = (c + 1)/(c - 1) \geq 0$, we impose the following assumption on the Gram matrix

$$
\kappa(\bar{c}) \equiv \min_{\|\delta_T\|_1 \leq \bar{c} \|\delta_T\|_1, \delta \neq 0} \frac{\sqrt{s} \|\delta\|_{2,n}}{\|\delta\|_1} > 0,
$$

Condition RE is a variant of the restricted eigenvalue (RE) condition that Bickel, Ritov, and Tsybakov (2009) introduce. It is an important assumption on the Gram matrix that guarantees nice statistical properties of the Lasso selector. As Bickel et al. (2009) demonstrate this condition is quite general and plausible. Condition RE can be easily satisfied as long as variables under the HAR framework are stationary. We know that $\{y_i\}$ and its lags are jointly covariance stationary, if $\{y_i\}$ itself is covariance stationary. Following Kemp (1997), any arbitrary linear combination of multiple jointly covariance stationary processes will themselves be covariance stationary. This implies that the terms $\tilde{y}_i^{(l)} \equiv l^{-1} \sum_{s=1}^{l} y_{i-s}$ are stationary for any $l$. Moreover, since $\tilde{y}_i^{(l)}$ is a linear combination of $y_i$ with different lags, it is straightforward to verify that $\tilde{y}_i^{(l)}$ can also be expressed as a sum of the error terms $e_i$ with infinite lags, for instance, $\tilde{y}_i^{(l)} = \sum_{k=0}^{\infty} b_k e_{i-k}$. Therefore, Condition RE can be fulfilled when we apply the Lasso estimator to the HAR framework.

Moreover, Belloni and Chernozhukov (2013) apply the following restricted sparse eigenvalue (RSE) condition to the empirical Gram matrix $\tilde{\kappa}(m)$, in order to analyze

---

10 In linear algebra, given a set $V$ of vectors (points in $\mathbb{R}^n$), the Gram matrix $G$ is the matrix of all possible inner products of $V$ such that the $ij^{th}$ element $g_{ij} = v_i^T v_j$. An important application is to compute linear independence: a set of vectors is linearly independent if and only if the Gram determinant (the determinant of the Gram matrix) is non-zero.
properties of the post-model selection estimators.

**Condition RSE.** For a given $m < n$,

$$\tilde{\kappa}(m)^2 = \min_{\|\delta_{Tc}\|_0 \leq m, \delta \neq 0} \frac{\|\delta\|_2^2}{\|\delta\|_2^2} > 0.$$  

Condition RSE can be viewed as an extension of the restricted isometry condition in Candes and Tao (2007). Here $m$ represents the restriction on the number of nonzero components outside the support $T$. This sparse condition is quite plausible for the HAR framework. In fact, as demonstrated in the following empirical exercise, we always end up with a few regressors that provide higher explanatory powers.

Since Conditions M, V, RE, and RSE are verified to be plausible under the HAR framework, we can apply the theoretical results of Belloni and Chernozhukov (2013) to the OLHAR estimator. This consolidates the theoretical background of our OLHAR estimator and ensures its superiority over the conventional Lasso estimator.

### 3.4 Empirical Applications

We collect the data from the TAQ database of Warton Research Data Service (WRDS). Our sample period spans from January 2, 1990 to October 6, 2016, totaling 6717 daily observations. Following Fernandes et al. (2014), the full sample is used for the in-sample descriptive statistics, whereas a rolling window of 1000 observations is

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11 Condition RSE in Belloni and Chernozhukov (2013) also defines a parameter $\phi(m) \equiv \max_{\|\delta_{Tc}\|_0 \leq m, \delta \neq 0} \frac{\|\delta\|_2^2}{\|\delta\|_2^2}$ for convenience. Since we are not going to duplicate their proof, it is not necessary to include the $\phi(m)$ term here.
employed for the estimation of all predictive regressions. This implies that the sample size for the out-of-sample analysis equals approximately 5650 observations after controlling for starting values.

First some summary statistics for the logarithm of the VIX index are described in Table 3.1. For the comparison of changes between subsample periods, the full sample is divided into two parts of equal size. Table 3.1 documents the results of the sample mean, median, minimum, maximum, standard deviation, skewness, and kurtosis for the logarithm of the VIX over two subsample periods and a full sample period. At the lower panel of Table 3.1, we report the \( p \) -values for the Jarque-Bera test for normality and also the \( p \) -values of the Augmented Dickey-Fuller (ADF) and Phillips-Peron (PP) tests for unit root. In addition, we report the statistics of the KPSS tests for the null hypothesis of stationarity. Finally, \( V/S \) refers to the value of the rescaled variance test statistic for long memory. These descriptive statistics do not seem to change much over different sample periods except skewness and kurtosis coefficients. The skewness coefficient greatly increases during the second half of the sample, while a similar thing occurs to the kurtosis coefficient to a less extent.

The null hypothesis of a unit root is strongly rejected by the ADF and PP tests in two subsamples as well as in the full sample at 5\% level of significance. The KPSS test also confirms that the null hypothesis of stationarity can not be rejected at any level of significance. Nevertheless, the \( V/S \) test smoothly rejects the null hypothesis of short memory, which is especially the case for the first subsample period. Overall, our sample confirms that the VIX series are leptokurtic, non-normal and far from Gaussian.

We then illustrate how the predictors selected by the Lasso turn out to be different
Table 3.1: Descriptive Statistics for the Logarithm of the VIX

<table>
<thead>
<tr>
<th>Sample Statistics</th>
<th>First Half</th>
<th>Second Half</th>
<th>Full Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>2.9587</td>
<td>2.8783</td>
<td>2.9185</td>
</tr>
<tr>
<td>Median</td>
<td>2.9801</td>
<td>2.8088</td>
<td>2.8831</td>
</tr>
<tr>
<td>Minimum</td>
<td>2.2311</td>
<td>2.2915</td>
<td>2.2311</td>
</tr>
<tr>
<td>Maximum</td>
<td>3.8230</td>
<td>4.3927</td>
<td>4.3927</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.3175</td>
<td>0.3615</td>
<td>0.3425</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.1024</td>
<td>1.1480</td>
<td>0.6704</td>
</tr>
<tr>
<td>Kurtosis</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>ADF</td>
<td>0.0010</td>
<td>0.0008</td>
<td>0.0001</td>
</tr>
<tr>
<td>PP</td>
<td>0.0001</td>
<td>0.0008</td>
<td>0.0005</td>
</tr>
<tr>
<td>KPSS</td>
<td>0.5827</td>
<td>0.1821</td>
<td>0.2911</td>
</tr>
<tr>
<td>V/S</td>
<td>11.5529</td>
<td>6.5511</td>
<td>5.2852</td>
</tr>
</tbody>
</table>

The first half is for the subsample period ranging from January 2, 1990 to March 26, 2003, while the second half is for the subsample period ranging from March 27, 2003 to October 6, 2016.

from those ex-ante imposed by the standard HAR model. Table 3.2 reports the forecast estimation results for the standard HAR model (Corsi, 2009) with \( l^0 \equiv [1, 5, 10, 22, 66] \) as well as for our proposed OLHAR with the full sample of the VIX. The OLHAR with five predictors (OLHAR(5)) relies on the data to select the vector of indices \( l \). The OLHAR provides unbiased coefficient estimates of lagged predictors (Belloni and Chernozhukov, 2013). The coefficient estimates for different forecast horizons are also reported, ranging from the shortest horizon (1-day ahead) to the longest horizon (22-day ahead). For the conservation of space, we omit reporting the duplicative parameter estimates of the HAR and OLHAR specifications.

We observe several interesting results when comparing parameter estimates of the two models. First, the predictors selected by the OLHAR(5) differ greatly from the predefined predictors with nonzero coefficients in the standard HAR model. For instance, the OLHAR(5) chooses the vector of indices to be \( l = [1, 2, 3, 4, 5] \) for 1-day, 5-day, 10-day ahead predictions, unlike \( l^0 \equiv [1, 5, 10, 22, 66] \) in the standard HAR
model. Second, the OLHAR(5) tends to select predictors not as far back as the standard HAR for the considered sample period. For example, although lags between $\tilde{y}_{t}^{(1)}$ and $\tilde{y}_{t}^{(5)}$ are identified as significant by the OLHAR(5) for all forecast horizons, lags beyond $\tilde{y}_{t}^{(6)}$ never get selected by the OLS post-Lasso estimator. Third, the maximum orders of lags ($p = 6$ in the case of the 22-day ahead forecasts and $p = 5$ for other forecast horizons) of the OLHAR(5) specifications are always significant and of large magnitudes, similar to what happens to those lags, closest to them in the standard HAR model ($l_2 = 5$ in the case of the 22-day ahead forecasts and $l_3 = 10$ for other forecast horizons). This actually reflects the asymmetric effects of volatilities at different time horizons, where long-term volatilities seem to dominate short-term volatilities at affecting the volatility dynamics.

We conduct an out-of-sample evaluation in Table 3.3, where the performance of the OLHAR(5) is compared with that of other models for the VIX index in the literature (Corsi, 2009; Fernandes et al., 2014). In addition to the OLHAR(5), the following specifications are considered: random walk with drift (RW), heterogeneous autoregression with exogenous variables (HARX), heterogeneous autoregression with exogenous variables and asymmetric effects (AHARX) and Lasso heterogeneous autoregression (LHAR).

To evaluate and compare the performance of various models, we specifically report the mean forecast error (MFE) and standard deviation of the forecast error (SDFE), mean squared forecast error (MSE), mean absolute forecast error (MAE) and R-squared. Like Fernandes et al. (2014), we include the following exogenous variables both contemporaneously and with one lag in relevant candidate models (i.e., HARX and AHARX): the $\kappa$-day continuously compounded return on the S&P 500 index;
Table 3.2: Parameter Estimates of HAR and OLHAR Models on the Logarithm of the VIX at Different Horizons

<table>
<thead>
<tr>
<th>Lag</th>
<th>1 Day Ahead</th>
<th>5 Day Ahead</th>
<th>10 Day Ahead</th>
<th>22 Day Ahead</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HAR OLHAR(5)</td>
<td>HAR OLHAR(5)</td>
<td>HAR OLHAR(5)</td>
<td>HAR OLHAR(5)</td>
</tr>
<tr>
<td>1</td>
<td>0.888 (0.019)</td>
<td>0.878 (0.037)</td>
<td>0.624 (0.027)</td>
<td>0.658 (0.061)</td>
</tr>
<tr>
<td>2</td>
<td>-0.006 (0.077)</td>
<td>0.004 (0.130)</td>
<td>-0.057 (0.167)</td>
<td>-0.007 (0.207)</td>
</tr>
<tr>
<td>3</td>
<td>0.053 (0.108)</td>
<td>-0.014 (0.191)</td>
<td>0.065 (0.244)</td>
<td>0.183 (0.300)</td>
</tr>
<tr>
<td>4</td>
<td>-0.159 (0.125)</td>
<td>-0.520 (0.239)</td>
<td>-0.407 (0.294)</td>
<td>-0.362 (0.272)</td>
</tr>
<tr>
<td>5</td>
<td>-0.007 (0.030)</td>
<td>0.221 (0.075)</td>
<td>0.061 (0.052)</td>
<td>0.821 (0.138)</td>
</tr>
<tr>
<td>6</td>
<td>0.538 (0.113)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>0.104 (0.031)</td>
<td>0.267 (0.054)</td>
<td>0.294 (0.064)</td>
<td>0.081 (0.087)</td>
</tr>
<tr>
<td>22</td>
<td>-0.015 (0.019)</td>
<td>-0.075 (0.036)</td>
<td>-0.150 (0.042)</td>
<td>-0.051 (0.058)</td>
</tr>
<tr>
<td>66</td>
<td>0.020 (0.008)</td>
<td>0.087 (0.015)</td>
<td>0.154 (0.018)</td>
<td>0.238 (0.024)</td>
</tr>
</tbody>
</table>

The sample period runs from January 2, 1990 to October 6, 2016 (6717 observations). The figures reported in parentheses are heteroskedasticity-robust standard errors. We omit reporting the duplicative parameter estimates of the HAR and OLHAR specifications.
the first difference of the logarithm of the volume of the S&P 500 index (S&P 500 volume change); the j-day continuously compounded return on the one-month crude oil futures contract (oil j-day return); the first difference of the logarithm of the trade-weighted average of the foreign exchange value of the US dollar index against the Australian dollar, Canadian dollar, Swiss franc, euro, British sterling pound, Japanese yen, and Swedish kroner (USD change); the excess yield of the Moody’s seasoned Baa corporate bond over the Moody’s seasoned Aaa corporate bond (credit spread); the difference between the 10-Year and 3-month treasury constant maturity rates (term spread); and the difference between the effective and target Federal Fund rates (FF deviation).

