Economic Fluctuations and Corporate Bond Spreads: Evidence from Canadian Bond Markets

by

Husna Rashid Memon
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Name: **Husna Rashid Memon**

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Committee:

Dr. Christina Atanasova
Senior Supervisor
Associate Professor

Dr. Eduardo Schwartz
Second Reader
Professor

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Abstract

This paper attempts to address the question whether the signaling properties of credit spreads in Canada are useful for predicting future economic activity. This It extents Gilchrist, et al. (2009) paper "Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets" by examining the predictive power of credit spreads on corporate debt for future economic activity in Canada. In this paper, the credit spreads were constructed using monthly data on prices corporate bond traded over the 2002 -2017 period issued by 60 Canadian corporations. Overall the results suggest that movements specific to credit markers account for a considerable fraction of volatility in Canadian economic activity during the period under study.

Keywords:
Bond Credit Spreads, Economic Fluctuations

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List of Acronyms

CANSIM- Canadian Socio-economic Information and Management System Database
CD- Certificate of Deposits
CRSP- Center for Research in Security Prices
EMP- Nonfarm Payroll Employment
FEVD- Forecast Error Variance Decomposition
IP- Industrial Production
IRF- Impulse Response Function
LTCM- Long-Term Capital Management
MSFE- Mean Square Forecast Error
PVAR- Panel Vector Auto regression
ROA- Return on Assets
T-Bills- Treasury bills
WRDS- Wharton Research Data Services

1: Introduction

This paper aims to extent Gilchrist, et al. (2009) paper "Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets" by examining the predictive power of credit spreads on corporate debt for future economic activity in Canada.

Gilchrist et al. [2009] find corporate bond spreads spearhead real activity on the footing of financial accelerator mechanisms, increase cyclicality or because they of their forward-looking nature. This paper re-examines this evidence using a broad array of credit spreads constructed directly from the secondary bond prices on outstanding debt issued by the companies in S&P/TSX 60. The relationship between real economic activity and financial market tightness was examined using data on 1043 corporate bonds between July 2002 and July 2017

I am interested in this research question because research on the role of asset prices in economic fluctuations has focused on the information content of various corporate credit spreads. Credit spreads are the investors' compensation for observable risks associated. The literature shows that the developments in corporate credit markets provide important information regarding the future course of economic activity and fluctuations of stock price. I would like to gauge the importance and the impact of credit spreads in predicting real economic activity in Canada.

Two empirical methods are employed to assess the predictive power of credit spread in economic fluctuations. First, the paper re-examines the relationship between bond spreads and credit risk. Second, the analysis evaluates the predictive content of corporate bond spreads in credit-risk portfolios for measures of economic activity such as the growth of nonfarm payroll employment and industrial production, and examine the forecasting power of credit spreads as emphasized in the literature.

This paper is different from the Gilchrist et al. paper in the following ways. 1) This paper includes both financial and Non-financial market participants. 2) This paper analyzes the evidence from the corporate bond market only; equity market has not been taken into consideration. 3) Gilchrist et. al. use Expected Default Frequency constructed and marketed by the Moody's/KMV Corporation (MKMV). Corporate and equity KMV model that Moody's employs to both compute the probability of credit default and as part of their credit risk management system. The Distance to Default (DD) is market-based measure of corporate default risk based on Merton's model. It measures both solvency risk and liquidity risk at the firm level. Gilchrist et al. examine the predictive power of credit spreads in the EDF-based bond portfolios and compare their forecasting performance—both in-sample and out-of-sample. Due to lack of access to KMV/Moody database, z-score were used as a proxy to default risk. (4) Gilchrist et al assess the impact on the macroeconomy of movements in credit spreads in their EDF-based bond portfolios within a structural factor augmented vector autoregression (FAVAR) framework. This empirical approach has not be used in this paper.

Empirical results for Canada show that corporate spreads have predictive ability for economic activity. This inclines to reinforce the theory-based assertion that movements in credit spreads are successful in predicting near-term changes in real economic activity. This tends to support the theory-based assertion that rising risk premia capture tightening credit market conditions. The forecasting performance of the four credit spreads evaluated in this paper is significant. The strongest evidence in favor of the predictive ability and economic significance of credit spreads comes from the high yield investment corporate bonds. Two other credit spreads, the 'Aaa Corporate Bond spread' and the 'Baa Corporate bond spread', have predictive power for some measures of economic activity. Much of the predictive power of bond spreads for economic activity is embedded in securities issued by intermediate-risk rather than low-risk firms. Overall, the results imply that credit market shocks have contributed to Canadian economic fluctuations during the June 2002– July 2017 period.