The MFEs for all the models are near zero, implying that most of the specifications have little bias. Examining the 1-day ahead forecasts, the standard HAR model beats other models by the SDFE and R-squared. The only exception is the LHAR model that performs equally well as the standard HAR, if evaluated by the MSE and MAE criteria. The story becomes remarkably different when it comes to 5, 10 and 22-day horizons. The OLHAR(5) strictly outperforms other specifications in terms of having the smallest SDFEs, MSEs and MAEs, and the highest R-squared.

To further verify our findings, we use the unconditional Giacomini-White test in Giacomini and White (2006) for the MAEs. Table 3.4 records the $p$ values of the null hypothesis that the column model performs equally well as the row model in terms of the MAE. The $p$ values with asterisks imply the null hypothesis cannot be rejected at 5% level of significance, while the $p$ values without asterisks imply the alternative hypothesis that the column model has better performance than the row model.

Except the standard HAR model, the LHAR and OLHAR(5) perform significantly
### 3.4. EMPIRICAL APPLICATIONS

#### Table 3.3: Forecasting Performance of Possible VIX Specifications

<table>
<thead>
<tr>
<th></th>
<th>MFE</th>
<th>SDFE</th>
<th>MSE</th>
<th>MAE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1 Day Ahead</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RW</td>
<td>-0.0000</td>
<td>0.0704</td>
<td>0.0049</td>
<td>0.0512</td>
<td>0.9598</td>
</tr>
<tr>
<td>ARX</td>
<td>-0.0001</td>
<td>0.0642</td>
<td>0.0041</td>
<td>0.0469</td>
<td>0.9665</td>
</tr>
<tr>
<td>HAR</td>
<td>0.0000</td>
<td>0.0634</td>
<td>0.0040</td>
<td>0.0464</td>
<td>0.9674</td>
</tr>
<tr>
<td>HARX</td>
<td>-0.0009</td>
<td>0.0642</td>
<td>0.0041</td>
<td>0.0469</td>
<td>0.9666</td>
</tr>
<tr>
<td>AHARX</td>
<td>0.0001</td>
<td>0.0654</td>
<td>0.0043</td>
<td>0.0476</td>
<td>0.9652</td>
</tr>
<tr>
<td>LHAR</td>
<td>-0.0001</td>
<td>0.0635</td>
<td>0.0040</td>
<td>0.0464</td>
<td>0.9673</td>
</tr>
<tr>
<td>OLHAR(5)</td>
<td>0.0003</td>
<td>0.0637</td>
<td>0.0041</td>
<td>0.0465</td>
<td>0.9671</td>
</tr>
<tr>
<td><strong>5 Day Ahead</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RW</td>
<td>-0.0003</td>
<td>0.1359</td>
<td>0.0185</td>
<td>0.1004</td>
<td>0.8501</td>
</tr>
<tr>
<td>ARX</td>
<td>-0.0007</td>
<td>0.1249</td>
<td>0.0156</td>
<td>0.0940</td>
<td>0.8733</td>
</tr>
<tr>
<td>HAR</td>
<td>-0.0002</td>
<td>0.1207</td>
<td>0.0146</td>
<td>0.0905</td>
<td>0.8817</td>
</tr>
<tr>
<td>HARX</td>
<td>-0.0031</td>
<td>0.1248</td>
<td>0.0156</td>
<td>0.0942</td>
<td>0.8735</td>
</tr>
<tr>
<td>AHARX</td>
<td>0.0019</td>
<td>0.1274</td>
<td>0.0162</td>
<td>0.0960</td>
<td>0.8682</td>
</tr>
<tr>
<td>LHAR</td>
<td>-0.0005</td>
<td>0.1211</td>
<td>0.0147</td>
<td>0.0908</td>
<td>0.8809</td>
</tr>
<tr>
<td>OLHAR(5)</td>
<td>0.0008</td>
<td>0.1202</td>
<td>0.0145</td>
<td>0.0898</td>
<td>0.8827</td>
</tr>
<tr>
<td><strong>10 Day Ahead</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RW</td>
<td>-0.0004</td>
<td>0.1690</td>
<td>0.0286</td>
<td>0.1265</td>
<td>0.7683</td>
</tr>
<tr>
<td>ARX</td>
<td>-0.0042</td>
<td>0.1593</td>
<td>0.0254</td>
<td>0.1211</td>
<td>0.7940</td>
</tr>
<tr>
<td>HAR</td>
<td>-0.0011</td>
<td>0.1514</td>
<td>0.0229</td>
<td>0.1148</td>
<td>0.8140</td>
</tr>
<tr>
<td>HARX</td>
<td>-0.0085</td>
<td>0.1604</td>
<td>0.0257</td>
<td>0.1221</td>
<td>0.7908</td>
</tr>
<tr>
<td>AHARX</td>
<td>0.0004</td>
<td>0.1654</td>
<td>0.0274</td>
<td>0.1263</td>
<td>0.7781</td>
</tr>
<tr>
<td>LHAR</td>
<td>-0.0013</td>
<td>0.1523</td>
<td>0.0232</td>
<td>0.1157</td>
<td>0.8117</td>
</tr>
<tr>
<td>OLHAR(5)</td>
<td>0.0011</td>
<td>0.1501</td>
<td>0.0225</td>
<td>0.1130</td>
<td>0.8174</td>
</tr>
<tr>
<td><strong>22 Day Ahead</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RW</td>
<td>0.0001</td>
<td>0.2248</td>
<td>0.0505</td>
<td>0.1674</td>
<td>0.5908</td>
</tr>
<tr>
<td>ARX</td>
<td>-0.0172</td>
<td>0.2279</td>
<td>0.0519</td>
<td>0.1715</td>
<td>0.5768</td>
</tr>
<tr>
<td>HAR</td>
<td>-0.0057</td>
<td>0.2032</td>
<td>0.0413</td>
<td>0.1565</td>
<td>0.6653</td>
</tr>
<tr>
<td>HARX</td>
<td>-0.0246</td>
<td>0.2316</td>
<td>0.0536</td>
<td>0.1751</td>
<td>0.5608</td>
</tr>
<tr>
<td>AHARX</td>
<td>-0.0110</td>
<td>0.2558</td>
<td>0.0654</td>
<td>0.1917</td>
<td>0.4689</td>
</tr>
<tr>
<td>LHAR</td>
<td>-0.0063</td>
<td>0.2038</td>
<td>0.0415</td>
<td>0.1566</td>
<td>0.6634</td>
</tr>
<tr>
<td>OLHAR(5)</td>
<td>0.0004</td>
<td>0.2001</td>
<td>0.0400</td>
<td>0.1530</td>
<td>0.6759</td>
</tr>
</tbody>
</table>

The sample period for the VIX index runs from January 2, 1990 to October 6, 2016, including 6717 observations. We use a rolling window of 1000 observations to estimate different models and then perform out-of-sample forecasting evaluation in the remaining of the series. Each panel in Table 3.3 stands for a specific forecasting horizon varying from 1 day to 22 days ahead.
### 3.4. EMPIRICAL APPLICATIONS

The sample period for the VIX index runs from January 2, 1990 to October 6, 2016, including 6717 observations. We use a rolling window of 1000 observations to estimate various models and then perform out-of-sample forecasting evaluation in the remaining of the series over various forecast horizons. We consider the same set of models as in Table 3.3. The $p$ value in each entry corresponds to the modified Giacomini-White test for the null hypothesis that the column model performs equally well as the row model in terms of the MAE. The figures without asterisks indicate the alternative hypothesis that the column model has better performance than the row model. The figures with asterisks imply that the column model performs equally well as the row model.

#### Table 3.4: Results of Giacomini-White Tests for the MAE

<table>
<thead>
<tr>
<th></th>
<th>RW</th>
<th>ARX</th>
<th>HAR</th>
<th>HARX</th>
<th>AHARX</th>
<th>LHAR</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1 Day Ahead</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARX</td>
<td>0.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HAR</td>
<td>0.0000</td>
<td>0.0022</td>
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<td></td>
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<tr>
<td>HARX</td>
<td>0.0000</td>
<td>0.8007*</td>
<td>0.0002</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>AHARX</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.0000</td>
<td>0.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LHAR</td>
<td>0.0000</td>
<td>0.0067</td>
<td>0.7417*</td>
<td>0.0010</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>OLHAR(5)</td>
<td>0.0000</td>
<td>0.0301</td>
<td>0.1015*</td>
<td>0.0197</td>
<td>0.0000</td>
<td>0.2294*</td>
</tr>
<tr>
<td><strong>5 Day Ahead</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARX</td>
<td>0.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HAR</td>
<td>0.0000</td>
<td>0.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HARX</td>
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<td>0.6967*</td>
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</tr>
<tr>
<td>AHARX</td>
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<td>0.0090</td>
<td>0.0000</td>
<td>0.0025</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LHAR</td>
<td>0.0000</td>
<td>0.0003</td>
<td>0.2223*</td>
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</tr>
<tr>
<td>OLHAR(5)</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0438</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0355</td>
</tr>
<tr>
<td><strong>10 Day Ahead</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARX</td>
<td>0.0134</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HAR</td>
<td>0.0000</td>
<td>0.0002</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HARX</td>
<td>0.0592</td>
<td>0.2972*</td>
<td>0.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AHARX</td>
<td>0.9367*</td>
<td>0.0014</td>
<td>0.0000</td>
<td>0.0016</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LHAR</td>
<td>0.0000</td>
<td>0.0017</td>
<td>0.0818*</td>
<td>0.0002</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>OLHAR(5)</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0182</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0042</td>
</tr>
<tr>
<td><strong>22 Day Ahead</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARX</td>
<td>0.4685*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HAR</td>
<td>0.0038</td>
<td>0.0009</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HARX</td>
<td>0.1984*</td>
<td>0.0830*</td>
<td>0.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AHARX</td>
<td>0.0008</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LHAR</td>
<td>0.0045</td>
<td>0.0010</td>
<td>0.9038*</td>
<td>0.0000</td>
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<td></td>
</tr>
<tr>
<td>OLHAR(5)</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.0467</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0490</td>
</tr>
</tbody>
</table>
better than other specifications at all horizons. At the 1-day horizon, however, we
can not reject the null hypothesis that the standard HAR performs equally well as
the LHAR and the OLHAR(5) at the 5% level of significance. At longer horizons
such as 5-day, 10-day and 22-day ahead, the LHAR model performs equally well as
the standard HAR model, which supports the findings of Audrino and Knaus (2016).
Remarkably, the OLHAR(5) dominates the standard HAR model at longer horizons
(5-day, 10-day and 22-day ahead). Comparing the relative performance of LHAR and
OLHAR(5) models, the OLHAR(5) significantly dominates the LHAR at 5, 10 and 22
day horizons and perform as well as the LHAR at 1 day horizon. Note that the sound
performance of the OLHAR(5) at longer horizons reflects the benefits of employing
the OLHAR, since the OLHAR can effectively minimize the accumulating forecasting
bias for the selected model and thus distinguishes itself at multi-step ahead forecast
exercises.

3.5 Robustness Check

In this section, we consider a robustness test on the out-of-sample performance of the
OLHAR, where we specially examine if the above results are altered by alternative
choices of the number of predictors. At no loss of generality, two other specifications
of OLHAR are examined: (i) those with less than five predictors, OLHAR(3); and
(ii) those with more than five predictors, OLHAR(10).\footnote{Note that we tune the penalty term \( \lambda \) so that the Lasso estimator chooses three and ten predictors respectively in the robustness analysis.}

Table 3.5 demonstrates the evaluation results of the out-of-sample exercise for
forecasts 1, 5, 10 and 22 days ahead, where three specifications of the OLHAR (OL-
HAR(3), OLHAR(5) and OLHAR(10)) compete with the standard HAR. The MFEs
of all specifications are very close to zero, indicating that there are no worries about
the bias of estimated models and its contribution to the MSEs. Evaluated by the
SDFEs, the standard HAR model perform the best for 1-day ahead forecast, but is
inferior to other OLHAR models for the 5, 10 and 22-day ahead forecasts. Among
all the OLHAR specifications, the OLHAR (10) model has the smallest SDFEs, for
all forecast horizons except the 1-day ahead forecasts. A similar conclusion can be
drawn by the MSE and MAE criteria. The standard HAR model leads to the best
1-day ahead forecast. The performance of the OLHAR (3), OLHAR (5) and OLHAR
(10) is very close and fare better than the standard HAR for the 5, 10 and 22-day
ahead forecasts.

We then complement the above results with the unconditional Giacomini-White
test for the MAE. Table 3.6 reports the $p$ values of the null hypothesis that the column
model performs equally well as the row model in terms of the mean absolute forecast
error. We can not reject the null hypothesis at the 5% level that the standard HAR
model and the OLHAR models perform equally well in terms of the MAE at the
1-day horizon. Nevertheless, compared with the standard HAR model, the OLHAR
models forecast significantly better the VIX index 10 and 22 days ahead. The same
conclusion holds for the OLHAR (5) and OLHAR (10) models at the 5-day horizon.
As for the relative performances of the OLHAR models, the Giacomini-White test
can not distinguish which of them performs the best.

Overall, the robustness check confirms that the OLHAR specification clearly out-
performs the standard HAR model for the 5, 10, and 22-day ahead forecasts, but
their advantages over the standard HAR model are not remarkable for the 1-day
ahead forecasts.
### 3.6. CONCLUSIONS

Table 3.5: Forecasting Performance for Robustness Check

<table>
<thead>
<tr>
<th></th>
<th>MFE</th>
<th>SDFE</th>
<th>MSE</th>
<th>MAE</th>
<th>$R^2$</th>
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<td></td>
<td></td>
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<td>HAR</td>
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<td>0.0634</td>
<td>0.0040</td>
<td>0.0464</td>
<td>0.9674</td>
</tr>
<tr>
<td>OLHAR(3)</td>
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<td>0.0636</td>
<td>0.0040</td>
<td>0.0465</td>
<td>0.9671</td>
</tr>
<tr>
<td>OLHAR(5)</td>
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<td>0.0637</td>
<td>0.0041</td>
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<td>0.9671</td>
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<tr>
<td>OLHAR(10)</td>
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<td>0.0636</td>
<td>0.0040</td>
<td>0.0465</td>
<td>0.9672</td>
</tr>
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<td><strong>5 Day Ahead</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>0.0900</td>
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<td>0.0145</td>
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<td>OLHAR(10)</td>
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<td>0.1201</td>
<td>0.0144</td>
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<td>0.8829</td>
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<td><strong>10 Day Ahead</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HAR</td>
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<td>0.1514</td>
<td>0.0229</td>
<td>0.1148</td>
<td>0.8140</td>
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<td>OLHAR(5)</td>
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<td>0.0225</td>
<td>0.1130</td>
<td>0.8174</td>
</tr>
<tr>
<td>OLHAR(10)</td>
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<td>0.1500</td>
<td>0.0225</td>
<td>0.1129</td>
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<td><strong>22 Day Ahead</strong></td>
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<tr>
<td>OLHAR(3)</td>
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<td>0.0401</td>
<td>0.1530</td>
<td>0.6754</td>
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<td>0.0400</td>
<td>0.1530</td>
<td>0.6759</td>
</tr>
<tr>
<td>OLHAR(10)</td>
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<td>0.2000</td>
<td>0.0400</td>
<td>0.1529</td>
<td>0.6759</td>
</tr>
</tbody>
</table>

The sample period for the VIX index runs from January 2, 1990 to October 6, 2016, including 6717 observations. We use a rolling window of 1000 observations to estimate various models and then perform out-of-sample forecasting evaluation in the remaining of the series. Each panel in Table 3.5 stands for a specific forecasting horizon ranging from 1 day to 22 days ahead.

#### 3.6 Conclusions

This chapter contributes to the volatility forecasting literature by proposing an application of the OLS post-Lasso method to the standard HAR model. In this way, the choice of predictors of a standard HAR model is data driven. Applying the OLHAR model to the VIX index forecasting circumvents the trouble of searching over a large number of potential set of models in model selection. At the same time, it permits the convenient estimation of the selected predictors by the OLS estimator.
Our analysis reveals that the priorly imposed predictors of the standard HAR model (i.e., \( l_0 = [1, 5, 10, 22, 66] \)) is inconsistent with those chosen by a model selection method such as the Lasso. In our sample period, the OLS post-Lasso method chooses averaged predictors of near lags, which supports the findings of Audrino and Knaus (2016) and Chen, Härdle, and Pigorsch (2010) that the volatility dynamics may be better captured by shorter horizon models so as to allow regime shifts and structural breaks.
We also assess how various models on the VIX perform in a multistep ahead forecasting exercise. From an out-of-sample performance point of view, the OLHAR outperforms other peer models in predicting the VIX index either weekly, biweekly, or monthly ahead; however, we cannot distinguish its performance from the standard HAR model for the one-day ahead forecasts. This superiority of the OLHAR is robust to the choice of the total number of predictors, as verified by our robustness test. Furthermore, we draw from Belloni and Chernozhukov (2013) by discussing the statistical foundations of why the OLHAR improves on the standard HAR and the conventional LHAR.

The simplicity of the proposed method allows it to be easily extended in various ways. To investigate how the OLHAR performs in nonlinear situations, we can extend the OLHAR model to account for nonlinear effects like jump measures, leverage effects, structural breaks, and other general nonlinear effects in volatility surveyed in Corsi et al. (2012). Because the parameters of a HAR model carry economically meaningful explanations, it would also be very interesting to explore how the arrival of news shocks affects and alters the choice of predictors of the OLHAR.
Chapter 4

Commodity Price Shocks and Tail Risks at Small Commodity-Exporting Economies

4.1 Introduction

The 2011-2015 commodity price crash has inspired a debate on how the commodity price downturn will depress the GDP growth and affect the financial stability in SCEEs.

To my best knowledge, the literature gives a limited number of answers to the above debate. The most related paper is Crean and Milne (2015). They have provided the evidence that the estimated syndicated corporate loan losses concentrate on a small number of systematically important real sectors.\(^1\) Theoretical papers such as Acemoglu, Ozdaglar, and Tahbaz-Salehi (2013), Atalay (2014), and Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017), develop a multi-sector general equilibrium model that can gauge the relative contribution of industry-specific shocks to the tail real risk and even account for the tail departure of GDP distributions away from

\(^1\)They find that the systematically important real sectors share a set of common characteristics: high asset levels to revenues, high financial leverage, low marginal costs, strong competition, uncertain cash flows and high borrowing from banks.
a normal distribution.\footnote{Acemoglu et al. (2017) provide statistical conditions on the microeconomic shocks that could lead to macroeconomic tail risks. Moreover, using the input-output analysis, economies can present tail real risks from the interaction of microeconomic shocks and sectoral heterogeneity (i.e., the differential roles of sectors as input-suppliers).} Using sectoral data, Carvalho and Gabaix (2013) and Atalay and Drautzburg (2015) attempt to quantify the contribution of sectoral shocks to aggregate output and employment tail risks, and determine that the durable goods manufacturing accounts for a majority of the measured tail real risks in U.S. economy.

In this chapter, I contribute to the debate by providing a framework that allows for assessing the importance of commodity price fluctuations for tail financial risk in SCEEs. I achieve this by developing a tail risk forecasting system that predicts tail real and financial risks in Canada, and allows the tail risk measures to be affected by foreign macroeconomic and world commodity price factors. Following De Nicolò and Lucchetta (2017), I adopt a factor-based linear conditional quantile projection to forecast tail risks, which delivers a set of one quarter-ahead forecasts of tail real and financial risk indicators.\footnote{Note that I am not the first to use quantile regressions in the application of systemic risk predictions. Brunnermeier et al. (2012) employ conditional quantile regressions to investigate the effects of noninterest income ratios on the probability of a systemic risk.} The estimator for the conditional quantile regression draws from Koenker (2005). I use quantile projections, because, as pointed out by Komunjer (2013), quantile projections do not require assumptions about the underlying distribution of the variable to be forecast and thus allow for capturing any type of asymmetry. Moreover, De Nicolò and Lucchetta (2017) prove that they exhibit outstanding out-of-sample performance in tail risk analysis with U.S. data. The proposed framework is an extension of the DFM in Chapter 2, and is thus tailored to those features of SCEEs.

I construct tail risk measures by using a conventional risk management approach. Tail real risks are measured by the VaR of GDP-Oil, because I focus on the impact of
commodity price changes on the real economy. Tail financial risks are measured by the VaR of NPL ratios for individual Big Six banks, because Big Six banks are more crucial than other domestic banks, and control approximately 90% of total assets in the Canadian banking industry. I estimate the quantile regressions using 439 quarterly series of foreign, Canadian macroeconomic and banking data for the period 1996Q1-2016:Q1, which reflects what I employ in Chapter 2. Due to the relatively short sample size, I estimate and forecast using an expanding window of data, because a moving window scheme could lead to less precise parameter estimates.

My analysis leads to following results. First, my framework forecasts the largest increase in tail real risk at 2009Q2, as shown by the steepest decline in the VaR of GDP-Oil. Second, the largest increases in tail financial risk, measured by the VaR of the NPL ratios for individual Big Six banks, are captured to different extents. For BMO and CIBC, the increases in VaR forecasts of the NPL ratios (i.e., 2010Q1 for BMO and 2010Q2 for CIBC) do predict one-quarter ahead the large increases of the actual data. The VaR forecasts of the NPL ratios for other Big Six banks do not have the same accuracy as those for BMO and CIBC. This reflects how closely the tail quantiles of the NPL ratio of each bank is correlated with the estimated factors.

Third, I show that for BMO and CIBC, the banking factors make the most contribution (i.e., 51.05% for BMO and 70.82% for CIBC) to the peaks in the VaR forecasts for the NPL ratios, and the contribution from Canadian macroeconomic factors are second to that of the banking factors (i.e., 31.83% for BMO and 15.86% for CIBC). The direct contribution from real commodity price factors is the lowest (i.e., 13% for BMO and 6.09% for CIBC), compared with those from other blocks of the estimated
4.2. TAIL RISK MEASURES

factors. But the magnitudes of the commodity price contribution are not trivial, considering how much they occupy the total contribution from the global factors (i.e., 13% out of 17.11% for BMO and 6.09% out of 10.43% for CIBC).

The remainder of this chapter consists of four sections. Section 4.2 describes my choice of tail real and financial risk measures. Section 4.3 lays out the details of my framework, its estimation, and the procedure of obtaining quantile projections. Section 4.4 provides the empirical results and Section 4.5 concludes the chapter.

4.2 Tail Risk Measures

Following DeNicolò and Lucchetta (2011) and Brunnermeier et al. (2012), my tail risk measures are the \( \text{VaR}_\alpha \)'s of interested indicators of financial risk and real activity, with probability levels of \( \alpha \).\(^4\) Tail real risks are measured by the \( \text{VaR}_\alpha \) of GDP of mining, quarrying, and oil and gas extraction (GDP-Oil), which is denoted by \( \text{VaR}_\alpha \)(Oil), because I focus exclusively on the impact of commodity price shocks on the real economy.\(^5\) Probability \( \alpha \) is set equal to 5% or 10% for tail real risks (i.e., \( \alpha \in \{0.05, 0.10\} \)).

Tail financial risks in the banking sector are measured by the \( \text{VaR}_\alpha \) of NPL ratios for individual Big Six banks, denoted by \( \text{VaR}_\alpha \)(the name of each Big Six bank). As shown in Chapter 2, since Big Six banks are more internationalized, larger in total assets than other small local banks, and quite responsive to various types of commodity price shocks, I focus on their \( \text{VaR}_\alpha \)'s of NPL ratios exclusively. In this case,

\(^4\) Depending on the target variable \( X \), \( \text{VaR}_\alpha(X) \) may focus on either the left-tail quantile or the right-tail quantile of the distribution of \( X \). If \( X \) is an approximation for losses (gains), I mainly concentrate on the right-tail (left-tail) of the distribution, in which \( \alpha \) is usually a large (small) number.

\(^5\) DeNicolò and Lucchetta (2011) and De Nicolò and Lucchetta (2017) employ VaRs of real GDP, industrial production, and total employment to capture tail real risks.
probability $\alpha$ is set equal to 90% or 95% for tail financial risks (i.e., $\alpha \in \{0.90, 0.95\}$). High levels of NPL ratios can exert strong negative pressure on banks’ balance sheets, with possible adverse effects on banks’ lending operations.

The NPL ratio has been used by the literature as a major indicator to measure bank risk. Berger and Bouwman (2009) use the NPL ratio as a measure of asset risk to test if bank competition increases bank fragility. Nkusu (2011) finds out that the NPL ratio plays a central role in the linkages between credit market frictions and macroeconomic vulnerabilities. Berger et al. (2016) recently investigate the relationship between internationalization and bank risk. Using the NPL ratio as one of their bank risk measures, Berger et al. (2016) conclude that internationalization may increase banks’ risk depending on the market-specific factors in foreign markets and its correlation with the domestic economy.