The remainder of the paper is organized as follows. Section 2 contains the Literature Review. Section 3 discusses and summarizes the key characteristics of the underlying fixed-income security-level data. Section 4 focuses on methodology and results for the statistical relationships between credit spread and Expected Probability of default. It also presents the results of the forecasting exercise. Section 5 states the results of robustness checks. Section 6 puts forward the limitation. Section 7 concludes.

2: Literature Review

Financial instruments represent rights on the real economy and therefore the financial asset prices convey useful information for the state of the economy and risks to the economic outlook. Chan-Lau and Ivaschenko [2002] argue that the financial markets are relatively efficient in reflecting new information in prices. In contrast, economic information is usually gathered and reported with considerable lags so it's validated to use financial prices for forecasting purposes. Since prices of financial instruments embody the forward-looking information and are available at high frequencies, they have been expansively analysed as indicators of real economic activity and several of them have done well in the past.

In particular, previous research on the role of asset pricing in predicting future economic conditions and in proliferating economic fluctuations has accentuated the information content of corporate credit spreads for market's expectations about future economic development. The tremors in financial markets has always drawn attention to the imperative role of credit for real economic activity.

The corporate spread is stated as the difference between the yields various corporate debt instruments and default risk-free benchmark securities of comparable maturity. This spread manifests a number of risks related with corporate bonds such as default risk, liquidity risk and tax risk amongst others. Default risk is evidently cyclical and disposed to increase before the onset of recessions, whereas it can be easily assumed liquidity and tax risks are relatively uncorrelated with business cycles. Many papers support this including Friedman and Kuttner [1993]; Duca [2000]; Chan-Lau and Ivaschenko [2002] and Kwark [2002].

In general, two questions are emphasized when exploring the behavior of credit markets as economic states change. They involve the recognition of shifts in credit outstanding and the reasons underlying changes in the composition of credit. When credit dwindles in a financial crisis the production of goods and services trails pattern. Though this process is sufficiently comprehended, there remains the significant question of whether the decline in aggregate credit is due to a decrease in the supply of credit, the demand for credit, or a combination of both. The other question pertains to the behavior of credit providers as the economic outlook changes.

According to Bernanke, Gertler, and Gilchrist [1999], the upsurge in credit spreads reveal commotion in the supply of credit resulting from the weakening in the quality of corporate financial position or from the decline in the state of financial intermediaries that supply credit. A tightening in credit supply triggers asset values to fall, probability to default to increase, and yield spreads on private debt instruments to expand before economic downturns, as lenders want reparation for the anticipated rise in defaults. Furthermore, Philippon [2008] explains that the corporate bond spreads have the predictive content to exhibit a drop in economic fundamentals rooting from a descent in the expected present value of corporate cash flows prior to a cyclic depression. Philippon [2009] shows that a variation of Tobin's q, which changes proportionately with a credit spread based on US corporate and government bond yields, predicts capital investment much better than the standard Tobin's q based on equity prices.

For assessing the information content of corporate credit spreads for economic activity, the maturity structure of the underlying credit instruments needs to be controlled tactfully. The maturity structure of corporate bond spread indexes such as the Aaa-Baa or high-yield spread is much longer. While, the paper-bill spreads are based on short maturity instruments commonly between one and six months. As expected, short-term credit instruments manifest near-term default risk, whereas longer-maturity instruments are suitable for encapsulating expectations about future economic conditions one to two years ahead, a forecast horizon generally related with business cycle fluctuations. Gilchrist, et al. [2009] advise that the accurate assessment of the predicting ability of credit spreads at market state frequencies necessitates careful focus to the maturities of bonds used to create credit spreads.

Bleaney et al. [2012] have provided strong support for the Gilchrist et al. [2009] and Gilchrist and Zakrajšek [2012] model using data from outside the United States. They argue that bond spreads are strong predictors of financial market tension and can forecast fluctuations in economic movement in Europe for a range of conditions They contrasted the extrapolative content of the corporate bond spreads and the excess bond premium in single countries inside and outside the Euro Area. They concluded that only the core European countries have comparable forecasting content in the bond spreads. Other countries in the Euro Area, and the UK, do not have comparable forecasting content in the bond spreads. They also concluded that the spread is significant even after the inclusion of other indicators of economic confidence and sentiment to control for anticipated changes in real economic activity.