Table 4.1 reports some descriptive statistics of the series underlying our tail risk indicators and their correlation matrix. Tests for non-stationarity, structural breaks, outliers and unit roots are also provided here. Panel A reports the sample mean, standard deviation, and correlation for the raw data, which has not been stationarized, standardized, and demeaned. As Panel A demonstrates, all the raw data exhibits non-stationarity, multiple structural breaks, and contains some outliers. Therefore, I transform the series according to the algorithm described in Appendix A and present the standardized data in Panel B. The standardized data are stationary with no breaks or outliers. The sample mean and standard deviation are controlled to be 0 and 1, respectively. Noticeably, the NPL ratio for every Big Six bank is negatively correlated with the indicator of real activity, GDP-Oil.
4.3 Forecasting Model

In this section, I first revisit the DFM discussed in Chapter 2. I then describe how tail forecasts can be obtained by implementing the quantile projection method (De Nicolò and Lucchetta, 2017) in the context of my DFM.

4.3.1 Dynamic Factor Model

Following the framework in Chapter 2, the states of the global economy, the Canadian economy and its banking sector are characterized by $K$ unobserved factors $F_t$ such that

$$F_t = \left[ F^G_t, F^C_t, F^B_t \right]^\top,$$

where superscripts $G$, $C$, and $B$ represent global, Canadian macroeconomic, and Canadian banking factors, respectively.

Factors $F^G_t$ consist of three individual components such that

$$F^G_t = \left[ F^G_{Y,t}, F^G_{\pi,t}, F^G_{P,t} \right]^\top.$$

The first factor $F^G_{Y,t}$ summarizes information about global real activity and is extracted from a panel of global and regional outputs, industrial production, and trade series, $X^G_{Y,t}$; the second factor $F^G_{\pi,t}$ approximates the comovement of global inflation and is extracted from data of international consumer/producer prices and GDP deflators, $X^G_{\pi,t}$; the last factor $F^G_{P,t}$ captures the comovement of real commodity price indices and is extracted from the price indices of a wide variety of industrial commodities $X^G_{P,t}$.

The domestic factors $F^C_t$ are constructed from a large set of macroeconomic and financial data for Canada $X^C_t$. Similarly, I construct the $K - J - 3$ banking factors $F^B_t$ from a large panel of individual bank-level variables $X^B_t$. 
### Table 4.1: Descriptive Statistics and Correlations of GDP-Oil and NPL Ratios

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<th></th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>Oil</th>
<th>BMO</th>
<th>CIBC</th>
<th>BNS</th>
<th>NB</th>
<th>RBC</th>
<th>TD</th>
<th>NS</th>
<th>SB</th>
<th>OC</th>
<th>DF</th>
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<td><strong>Panel A: Raw Data</strong></td>
<td></td>
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<td></td>
<td></td>
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<td>GDP-Oil</td>
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<td>Yes</td>
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<td>No</td>
<td>No</td>
<td>No</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NPL-NB</td>
<td>0.0000</td>
<td>1.0000</td>
<td>-0.2243</td>
<td>0.3880</td>
<td>0.3747</td>
<td>0.1925</td>
<td>1.0000</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NPL-RBC</td>
<td>0.0000</td>
<td>1.0000</td>
<td>-0.3601</td>
<td>0.3603</td>
<td>0.3333</td>
<td>0.1401</td>
<td>0.0909</td>
<td>1.0000</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>NPL-TD</td>
<td>0.0000</td>
<td>1.0000</td>
<td>-0.2079</td>
<td>-0.0952</td>
<td>0.0850</td>
<td>0.0520</td>
<td>-0.0813</td>
<td>-0.2542</td>
<td>1.0000</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
</tbody>
</table>

1. NS stands for non-stationarity. I apply the adjusted Dicky-Fuller test to each series and examine if it is non-stationary.
2. SB stands for structural break, which are detected by the sequential multiple breakpoint test of Bai and Perron (2003).
3. OC stands for outliers. I define outliers as observations with absolute median deviations larger than six times the interquartile range following Buch et al. (2014b).
4. DF stands for differencing. If after adjusting for outliers and being stationarized, the series still exhibit strong unit roots, I take the difference among observations. Note that only GDP-Oil requires such transformation.
4.3. FORECASTING MODEL

The three blocks of factors are assumed to be related to observables, according to the following measurement equation:

\[
\begin{bmatrix}
X_{Y,t}^G \\
X_{\pi,t}^G \\
X_{P,t}^G \\
X_t^C \\
X_t^B
\end{bmatrix}
= \begin{bmatrix}
\Lambda_Y^G & 0 & 0 & 0 & 0 \\
0 & \Lambda_\pi^G & 0 & 0 & 0 \\
0 & 0 & \Lambda_P^G & 0 & 0 \\
\Lambda_Y^C & \Lambda_\pi^C & \Lambda_P^C & \Lambda_H^C & 0 \\
\Lambda_Y^B & \Lambda_\pi^B & \Lambda_P^B & \Lambda_H^B & \Lambda_U^B
\end{bmatrix}
\begin{bmatrix}
F_{Y,t}^G \\
F_{\pi,t}^G \\
F_{P,t}^G \\
F_t^C \\
F_t^B
\end{bmatrix}
+ \begin{bmatrix}
e_{Y,t}^G \\
e_{\pi,t}^G \\
e_{P,t}^G \\
e_t^C \\
e_t^B
\end{bmatrix},
\]

(4.1)

where \(\Lambda_i^j\) for \(i = G, C, B\) and \(j = Y, \pi, P, H, U\) are factor loading matrices for global, Canadian, and banking factors, respectively; and \(e_t^G = [e_Y^G, e_\pi^G, e_P^G, e_H^C, e_U^B]^T\), \(e_t^C\), and \(e_t^B\) are zero-mean i.i.d. measurement errors that are assumed to be uncorrelated with the corresponding factors. In order for global factors \(F_t^G\) to have economic interpretations, some components of the factor loading matrix are assumed to be zero. See Chapter 2 for a more detailed discussion.

Once the three blocks of common factors are estimated, I can model the dynamic relationships of these blocks of factors using the following restricted SVAR:

\[
\begin{bmatrix}
F_t^G \\
F_t^C \\
F_t^B
\end{bmatrix}
= \begin{bmatrix}
\Phi_{11}(L) & 0 & 0 \\
\Phi_{21}(L) & \Phi_{22}(L) & \Phi_{23}(L) \\
\Phi_{31}(L) & \Phi_{32}(L) & \Phi_{33}(L)
\end{bmatrix}
\begin{bmatrix}
F_{t-1}^G \\
F_{t-1}^C \\
F_{t-1}^B
\end{bmatrix}
+ \begin{bmatrix}
u_t
\end{bmatrix},
\]

(4.2)

where \(\Phi(L)\)s are lag polynomials of the finite order \(p\) and \(u_t\) denote a normally distributed error term with mean 0 and variance \(\Omega\). As discussed in Chapter 2, given the small-size nature of SCEEs, the Canadian macroeconomic and banking factors are assumed to have no effects on the dynamics of the global factors. This implies
that the corresponding components in the the right upper $3 \times (K - 3)$ block of the coefficient matrix are constrained to be zeros.

### 4.3.2 Quantile Projection

I make use of a conditional quantile projection to construct one-quarter ahead quantile forecasts of interested real and financial risk variables, which delivers a way of tail risk forecasting. The details are discussed as follows.

Once I estimate the coefficient matrix $\hat{\Phi}$ for Equation (4.2), I can make one-step ahead forecast of $\hat{F}_{t+1}$ by $\hat{F}_{t+1} = \hat{\Phi}F_t$. After obtaining $\hat{F}_{t+1}$, I can infer the one-quarter ahead VaR$_\alpha$ forecasts of GDP-Oil and NPL ratios using quantile projections similar to those in De Nicolò and Lucchetta (2017).

Remember, my targeted tail real and financial risks are measured by the VaR$_\alpha$s of GDP-Oil and NPL ratios of individual Big Six banks. These underlying series belong to the observable matrix $X_t = [X^C_t, X^C_{t-1}, X^B_t]$ and are thus related to the estimated factors by equation (2.1). For any $X^i_t \in X_t$, let $Pr(X^i_t|F_t)$ denote the distribution of $X^i_t$ conditional on $F_t$. For any given $\alpha \in (0, 1)$, a quantile projection $q^i_\alpha(F)$ satisfies $Pr(X^i_t \leq q^i_\alpha(F)|F_t = F) = \alpha$, where $q^i_\alpha(F)$ is monotonically increasing in $\alpha \in (0, 1)$.

Following Koenker (2005) and Komunjer (2013), I assume a linear quantile function $q^i_\alpha(F) = \Lambda^i(\alpha)F$.

Komunjer (2013) suggests that quantile regressions for time series are usually estimated by the conditional quantile estimator. Proposed by Koenker and Bassett (1978), the conditional quantile regression models the relationship between predictors ($F_t$) and the conditional quantiles $q^i_\alpha(F)$, given available information at time $t$ ($F_t = F$).
4.3. FORECASTING MODEL

The conditional quantile regression is estimated by the following procedure. Let $X_i^t$ be a real valued random variable with a cumulative distribution function $F_{X_i^t}(x) = \Pr(X_i^t \leq x)$. The $\alpha$th quantile of $X_i^t$ is given by

$$Q_\alpha = F_{X_i^t}^{-1}(\alpha) = \inf \{ x : F_{X_i^t}(x) \geq \alpha \}$$

where $\alpha \in [0, 1]$. Define the loss function as $\rho_\alpha(x) = x(\alpha - \mathbb{I}_{x<0})$, where $\mathbb{I}$ is an indicator function. A specific quantile can be found by minimizing the expected loss of $X_i^t - u$ with respect to $u$, where $u$ represents the estimated values of the quantile function given available predictors:

$$\min_u \mathbb{E}(\rho_\alpha(X_i^t - u)) = \min_u (\alpha - 1) \int_{-\infty}^u (x - u) dF_{X_i^t}(x) + \alpha \int_u^\infty (x - u) dF_{X_i^t}(x).$$

Suppose the $\alpha$th conditional quantile function is $Q_{X_i^t|F_t}(\alpha) = F_t^\top \Lambda^i(\alpha)$, where $F_t$ is the vector of relevant predictors. Given the distribution function of $X_i^t$, $\Lambda^i(\alpha)$ can be obtained by solving

$$\Lambda^i(\alpha) = \arg \min_{\Lambda^i(\alpha) \in \mathbb{R}^k} \mathbb{E}(\rho_\alpha(X_i^t - F_t^\top \Lambda^i(\alpha))).$$

Solving the sample analog gives the estimates of coefficient vector $\Lambda^i(\alpha)$:

$$\hat{\Lambda}^i(\alpha) = \arg \min_{\Lambda^i(\alpha) \in \mathbb{R}^k} \sum_{j=1}^n (\rho_\alpha(X_j^t - F_t^\top \Lambda^i(\alpha))).$$

where $n$ is the sample size of $X_i^t$. Once the estimated quantile coefficients $\hat{\Lambda}^i(\alpha)$ are
obtained, the one-step ahead quantile projection of $X_i$ is given by

$$\hat{Q}_{X_{i+1} | F_{i+1}}(\alpha) = \hat{\Lambda}_i(\alpha) \hat{F}_{t+1},$$

(4.3)

where $\hat{F}_{t+1}$ is the one-step ahead forecast of the estimated factors given by Equation (4.2).

### 4.4 Empirical Results

In this section, I conduct estimation and forecasting in pseudo-real time. I collect global, Canadian macroeconomic, and Canadian bank-level data over the period 1996Q1 to 2016Q1, with quarterly frequency. In total, there are 439 time series for 81 quarters. Appendix A.2 gives a detailed description for all the time series, including their original sources and the algorithm I use to construct and polish the data.

An expanding window exercise only is considered here, since I have a relatively short sample size. I divide the whole sample into two sets: a training set that is used for estimation and forecasting (1996Q1-2009Q1) and an evaluation set that is used to evaluate the forecasting results (2009Q2-2016Q1). I start at 2009Q1 using 53 observations to make one quarter-ahead quantile forecasts for 2009Q2. Once the forecasting results are obtained, I include the observations at 2009Q2 in the new training data set and use the expanded 54 observations to renew the forecast for the next quarter. I keep rolling the one-quarter ahead forecasts until I reach 2015Q4, at which the quantiles of 2016Q1 are forecasted and evaluated.

When forecasting the VaR$\alpha$ for GDP-Oil, I set the level of confidence $\alpha_{\text{Oil}} = 0.05$ or 0.10. Since risk measures for GDP-Oil concern about low values of the oil sector GDP growth, I am interested in the left tail of the distribution. On the other hand,
since risk measures for NPL ratios of individual Big Six banks care about high values of NPLs, I concentrate on the right tails of the distributions of these series and set \( \alpha_{\text{NPL}} = 0.95 \) or 0.90.

### 4.4.1 Quantile Projections

I first report the pseudo-\( R^2 \) for individual quantile regressions on the estimated factors in Table 4.2. The \( R^2 \)'s in Table 4.2 clearly imply that the quantile forecasts of NPL-BMO, NPL-CIBC and GDP-Oil are better explained by the information from estimated factors \( F_t \), whereas those for the NPL ratios of other Big Six banks are relatively poorly explained.

Table 4.2: Pseudo-\( R^2 \) of Conditional Quantile Regressions for GDP-Oil, NPL Ratio for Big Six Banks

<table>
<thead>
<tr>
<th>Quantile</th>
<th>NPL-BMO</th>
<th>NPL-CIBC</th>
<th>NPL-BNS</th>
<th>NPL-NB</th>
<th>NPL-RBC</th>
<th>NPL-TD</th>
</tr>
</thead>
<tbody>
<tr>
<td>95%</td>
<td>0.6234</td>
<td>0.8575</td>
<td>0.3922</td>
<td>0.4387</td>
<td>0.3816</td>
<td>0.2769</td>
</tr>
<tr>
<td>90%</td>
<td>0.6502</td>
<td>0.8126</td>
<td>0.3787</td>
<td>0.4456</td>
<td>0.3404</td>
<td>0.2551</td>
</tr>
</tbody>
</table>

Panel B: Conditional Quantile for GDP-Oil

<table>
<thead>
<tr>
<th>Quantile</th>
<th>NPL-BMO</th>
<th>NPL-CIBC</th>
<th>NPL-BNS</th>
<th>NPL-NB</th>
<th>NPL-RBC</th>
<th>NPL-TD</th>
</tr>
</thead>
<tbody>
<tr>
<td>5%</td>
<td>0.4909</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10%</td>
<td>0.4468</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

I then proceed to report the VaR\(_{0.95}\) forecasts of the NPL ratios for every Big Six bank in Figure 4.1. The six panels in Figure 4.1 depict the actual data and VaR\(_{0.95}\) one-quarter ahead forecasts of the NPL ratios for Big Six banks, respectively. From Figure 4.1, I see that the extreme movements of the NPL ratios for Big Six banks are captured to different extents by the conditional quantile projection. For BMO and CIBC, increases in VaR\(_{0.95}\) forecasts of the NPL ratios do predict one-quarter ahead the large increases of the actual data. For BMO, the forecast indicates 2010Q1, and
Figure 4.1: Actual Data and VaR\(_{0.95}\) of NPL Ratios for Individual Big Six Banks (Conditional Quantile Regression, 95%)
for CIBC, the forecast indicates 2010Q2. The VaR forecasts of the NPL ratios for other Big Six banks do not have the same accuracy as those for BMO and CIBC. Moreover, I see that the VaR$_{0.95}$ forecasts for other Big Six banks sometimes move in opposite directions and thus give out false signals of the banks’ financial risk. This is especially the case for TD and BNS. Low $R^2$s of conditional quantile regressions in Table 4.2 may partially explain the above results.

The comparison of forecasts on tail real and financial risks is illustrated in Figure 4.2 and Figure 4.3, which depicts actual data and VaR$_{\alpha}$ one-quarter ahead forecasts for GDP-Oil at-risk and the NPL ratio at-risk. Note that I focus on the VaR$_{\alpha}$ of NPL ratios for BMO and CIBC, which are shown to be relatively better predicted by the estimated factors $F_t$. I take on two sets of $\alpha$ values (i.e., $\alpha \in \{0.05, 0.10\}$ for VaR(Oil), and $\alpha \in \{0.95, 0.90\}$ for VaR(BMO) and VaR(CIBC)). As expected, the points where the NPL ratio at-risk is the highest (i.e., 2010Q1 for VaR(BMO) and 2010Q2 for VaR(CIBC)) lag a few quarters behind the point where GDP-Oil is at its lowest level (i.e., 2009Q2). It is interesting to find out that the 2007-2009 crisis first depressed the GDP-Oil and subsequently affected the credit quality of Canadian bank loans, which explains what happens in Figure 4.2 and Figure 4.3.

My forecasts also accord with the fact that McKeown (2015) presents in his Figure 17 about the provision for credit loss (PCL) of the Big Six banks. For convenience, I quote it in Figure 4.4. As argued by McKeown (2015), an increase in the PCL usually precedes an increase in the NPL ratio.\footnote{As explained by McKeown (2015), the PCL reflects the opinion of management on the amount that shall be reserved for current and future loan losses. Since the PCL is somewhat forward-looking, an increase in the PCL is very likely to lead to future increases in the NPL ratios.} It can be seen that my predictions reflect exactly the above argument. The highest forecast VaRs of the NPL ratios for BMO and CIBC in 2010 follow the peaks of the PCL for the corresponding banks in 2009.
4.4. EMPIRICAL RESULTS

Figure 4.2: Actual Data and VaR Forecasts for GDP-Oil (5%), NPL-BMO, and NPL-CIBC (95%) (Conditional Quantile Regression)

(a). VaR_{0.05}(Oil)

(b). VaR_{0.95}(BMO)

(c). VaR_{0.95}(CIBC)

Note: This figure shows the data and one-quarter ahead forecasts of VaR_{\alpha} for GDP-Oil, NPL-BMO, and NPL-CIBC respectively. The actual data is presented by dashed lines and VaR forecasts are presented by solid lines.
Figure 4.3: Actual Data and VaR Forecasts for GDP-Oil (10%), NPL-BMO, and NPL-CIBC (90%) (Conditional Quantile Regression)

Note: This figure shows the data and one-quarter ahead forecasts of VaR$_{\alpha}$ for GDP-Oil, NPL-BMO, and NPL-CIBC respectively. The actual data is presented by dashed lines and VaR forecasts are presented by solid lines.
4.4. EMPIRICAL RESULTS

Figure 4.4: Provision for Credit Losses and Pre-tax Income for the Big Six Banks

Note: This figure is quoted from Figure 17 of McKeown (2015). The provision for credit losses and the pre-tax income of the Big Six banks are presented by solid lines and grey dashed lines, respectively.

4.4.2 What Drive the Peaks of VaR$_\alpha$ Forecasts for the NPL Ratio?

Since the GDP of the resource sector makes up 28.1% of the total GDP for goods-producing industries in Canada, there has always been a debate if the commodity price crash will contribute most to the instability of the Canadian banking industry. In this section, I provide some evidence for the debate.

For the conditional quantile projection of any $X_{t+1}^i$, I can disentangle various factors driving it and compute their respective contribution by Equation (4.3). Equation (4.3) can be rewritten in the below form, which lists the contributions from each block
of estimated factors $F_t$:

$$
\hat{Q}_{X_{t+1} | F_{t+1}}(\alpha) = \hat{\Lambda}^i(\alpha) \hat{F}_{t+1} = \hat{\Lambda}^{i,G}(\alpha) \hat{F}^G_{t+1} + \hat{\Lambda}^{i,C}(\alpha) \hat{F}^C_{t+1} + \hat{\Lambda}^{i,B}(\alpha) \hat{F}^B_{t+1},
$$

(4.4)

The superscripts $G$, $C$, and $B$ indicate that the associated factors and factor loadings for global, Canadian macroeconomic, and banking factors, respectively. Recall from Chapter 2, that the banking factors $\hat{F}^B_{t+1}$ possibly capture linkages between individual banks, running through the interbank market or through exposure to common shocks not modeled explicitly in my DFM. For instance, they could be shocks to the balance sheets of the nonfinancial private sector or shocks to the international financial markets propagated through the banking system. Note that since $\hat{F}^G_{t+1}$ consist of three components: $F^G_{Y,t+1}$, $F^G_{\pi,t+1}$, and $F^G_{P,t+1}$, I can further decompose the contributions to $\hat{Q}_{X_{t+1} | F_{t+1}}(\alpha)$ from world real activities, world inflation, and real commodity price changes. I examine the values of each item on the right hand side of Equation (4.4) and use them to determine which estimated factors drive the most of large increases in the $\text{VaR}_\alpha$ forecasts of the NPL ratios for BMO and CIBC.

Table 4.3 reports the maximum $\text{VaR}_{0.95}(\text{BMO})$ and $\text{VaR}_{0.95}(\text{CIBC})$ forecasts for the NPL ratios of BMO and CIBC, which are at 2010Q1 and 2010Q2, respectively. In addition, this table reports the contributions from each block of estimated factors $\hat{F}_{t+1}$ in percentage terms, to the highest points of $\text{VaR}_{0.95}(\text{BMO})$ and $\text{VaR}_{0.95}(\text{CIBC})$. I decompose them into the contributions from global, commodity price, Canadian macroeconomic and banking factors. Note that I separate the contribution of commodity price factors from the total contribution of global factors $\hat{F}^G_{t+1}$ and report it individually. As expected, the banking factors contribute the most (i.e., 51.05% for BMO and 70.82% for CIBC) to the largest increases in the VaR forecasts for the
NPL ratios, and the contribution from Canadian macroeconomic factors are second
to that of the banking factors (i.e., 31.83% for BMO and 15.86% for CIBC). The di-
rect contribution from real commodity price factors is the lowest (i.e., 13% for BMO
and 6.09% for CIBC). However, their magnitudes are not trivial, considering how
much they constitute of the total contribution from the global factors (i.e., 13% out
of 17.11% for BMO and 6.09% out of 10.43% for CIBC).

Information from Financial Reports on the Peaks of the NPL Ratios

In this section, I collect some specific information from quarterly financial reports of
BMO and CIBC, which disclose the details driving the high NPL ratios at 2010Q2
and 2010Q3, respectively.

At 2010Q2, BMO acquired the Rockford, a Illinois-based bank, from Federal De-
posit Insurance Corporation (FDIC), which added $437 million to the quarterly
balance of gross impaired loans (GILs) (i.e., $3405 million) for BMO.

At 2010Q3, CIBC suffered $72 million of impaired loans from the exposure to the
European leveraged finance,\footnote{As quoted from their quarterly financial report, CIBC provides the leveraged finance to non-investment grade customers in Europe to facilitate their buyout, acquisition and restructuring activities.} $354 million from the exposure to the U.S. real estate
finance,\footnote{As quoted from their quarterly financial report, the U.S. real estate finance business originates commercial mortgages to mid-market clients, under three programs. The construction program offers floating-rate financing to properties under construction. The interim program offers fixed and floating-rate financing for properties that are fully leased or with some leasing or renovation yet to be done. These programs provide feeder product for the group’s permanent fixed-rate loan program and typically have an average term of one to three years.} and $14 million from the exposure to the U.S. leveraged finance. The above
items constitute $441 million of $2042 million quarterly balance of GILs.

As implied by the above analysis, banking factors for Canadian banks possibly
Table 4.3: Contribution of Each Block of Factors to the Largest Increases of VaR$_{0.95}$(BMO) and VaR$_{0.95}$(CIBC)

<table>
<thead>
<tr>
<th>Forecast Value</th>
<th>VaR$_{0.95}$(BMO) at 2010Q1</th>
<th>VaR$_{0.95}$(CIBC) at 2010Q2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.1662</td>
<td>3.0192</td>
</tr>
<tr>
<td>Percentage of</td>
<td>Global 17.11%  Commodity* 13.00%</td>
<td>Global 10.43%  Commodity* 6.09%</td>
</tr>
</tbody>
</table>

This table reports the maximum VaR$_{0.95}$(BMO) and VaR$_{0.95}$(CIBC) forecasts for the NPL ratios of BMO and CIBC, which are at 2010Q1 and 2010Q2, respectively. In addition, this table reports the contributions from each block of estimated factors $\hat{F}_{t+1}$ to the highest points of VaR$_{0.95}$(BMO) and VaR$_{0.95}$(CIBC). I decompose them into the contributions from global, Canadian macroeconomic and banking factors. Note that I separate the contribution of commodity price factors (*) from the total contribution of global factors $\hat{F}_{t+1}^G$ and report it individually.
4.5. CONCLUSIONS

capture those common shocks (e.g., the 2007-2009 global financial crisis) to the balance sheets of foreign institutions, which are not seized by the global factors in my model. This further explains why the estimated banking factors contribute the most to the largest increases in the VaR forecasts for the NPL ratios.