Zhang [2002], analyzing Canadian data, finds that credit spreads dominate the term spread, federal funds rate, paper-bill spread, stock market movements, consumer sentiment index, and shifts in the Conference Board leading indicator in terms of output forecasts up to one year ahead, both in-sample and out-of-sample.

For the predictive ability of credit spread for forecasting macroeconomic conditions, the empirical success of this stratum of research is substantial. However, results differ considerably across diverse financial assets underlying the credit spreads under analysis as well as through various time periods.

For instance, the support for the tendency of the paper-bill spread, difference between the respective interest rates on commercial paper and comparable maturity T-bills, to widen shortly before the inception of recessions and to narrow again before recoveries is thoroughly documented (Friedman and Kuttner [1993]; Gilchrist, et al. [2009]; Guidolin and Tam [2010]).

It is important to consider that some papers have set forth that the paper-bill spread has lost much of its forecasting power since the early 1990s. According to Thoma and Gray [1998] and Emery [1999], the forecasting gist of the paper-bill spread may indicate one-time occurrences.

Friedman and Kuttner [1998] argue that the paper–bill spread did not predict the 1990–1991 recession and provide two key reasons for this digression from past experience. Firstly, the paper–bill spread's role as a barometer of monetary policy gives it signalling ability for market expectations and business cycle fluctuations. But then the 1990–1991 recession was not immediately triggered by tight monetary policy. The second explanation is that a few years just earlier than the 1990–1991 recession, movements of the spread were significantly affected by changes in the relative quantities of T-bills, commercial paper and bank CDs that happened for reasons extraneous to the business cycle. This second predict finding underlines the problems related with using relative interest rate relationships as business cycle indicators.

It is important to note that they have assembled evidence in their paper that, claim to a certain extent in the case of commercial paper and T-bills, changes in asset quantities affect interest rate spreads. Some changes in asset quantities take place due to business cycle frequencies, while others do not, but both types of changes influence the corresponding spreads. When using any particular interest rate spread to predict business fluctuations, one should be sensitive to the chance of idiosyncratic movements in the corresponding asset quantities and consequently making due allowance for those movements if they are present to avoid mistakes. Thus, in this aspect at least, interest rate spreads have much in mutual with other classes of business cycle indicators.

Past studies such as Ng and Wright (2013) find, analyzing US data, the predictive ability of the credit spread to improve markedly while that of the term spread disappears altogether in the latter part of the 1985-2012 sample period. They infer that the increased forecasting performance of the credit spread may outcome of the extensive growth of the financial sector relative to the other sectors of the US economy in shaping the US business cycle during the 1990s up to the early 2000s and due to higher leverage.

In contrast, according to Gertler and Lown [1999], yield spreads based on indexes of high yield corporate bonds have done remarkably well at projecting output growth during the last decade. They used quarterly data to compare the in-sample forecasts from the high-yield spread and other variables to substantiate the predictive power of the high-yield bond spread. Mody and Taylor [2004] have also supported this finding. Duca (1999) points out that the conclusion of the experiment mainly depends on the downfall of the high-yield bond market in the late 1980s and early 1990s, which could be accidental.

Chan-Lau and Ivaschenko [2001, 2002] illustrate the predictive power of the investment-grade spread. Saito and Takeda [2000] find that the corporate term structure of AAA-rated bonds outperformed the treasury term structure in both in-sample and out-of-sample forecasting. They concluded that AAA corporate yield had valuable information about the probability of recession. Krishnamurthy and Muir (2015) realize that credit spreads conjoined with information about pre-crisis credit growth forecast the gravity of financial crises.

To sum up, for the periods of credit market mayhem, credit spread, due to their forward-looking content, are particularly informative of linkages between the real and financial sides of economy. Movements in corporate spread can impart initial warning signals for such economic downturns and can be applied to assess the level of strains in financial markets. Stein (2014) discusses that observing credit spreads is important for making good decisions on monetary policy. Curdia and Woodford (2011) postulate theoretical support that in a slow economy, central bank can offset a mounting credit spread with easing monetary policy. They state that an adjustment for changes in credit spreads can better the standard Taylor rule, however the appropriate size of adjustments is subject to the source of the change in credit spreads.