4.5 Conclusions

In this chapter I develop a tail risk forecasting system that extends the framework of De Nicolò and Lucchetta (2017) to the context of SCEEs. I limit my focus to the case of Canada and those foreign economic shocks transmitted to Canada, mainly through commodity price fluctuations and global real GDP growth. I use the VaRs of GDP-Oil and the NPL ratios of individual Big Six banks as my measures of tail real and financial risks, respectively. My framework delivers a set of one-quarter ahead tail real and financial risk forecasts, based on the projections of conditional quantile regressions (Koenker, 2005). The predictors for the quantile regressions are the estimated factors $F_t$, which can effectively condense the information from a wide variety of international and domestic macroeconomic, and individual bank-level variables.

My results do forecast one-quarter ahead the largest increase in tail real risk at 2009Q2, as indicated by the steepest decline of Canadian GDP-Oil. Regarding the accuracy of tail financial risk forecasts, the result depends on how closely the tail quantiles of the underlying financial risk indicator (i.e., the NPL ratios of individual Big Six bank) are correlated with the estimated factors. For BMO and CIBC, the increases in VaR forecasts of the NPL ratios (i.e., 2010Q1 for BMO and 2010Q2 for CIBC) do predict one-quarter ahead the large increases of the actual data. The VaR forecasts of the NPL ratios for other Big Six banks sometimes miss the large
4.5. CONCLUSIONS

movements of the actual data.

My analysis also demonstrates that for BMO and CIBC, the banking factors contribute the most (i.e., 51.05% for BMO and 70.82% for CIBC) to the largest increases in the VaR forecasts for the NPL ratios, and the contribution from Canadian macroeconomic factors are second to that of the banking factors (i.e., 31.83% for BMO and 15.86% for CIBC). The direct contribution from real commodity price factors is the lowest (i.e., 13% for BMO and 6.09% for CIBC). However, their magnitudes are not trivial, considering how much they compose the total contribution from the global factors (i.e., 13% out of 17.11% for BMO and 6.09% out of 10.43% for CIBC).

Overall, the results in this chapter provide some evidence on the importance of commodity price shocks for financial stability in SCEEs. There is some limitation of the econometric technique used here, because quantile forecasts are based on the distribution of the factor loading matrix in the measurement equation. To improve the accuracy of quantile forecasts in the future, I shall use the Baynesian multivariate method in Koop and Korobilis (2010) to further account for the coefficient distribution of the SVAR equation in Chapter 2. In addition, I can also extend my study using the partial quantile regression proposed by Giglio, Kelly, and Pruitt (2016), an alternative quantile estimator to the factor-based conditional quantile regression. The partial quantile regression is a method which emphasizes on each predictor’s quantile covariation with the forecast target. In contrast, the factor based quantile regression summarizes the information according to the covariance between predictors.
Chapter 5

Summary and Conclusions

In this dissertation, I focus on the risk implications of commodity price fluctuations for banks in SCEEs, and improve forecasting the VIX index, an important indicator for financial market practitioners to monitor.

In Chapter 2, I propose a SDFM to decompose underlying forces that drive real commodity price changes and analyze their dynamic effects on banks and pertinent macroeconomic indicators in SCEEs such as Canada. Utilizing sign restrictions that Kilian and Murphy (2012) propose and a conventional recursive identification scheme, I identify global demand, commodity market-specific, and global inflation shocks that underlie real commodity price changes. I find that the first two shocks explain most of the volatility in real commodity prices.

I also find out that different sources of shocks that drive changes in real commodity prices can not be ignored, because they can have heterogeneous impacts on bank risk and lending. Only an expansionary global demand shock that increases real commodity prices can bring about significant increases in bank lending for all the median banks, consistent with an increased demand for investment during boom periods (see, e.g., Zhang (2009)). The responses of bank risk provide mixed answers,
depending on which measure of bank risk is taken. The NPL ratios of all of the median banks decline after an expansionary global demand shock and rise after a negative commodity market-specific shock, which drives up real commodity price more than an expansionary global demand shock. If the bank risk is measured by the noninterest income ratio, only the large median banks (i.e., the median Big Six bank and foreign subsidiary) significantly increase their shares of noninterest income following an expansionary global demand shock. In contrast, the noninterest income ratios of all the median banks decline after a negative commodity market-specific shock.

I also discover substantial heterogeneity across bank responses to a common commodity price shock. The magnitudes of responses of the median Big Six bank and foreign subsidiary are larger than those of the small median local bank, in terms of the total loan growth and noninterest income ratio.

Chapter 3 proposes an application of the OLS post-Lasso method (Belloni and Chernozhukov, 2013) to the standard HAR model to allow the choice of predictors to be data driven. By applying the proposed OLHAR model to forecasting the VIX index, we confirm that the ex ante assigned predictors of the standard HAR model (i.e., \( l_0 = [1, 5, 10, 22, 66] \)) is inconsistent with those selected by a model selection method such as the Lasso. We also implement a multistep ahead forecasting exercise to assess how various forecasting models for the VIX perform. The out-of-sample exercise implies that the OLHAR outperforms other peer models in predicting the market volatility index either weekly, biweekly, or monthly ahead; however, we cannot distinguish its performance from that of the standard HAR model for one-day ahead forecasts. This superiority of the OLHAR model is robust to the total number of
predictors, as verified by our robustness test.

Finally, Chapter 4 aims to assess the importance of commodity price fluctuations for tail financial risk in Canada. Drawing from De Nicolò and Lucchetta (2017), I develop a tail risk forecasting system for SCEEs, which delivers a set of one-quarter ahead tail real and financial risk forecasts and is based on the projections of factor conditional quantile regressions (Koenker, 2005). I use the VaRs of GDP-Oil and the NPL ratios of individual Big Six banks as my measures of tail real and financial risks, respectively.

My results predict one-quarter ahead the largest increase in tail real risk at 2009Q2, as indicated by the steepest decline of GDP-Oil. For BMO and CIBC, the increases in VaR forecasts of the NPL ratios (i.e., 2010Q1 for BMO and 2010Q2 for CIBC) do predict one-quarter ahead the large increases of the actual data. The VaR forecasts of the NPL ratios for other Big Six banks sometimes miss the large movements of the actual data.

My analysis also demonstrates that for BMO and CIBC, the banking factors contribute the most to the peaks in the VaR forecasts for the NPL ratios, and the contribution from Canadian macroeconomic factors are second to that of the banking factors. The direct contribution from real commodity price factors is the lowest. However, their magnitudes are not trivial, considering how much they compose the total contribution from the global factors (i.e., 13% out of 17.11% for BMO and 6.09% out of 10.43% for CIBC).

There is little doubt that financial regulations in each country need to account for structural characteristics of their own economies. In this dissertation, I solely focus on the impacts of commodity price shocks on bank lending and risk in SCEEs,
because the commodity sector is a systemically important real sector for SCEEs (Crean and Milne, 2015). Future studies may find it very interesting to extend my analysis in the direction of identifying the multiple foreign shocks crucial for banks in SCEEs. However, to my best knowledge, I have not found a structural model that can simultaneously identify other foreign shocks, along with the structural shocks that drive real commodity prices. Another possible extension is to modify and tailor my framework to study international risk spill-over effects for banks in other countries, which have different microeconomic compositions than that of SCEEs.
Bibliography


Appendix A

Commodity Price Shocks and Bank Risk in Small Commodity-Exporting Economies

A.1 Bayesian Estimation Method

The section discusses the detailed steps about the estimation of my DFM by a likelihood-based Gibbs sampling method.

I rewrite the measurement equation (2.1) from the main text in the following general form:

\[ X_t = \Lambda F_t + e_t, \]  \hspace{1cm} (A.1)

where \( X_t \) is a \( N \times 1 \) vector of observed times series \( (N = N^G + N^C + N^B) \), \( \Lambda \) denotes a \( N \times K \) factor loading matrix with zero restrictions as presented in equation (2.1), \( F_t \) is a \( K \times 1 \) vector of estimated factors, and \( e_t \) is a \( N \times 1 \) error vector which is assumed to be normally distributed with mean \( 0 \) and diagonal variance \( R \).

I generalize the restricted SVAR model (2.2) from the main text in the following form:

\[ F_t = G_t \phi + v_t, \]  \hspace{1cm} (A.2)
where $F_t$ is a vector of $K \times 1$ factors, $G_t$ is a $K \times M$ block-diagonal matrix with blocks $g_{k,t}^\top$ containing the current and lagged values of the factors relevant for the $k^{th}$ variable, $\phi$ is a $M \times 1$ vector of coefficients, and the $K \times 1$ error vector $v_t$ is assumed to be normally distributed with mean $0$ and variance $\Sigma$.

Following Koop et al. (2007) and Charnavoki and Dolado (2014), I regard $\Lambda$, $R$, $\phi$, and $\Sigma$ as random variables with possibly multiple estimates. Likelihood estimation by multi-move Gibbs sampling is adopted by alternately sampling the above parameters from conditional posterior distributions.\(^{1}\)

Given the structural dynamic factor model system presented in Equations (A.1) and (A.2), I summarize the Gibbs sampling method in the following four steps:

**Step (i)** I start with a set of initial values for parameters $\Lambda^{(0)}$, $R^{(0)}$, $\phi^{(0)}$, and $\Sigma^{(0)}$, using equation-by-equation OLS estimation.\(^2\)

**Step (ii)** Conditional on the data set ($X$, $F$, and $G$) and the initial variance estimates $R^{(0)}$ and $\Sigma^{(0)}$, I draw the coefficients $\Lambda^{(1)}$ and $\phi^{(1)}$ from the posterior densities $Pr(\Lambda|X,F,R^{(0)})$ and $Pr(\phi|F,G,\Sigma^{(0)})$ respectively.

Here I impose the popular Normal priors on the coefficients of the measurement equation (A.1).\(^3\) This implies that the posterior conditional distribution of the coefficients $\Lambda_i$ of the $i^{th}$ measurement equation is Normal, $\Lambda_i|X,F,R \sim N(\tilde{\Lambda}_i, R_{ii}M_i^{-1})$, where

---

\(^1\)I actually follow a MCMC algorithm for obtaining a sequence of observations approximated from a specified multivariate probability distribution. Gibbs sampling is particularly useful when a direct sampling is difficult. In my model, several zero restrictions are imposed on the system presented in Equations (A.1) and (A.2).

\(^2\)As discussed by Koop et al. (2007), initial values for the above parameters should not alter the final results asymptotically. Instead, I also tried the more robust GLS estimator and the results are quite similar to those of the OLS estimator.

\(^3\)Same prior set-up is adopted in other papers including Bernanke et al. (2005), Mumtaz and Surico (2009) and Charnavoki and Dolado (2014).
$R_{ii}$ is the $i$th diagonal element of $R$ and

$$
\bar{\Lambda}_i = \bar{M}_i^{-1}(M_i \Lambda_i + F_i^\top X_i),
$$
(A.3)

$$
\bar{M}_i = M_i + F_i^\top F_i
$$
(A.4)

with $F_i$ and $X_i$ being the regressors and dependent variables of the $i$th measurement equation respectively. Note that variables with underlines ($\bar{M}_i$ and $\bar{\Lambda}_i$) are priors parameters, which are discussed in details in Appendix A.1.1. For parameter $\phi$, a commonly adopted hypothetical distribution for the parameters of VAR system is the independent Normal-Wishart distribution. The conditional posterior distribution of the restricted VAR coefficients is given by $\phi|F, G, \Sigma^{-1} \sim N(\bar{\phi}, \bar{V})$, where

$$
\bar{V} = \left(V^{-1} + \sum_{t=1}^{T} G_t^\top \Sigma^{-1} G_t \right)^{-1},
$$
(A.5)

$$
\bar{\phi} = \bar{V} \left( V^{-1} \phi + \sum_{t=1}^{T} G_t^\top \Sigma^{-1} F_t \right).
$$
(A.6)

$V$ and $\bar{\phi}$ are prior variance and mean of the SVAR coefficients. Once I obtain the estimated coefficients $\Lambda^{(1)}$ and $\phi^{(1)}$, I proceed to obtain the next round of variance-covariance matrices estimates $R^{(1)}$ and $\Sigma^{(1)}$:

Step (iii) Conditional on the data set ($X$, $F$, and $G$) and newly generated coefficients $\Lambda^{(1)}$ and $\phi^{(1)}$, I draw a new set of values of the variance-covariance matrices $R^{(1)}$ and $\Sigma^{(1)}$ from the conditional distributions $\Pr(R|X, F, \Lambda^{(1)})$ and $\Pr(\Sigma|F, G, \phi^{(1)})$ respectively.

I assume that the prior distribution for the variance-covariance matrices follows a
A.1. BAYESIAN ESTIMATION METHOD

Inverse-Gamma distribution. The variance-covariance matrix $R$ is diagonal with elements $R_{ii}$ bearing a conditional posterior Inverse-Gamma distribution $R_{ii}|X, F, \Lambda \sim IG(\bar{\alpha}_i, \bar{\beta}_i)$, where $\bar{\alpha}_i = \alpha_i + T/2$ is a shape parameter and $\bar{\beta}_i = \beta_i + \frac{1}{2}(X_i - F_i\Lambda_i)^\top(X_i - F_i\Lambda_i)$ is a scale parameter. $T$ is the number of periods, while $\alpha_i$ and $\beta_i$ are priors.

As for $\Sigma$, the posterior distribution for $\Sigma^{-1}$ conditional on $\phi$ follows a Wishart distribution such that $\Sigma^{-1}|F, G, \phi \sim W(H, \bar{v})$, where

\[
H = \left( H^{-1} + \sum_{t=1}^{T} (F_t - G_t\phi)(F_t - G_t\phi)^\top \right)^{-1}, \quad (A.7)
\]

\[
\bar{v} = T + v. \quad (A.8)
\]

$H$ and $v$ are a scale matrix and degrees of freedom of the prior distribution respectively. Then I proceed to the step(iv), which involves an iteration process.

Step (iv) Repeat Step (ii) to Step (iii) until the empirical distributions for all posterior parameters $\Lambda, R, \phi$, and $\Sigma$ converge.

In practice, it is common to discard certain number of generated estimates at the beginning (the so-called burn-in period). The reason for this is that (i) ignoring the burn-in period will not harm the final result asymptotically, since successive samples are not independent of each other but form a Markov chain with some amount of correlation; and (ii) data within the burn-in period can be either explosive or misleading, as it may take a while for the stationary desired joint distribution of the Markov chain over the variables to be reached. I restrict the maximum number of replication to be 1,000,000. Following Koop et al. (2007), I set the burn-in period

---

4Together with the Normal priors on the coefficients of the measurement equation, I actually impose a conjugate Normal-Inverse Gamma priors on the parameters (coefficients and variance-covariance matrices), which is quite common in the Bayesian literature (Koop et al., 2007).
A.1. BAYESIAN ESTIMATION METHOD

to be $bp = 1,000$. In other words, I ignore the first 0.1% of the generated data from iterations.

A.1.1 Prior Set-up

In total, there are 8 prior parameters ($M_i$, $\Lambda_i$, $V$, $\phi$, $\mu_i$, $\beta_i$, $H$, $w$) that need to be determined before the execution of the 4-step-iteration procedure. Conformable to Sims and Zha (1998) and Bernanke et al. (2005), I estimate the model using both informative and uninformative priors.

Informative Priors

Priors related to the loading matrix coefficients $\Lambda_i$ of the $i$th measurement equation are set to

- $M_i = I_{K_i}$,
- $\Lambda_i = 0$.

The priors of the restricted VAR coefficient distribution $V$ and $\phi$ follow the famous Minnesota prior (Sims and Zha, 1998)

- $V$ and $\phi$: Minnesota prior,

in which elements of $\phi$ are independent and the conditional standard deviation of the coefficient on lag $l$ of variable $j$ in equation $i$ is given by $(\mu_1^2)/(l^2\mu_3)$, where $\mu_1$ and $\mu_3$ are hyperparameters that are set to $\mu_1 = 0.3$ and $\mu_3 = 1$.

Since all time series in $X_t$ are normalized so that the standard deviations of the measurement errors cannot exceed one, it is safe to specify the shape and scale parameters of the prior Inverse-Gamma distribution of $R_{ii}$ as
A.1. BAYESIAN ESTIMATION METHOD

• $\alpha_i = 1.5,$

• $\beta_i = 0,$

for all $i$. In fact, such set-up can be categorized as uninformative priors as well. Finally, priors on the Wishart distribution are set to

• $H^{-1} = diag \{ \sigma_1^2, \sigma_2^2, ..., \sigma_K^2 \},$

• $v = K + 2,$

where $\sigma_j$ are the standard deviations of residuals from AR(1) and $v$ represents degrees of freedom of the conditional prior Wishart distribution of the matrix $\Sigma^{-1}$.

**Uninformative Priors**

These are the priors that do not take any arbitrary values that significantly affect the posterior distributions. I set the uninformative priors as follows

• $M_i = 0,$

• $\Lambda_i = 0,$

• $V^{-1} = 0,$

• $\Phi = 0,$

• $\alpha_i = 1.5,$

• $\beta_i = 0,$

• $H^{-1} = 0,$

• $v = K + 2.$
A.1. BAYESIAN ESTIMATION METHOD

A.1.2 Identification Using Sign and Bound Restrictions

In this section, I discuss the rotation procedure proposed by Rubio-Ramírez et al. (2010) that I utilize to impose the sign restrictions. The estimation algorithm is summarized in the following steps:

Step (i) Let $\Omega^k$ be the reduced form variance-covariance matrix from the $k$th draw of posterior distribution $\Sigma^{-1}$. I make sure that the global factors are ordered first in $\Omega^k$.

Step (ii) I perform a Cholesky decomposition of $\Omega^k$ and obtain $B^k$ ($\Omega^k = B^kB^k^\top$).

Step (iii) Draw a $s \times s$ matrix $X$ from an independent standard normal distribution and perform a QR decomposition of $X$ such that $X = QR$, where the diagonal of $Q$ is normalized to be positive. $Q$ stands for a rotational orthogonal matrix and has the uniform or Haar distribution. Note that $s$ represents the number of global factors in my system.

Step (iv) Draw a $K \times K$ identity matrix $\tilde{Q}$. I modify the matrix $\tilde{Q}$ by replacing the upper-left block $3 \times 3$ of $\tilde{Q}$ by $Q^\top$, such that $\tilde{Q}\tilde{Q}^\top = I$.

Step (v) Construct $A^k = B^k\tilde{Q}$. Compute the impulse responses with the new structural shocks $A^k$ to check if the sign and bound restrictions are satisfied. Otherwise, I move to the next Gibbs iteration until conditions are met.
A.2 Detailed Data Description

A.2.1 Bank-level Data

The raw data for individual banks is obtained from the OSFI, which is an independent, self-financing authority that regulates and supervises all banks, federally incorporated or registered trust and loan companies, insurance companies, cooperative credit associations, fraternal benefit societies and private pension plans in Canada. I collect data from the monthly balance sheets, quarterly income statements and quarterly statement of impaired assets for all domestic banks, foreign subsidiaries, trust and loan companies, available from 1996Q1 to 2016Q1. A list of chartered financial institutions is presented in Table A.1.

Construction of Bank-Level Variables

I collect the following items from the monthly balance sheets:

(i) \( a_1 \): Total loans less allowance for impairment: sum of balance sheet entries nonmortgage loans, less allowance for impairment and mortgages, less allowance for impairment;

(ii) \( a_2 \): Sum of the shareholders’ equity;

(iii) \( a_3 \): Total assets.

Summary Income Statement:

(i) \( b_1 \): Net income: Prior to 2011Q1, Net income; After 2011Q1, Net income attributable to equity holders and non-controlling interests;

\[ \text{Following the fiscal quarter ends for most Canadian banks, I choose January, April, July and October balance sheet statements corresponding to the first, second, third and fourth quarterly balance sheets.} \]
Table A.1: List of Sampled Chartered Financial Institutions

Panel A: Domestic Banks (12)
(1) Bank of Montreal  
(2) Bank of Nova Scotia  
(3) Canadian Imperial Bank of Commerce  
(4) Canadian Western Bank  
(5) Citizens Bank of Canada  
(6) First Nations Bank of Canada  
(7) Laurentian Bank of Canada  
(8) Manulife Bank of Canada  
(9) National Bank of Canada  
(10) Royal Bank of Canada  
(11) Tangerine Bank  
(12) The Toronto-Dominion Bank

Panel B: Foreign Banks Subsidiaries (10)
(1) Amex Bank of Canada  
(2) Bank of China (Canada)  
(3) Bank of Tokyo-Mitsubishi UFJ (Canada)  
(4) BNP Paribas (Canada)  
(5) Citibank Canada  
(6) HSBC Bank Canada  
(7) Industrial and Commercial Bank of China (Canada)  
(8) KEB Hana Bank Canada  
(9) Mega International Commercial Bank (Canada)  
(10) SBI Canada Bank

Panel C: Loan and Trust Companies (5)
(1) League Savings and Mortgage Company  
(2) MCAN Mortgage Corporation  
(3) Peace Hills Trust Company  
(4) Peoples Trust Company  
(5) Sun Life Financial Trust Inc.

Data are collected from the online database compiled by the OSFI, named as the financial data for banks.
(ii) $b_2$: Total other income or Total noninterest income;

(iii) $b_3$: Total interest income;

(iv) $b_4$: Total interest expense;

Statement of Impaired Assets:

(i) $c_1$: Non-mortgage loans to individuals for non-business purpose: individual allowance for impairment;

(ii) $c_2$: Mortgage-residential: individual allowance for impairment;

(iii) $c_3$: Other non-mortgage loans: individual allowance for impairment;

(iv) $c_4$: Non-residential mortgage: individual allowance for impairment;

(v) $c_5$: Recorded investment: summation of impaired assets of loans under the above four categories to compute total nonperforming loans;

I also obtain the following variable for the next step:

(i) $a_{1g}$: Gross loans ($a_1 + c_1 + c_2 + c_3 + c_4$);

I first construct the 5 key variables for all banks

(i) $x_1$: Share of the nonperforming loans over total loans ($c_5/a_{1g}$);

(ii) $x_2$: Ratio of equity capital to total asset ($a_2/a_3$);

(iii) $x_3$: Return on assets ($b_1/a_3$);

(iv) $x_4$: Growth of gross total loans (log difference of $a_{1g}$);

(v) $x_5$: Share of noninterest income in net operating income ($b_2/(b_2 + b_3 - b_4)$);
Data Cleaning Process

With the variables obtained following the procedure described in Appendix A.2.1, I now perform the following data cleaning process. I want to make sure that my panel data set is balanced and does not include any missing or unrealistic observations.

(i) I omit observations with zero or missing values for more than 8 quarters.

(ii) I delete observations of $x_1, x_2, x_3$ and $x_5$, if they are greater than 1.

(iii) I drop those observations that fall into the bottom or top percentile in terms of mean total assets.\(^6\)

(iv) I drop those trust and loan companies that are subsidiaries of large domestic banks to avoid double counting.

(v) I approximate missing observations by applying the EM algorithm in Stock and Watson (2002).

Final Stage: Prepare the Data for Factor Analysis

The data polishing procedure in Appendix A.2.1 generates a balanced panel data for 27 banks and institutions including (i) 12 local banks; (ii) 10 foreign bank subsidiaries; and (iii) 5 loan and trust companies (2 and 3 respectively).

Since some of five key variables may be nonstationary and need to account for structural breaks in the means, they cannot be directly applied to the factor analysis. I therefore carry out the following data processing procedure in the spirit of Buch et al. (2014b).

\(^6\)Thus I discard Bank One Canada, J.P. Morgan Canada. Note Bank One Canada and J.P. Morgan Canada also suffered the problem of sharply declining total assets, which are below $25 million and make them unlikely to viable banks (Berger and Bouwman, 2009).
A.2. DETAILED DATA DESCRIPTION

(i) All series involved in the measurement Equation (2.1) from Chapter 2 are tested for stationarity by the augmented Dickey-Fuller test with a constant and the number of lags selected according to the Akaike information criterion. All series are then seasonally adjusted.

(ii) All series are demeaned. Structural breaks in the means are detected by applying the sequential multiple breakpoint test of Bai and Perron (2003) to all series, and I subtract the possibly shifted means from the series to correct structural breaks following Eickmeier (2009).

(iii) All outliers are replaced. Outliers are defined by Buch et al. (2014b) as observations with absolute median deviations larger than six times the interquartile range. I follow Buch et al. (2014b) to replace them by the median value of the preceding five observations. Then all series are standardized to have unit variances.

A.2.2 International Data

The main sources of international data are OECD, Datastream, World Bank GEM, Bank of Canada, IMF and Kilian’s personal website. All nonstationary data are transformed by first difference or first difference of logarithms. All series in percentage terms are first differenced if nonstationary.

(i) $z_1$: 4 series of real GDP data for OECD, G7, OECD Europe, and USA respectively.

\[7\text{Note that MATLAB and GAUSS routines are provided by Pierre Perron on his webpage.}\]
(ii) \( z_2 \): 7 series of industrial production index data for G7, OECD Europe, USA, Brazil, Russia, India, and China respectively.

(iii) \( z_3 \): 5 series of trade data for export volume (World), export volume (OECD), import volume (World), import volume (OECD), and the index of global real economic activity by Kilian (2009), respectively. A detailed description of Kilian (2009) is available in Appendix A.2.2.

(iv) \( z_4 \): 9 series of GDP deflator for OECD, G7, OECD Europe, EU15, USA, Brazil, India, Russia, and China respectively.

(v) \( z_5 \): 8 series of CPI (all items) for OECD, G7, OECD Europe, USA, Brazil, Russia, India, and China respectively.

(vi) \( z_6 \): 4 series of CPI (non-food, non-energy) data for OECD, G7, OECD Europe and USA respectively.

(vii) \( z_7 \): 2 series of USA total producer prices for manufacturing and finished goods, respectively.

(viii) \( z_8 \): 5 series of commodity price index with respective to energy, agriculture food, agriculture raw material, base metal, and fertilizer, respectively. These series are collected by the World Bank.

(ix) \( z_{8b} \): 4 series of IMF commodity price indices with respective to energy, metal, agriculture raw and food, respectively. 5 series of BOC commodity price indices categorized by energy, metal, forestry, agriculture and fish, respectively. These series are used for the robustness check.
Kilian (2009) Index

The Kilian index of global real economic activity was developed by Kilian (2009) to measure the effect of global demand fluctuations on industrials commodities. It is based on several representative single-voyage freight rates. The source of data can be found on his personal webpage spanning from January 1968 to August 2016. Since the data was originally in monthly frequency, it was arithmetically averaged to convert to the quarterly frequency.

A.2.3 Domestic Data

Domestic data are obtained from CANSIM, Bank for International Settlements, IMF and OECD.

(i) $w_1$: 25 series of real GDP by expenditure approach and its components

(a) GDP at market prices at chained 2007 prices, Seasonally Adjusted (henceforth, SA);

(b) 6 series of personal expenditure on consumer goods and services, consumer goods, durable goods, semi-durable goods, non-durable goods, and services at chained 2007 prices, SA;

(c) 3 series of government current expenditure on goods and services, government gross fixed capital formation and government investment in inventories at chained 2007 prices, SA;

\footnote{For details on how to construct the index of global real economic activity, please refer to page 1055-1057 in Kilian (2009). Data are downloadable from http://www-personal.umich.edu/~lkilian/paperlinks.html.}
(d) 5 series of business gross fixed capital formation, residential structures, non-residential structures and equipment, non-residential structures, machinery and equipment at chained 2007 prices, SA;

(e) 3 series of business investment in inventories, non-farm inventories and farm inventories at chained 2007 prices, SA;

(f) 3 series of exports of goods and services, goods, services at chained 2007 prices, SA;

(g) 3 series of imports of goods and services, goods, services at chained 2007 prices, SA;

(h) Final domestic demand at chained 2007 prices, SA.

(ii) $w_2$: 21 series of implicit price deflators for GDP by expenditure approach

(a) Price deflator of GDP, SA

(b) 6 series of price deflators of personal expenditure on consumer goods and services, consumer goods, durable goods, semi-durable goods, non-durable goods, and services, SA;

(c) 2 series of price deflators of government current expenditure on goods and services and government gross fixed capital formation, SA;

(d) 5 series of price deflators of business gross fixed capital formation, residential structures, non-residential structures and equipment, non-residential structures, machinery and equipment, SA;

(e) 3 series of price deflators of exports of goods and services, goods, services, SA;
A.2. DETAILED DATA DESCRIPTION

(f) 3 series of price deflators of imports of goods and services, goods, services, SA;

(g) Price deflator of final domestic demand.

(iii) \( w_3 \): 6 series of nominal effective exchange rate, nominal exchange rate CAD/USD, real effective exchange rate, real exchange rate CAD/USD, real exchange rate of traded goods and real exchange rate of internal relative prices.

(iv) \( w_4 \): 5 series of current account balance as % of GDP, trade balance of goods and services as % of GDP, all types of goods as % of GDP, primary commodities as % of GDP, goods except of primary commodities as % of GDP.

(v) \( w_5 \): 30 series of disaggregated real personal expenditure

(a) 3 series of personal expenditure on food and non-alcoholic beverages, alcoholic beverages, tobacco products at chained 2007 prices, SA;

(b) 2 series of personal expenditure on clothings and footwear at chained 2007 prices, SA;

(c) 10 series of personal expenditure on dwelling and property (paid rent, imputed rent, maintenance and repair of the dwelling, water supply and sanitation services, electricity and gas, furniture and furnishings, household textiles, household appliances, tools and equipment for house and garden, other goods and services) at chained 2007 prices, SA;

(d) 3 series of personal expenditure on medical cost (medical products, appliances and equipment, out-patient services, hospital services) at chained 2007 prices, SA;
(e) 3 series of personal expenditure on transportation (purchase of vehicles, operation of transport equipment, transport services) at chained 2007 prices, SA;

(f) 4 series of personal expenditure on education and leisure (communications, recreation and culture, education, food, beverage and accommodation services) at chained 2007 prices, SA;

(g) 5 series of personal expenditure on other service (insurance and financial services, personal care, personal effects, social services, and other unclassified services) at chained 2007 prices, SA;

(vi) $w_6$: 30 series of price deflators of personal expenditure on same types of goods and services described under $w_5$.

(vii) $w_7$: 40 series of industry-level real GDP

(a) 24 series of GDP by goods-producing industry (agriculture, forestry, fishing and hunting, mining, quarrying and oil and gas extraction, utilities, construction, manufacturing, food manufacturing, beverage and tobacco product manufacturing, textile, clothing and leather product manufacturing, wood product manufacturing, paper manufacturing, printing and related support activities, petroleum and coal product manufacturing, chemical manufacturing, plastics and rubber products manufacturing, non-metallic mineral product manufacturing, primary metal manufacturing, fabricated metal product manufacturing, machinery manufacturing, computer and electronic product manufacturing, transportation equipment manufacturing, furniture and related product manufacturing, miscellaneous manufacturing)
A.2. DETAILED DATA DESCRIPTION

at chained 2007 prices, SA;

(b) 11 series of service-producing industry (wholesale trade, retail trade, transportation and warehousing, information and cultural industries, finance, insurance, real estate and other professional services, educational services, health care and social assistance, accommodation and food services, other services except public administration, public administration) at chained 2007 prices, SA;

(c) 5 series of aggregated industry GDP (business sector-goods, business sector-services, goods-producing industries, service-producing industries, industrial production) at chained 2007 prices, SA;

(viii) $w_8$: 26 series of capacity utilization

(a) Total industrial, SA;

(b) Forestry and logging, SA;

(c) Mining and oil and gas extraction, SA;

(d) Electric power generation, transmission and distribution, SA;

(e) Construction, SA;

(f) 21 series of capacity utilization on manufacturing (total, food, beverage, tobacco, textiles, wood product, paper, printing and related support activities, petroleum and coal products, chemical, plastic product, rubber product, non-metallic mineral product, primary metal, fabricated metal product, machinery, computer and electronic product and electrical equipment and appliance and component, transportation equipment, furniture and related product), SA;
(ix) $w_9$: 7 series of CPI and PPI

(a) 6 series of CPI (all items, goods, services, all items excluding food and energy, food, energy), SA;

(b) PPI of manufacturing, SA.

(x) $w_{10}$: 13 series of unemployment and labour cost

(a) Unemployment rate, SA;

(b) 6 series of employment rate (total, agriculture, fishing, manufacturing, construction, and services), SA;

(c) 6 series of labour cost (hourly earnings, unit labour cost of total economy, industry, manufacturing, construction, and business service), SA;

(xi) $w_{11}$: 29 series of monetary base, interest rates, total credit and house prices

(a) 4 series of monetary base (total, M1++, M2+, M3), SA;

(b) Total household credit, SA;

(c) Total business credit, SA;

(d) Total foreign exchange reserves, SA;

(e) 8 series of interest rates (central bank rate, prime loans, prime corporate paper, treasury bill of 3 months, government bond 1-3 years, government bond 3-5 years, government bond 5-10 years, government bond over 10 years);

(f) S&P TSX Composite index.
A.3. IMPULSE RESPONSES: BIG SIX BANKS

(g) 13 series of the New Housing Price Index (Country-level, two region-levels and ten provincial-levels)

A.3 Impulse Responses: Big Six Banks

In this section, I present additional empirical results regarding the impulse responses of individual Big Six banks. Table A.2 presents the adjusted $R^2$ values for regressions of banking variables from each of the Big Six Banks on all the estimated factors. In general, volatilities of five bank-level variables for the Big Six Banks have been explained to a fair amount by the extracted factors. On average, the extracted factors have the best explanatory power for the noninterest income ratio of individual Big Six banks. A comparison among banks shows that Bank of Montreal has the highest correlations with the estimated factors, regarding the return on total assets, the total loan growth and the noninterest income ratio.

Table A.2: Adjusted $R^2$s for Regressions of Each Bank-Level Variable on All the Factors: Big Six Banks

<table>
<thead>
<tr>
<th>Variable</th>
<th>BMO</th>
<th>Scotia</th>
<th>CIBC</th>
<th>National</th>
<th>RBC</th>
<th>TD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonperforming Loans Share</td>
<td>0.5791</td>
<td>0.4250</td>
<td>0.6267</td>
<td>0.8153</td>
<td>0.5281</td>
<td>0.6208</td>
</tr>
<tr>
<td>Equity Capital Ratio</td>
<td>0.6839</td>
<td>0.5695</td>
<td>0.3126</td>
<td>0.6798</td>
<td>0.4239</td>
<td>0.4536</td>
</tr>
<tr>
<td>Return on Assets</td>
<td>0.9075</td>
<td>0.4994</td>
<td>0.5703</td>
<td>0.7138</td>
<td>0.8055</td>
<td>0.5540</td>
</tr>
<tr>
<td>Total Loan Growth</td>
<td>0.5921</td>
<td>0.5709</td>
<td>0.4226</td>
<td>0.5595</td>
<td>0.5259</td>
<td>0.3465</td>
</tr>
<tr>
<td>Noninterest Income Share</td>
<td>0.6434</td>
<td>0.6745</td>
<td>0.7316</td>
<td>0.6830</td>
<td>0.6261</td>
<td>0.5830</td>
</tr>
</tbody>
</table>

Figure A.1 plots the median impulse responses of five banking variables for each of the Big Six banks under a recursive identification, subject to one standard deviation increase in a positive global demand shock and a negative commodity market-specific shock respectively. I will focus on the impulse responses of the NPL ratio, the total
loan growth rate and the noninterest income ratio. After a positive global demand shock, I notice a persistent decrease in the share of NPLs for four of Big Six banks. The effects peak after four quarters. Among the four banks, CIBC has the largest decline in the ratio of NPLs. After a negative commodity market-specific shock, I observe that after an initial decline of NPLs for National, TD and CIBC banks, the median impulse responses of NPL ratios go up for all the Big Six banks.

After a positive global demand shock, four of six banks increase their loan growth rate with the maximum magnitudes ranging from 50 basis points to 100 basis points. In contrast, although four of six banks also increase their loan supply after a negative commodity market-specific shock, the magnitudes are much smaller, of which the maximum magnitudes range from 10 basis points to 50 basis points. Regarding the noninterest income ratio, I find a delayed increase in this ratio after a positive global demand shock, while this ratio initially increases and gradually falls for every Big Six bank after a negative commodity market-specific shock, indicating that banks become more conservative facing the recessionary effects caused by high commodity prices.

In summary, I reach similar conclusions on the responses of individual Big Six banks as what I conclude about the median banks in Chapter 2. In addition, it is interesting to notice that two risk measures of CIBC are the most sensitive to two major commodity price shocks. The total loan growth and the share of noninterest income of TD and National banks are also quite responsive to two major commodity price shocks.
Figure A.1: Impulse Response of Individual Big Six Banks to a Positive Global Demand and a Negative Commodity Market-Specific Shocks

Note: This figure shows the median impulse responses of five banking variables under a recursive identification for individual Big Six banks to one standard deviation increase of a positive global demand and a negative commodity market-specific shocks.