3: Data

The analysis is based on the significant information that comes from a large sample of fixed income securities issued by Canadian corporations. Specifically, for a sample of 60 publicly traded firms covered by the Center for Research in Security Prices (CRSP), daily market prices of their outstanding long-term corporate bonds were drawn from the WRDS Trace databases. The two data sources include market prices for a significant fraction of dollar-denominated bonds publicly issued in the Canadian corporate cash market. The Trace database is a data source of daily bond prices that starts in July 2002.

The credit spread at each point in time was calculating by matching the yield on each individual security issued by the firm to the estimated yield on the Treasury security of the same maturity. The month-end Treasury yields were taken from the Canadian Socio-economic Information and Management System Database (CANSIM).

To minimize the effect of outliers, the analysis excludes all observations with credit spreads greater than 5,000 basis points and smaller than 10 basis points. Furthermore, issues with a par value of less than $10,000 were excluded from observation as such small issues are likely badgered by considerable liquidity concerns. These selection criteria yielded a sample of 1,043 individual securities, covering the period from July 2002 to July 2017.

Table 1: Summary Statistics for Selected Bond Characteristics

Bond Characteristic	**Mean**	**SD**	**Min**	**Max**
Term to Maturity(years)	8.27	4.28	1	20
Duration (years)	5.81	1.93	0.06	18.7
S&P Quality Rating	-	-	C	A+
Market Value ($mil.)	57	121	0.1	733
Coupon Rate(pct.)	4.39	2.34	0	15.4
Annualized Yield(pct.)	3.96	3.37	0.494	51.35
Credit Spread (bps)[1]	103.8	7.45	10.02	4831
Panel Dimensions				
Observations: 13681 N= 1043Bonds				

[1] Measured relative to comparable maturity Treasury yield

Table 1 contains summary statistics for the selected characteristics of bonds in the sample. The maturity of these debt instruments is fairly long, the average term-to-maturity is about 8.27 years. Because corporate bonds typically generate significant cash flow in the form of regular coupon payments, the effective duration is considerably shorter, averaging about 5.81 years over the sample period. Though the sample spans the spectrum of credit quality from "single C" to "A+"—the median bond/month observation, at BBB, is still in the investment-grade category. The coupon rate on the sample of bonds averaged 4.39 percent during the sample period, and the average total return, as measured by the annualized yield, was 3.96 percent per annum. The distribution of the market values of the bonds in the sample range from $1 million to nearly $733 million.

A fraction of observed credit spreads manifests compensation required by investors for tolerating the risk that a firm who issued the bonds will default on its payment obligations. To measures this firm-specific likelihood of default at each point in time, Altman Z score was used a proxy for Expected Default Risk for the non-financial companies and the quarterly data for the sample firms was retrieved from the Bloomberg Terminal.

The z-score for manufacturing firms was calculated as;

Z-Score = ([Working Capital / Total Assets] x 1.2) + ([Retained Earnings / Total Assets] x 1.4) + ([Operating Earnings / Total Assets] x 3.3) + ([Market Capitalization / Total Liabilities] x 0.6) + ([Sales / Total Assets] x 1.0)

The z-score for non-manufacturing firms was calculated as;

Z-Score = ([Working Capital / Total Assets] x 1.2) + ([Retained Earnings / Total Assets] x 1.4) + ([Operating Earnings / Total Assets] x 3.3) + ([Market Capitalization / Total Liabilities] x 0.6)

The papers that support the use of the bank z-score for evaluating the stability of financial institutions and predictive bankruptcy risk which the banks are exposed to include Boyd and Runkle (1993); Demirguc-Kunt, Detragiache, and Tressel (2008); Laeven and Levine (2009); Poli, Chiaramonte, and Croci, (2015). Its accuracy level has been validated by the empirical research carried out in the Italian banking system (Altman, Danovi and Falini [2012]), the French banking system (Lepetit and Strobel [2014]), the Islamic banking system (Cihak and Hesse[2008]).

Bank Z-score matches a bank's buffers, i.e. capitalization and returns, with the volatility of the returns. It is estimated as (ROA+(equity/assets))/sd(ROA) where sd(ROA) denotes the standard deviation of ROA.

As a measure of financial stability, perhaps the main limitation is that the z-scores are based purely on accounting data. They are thus only as good as the underlying accounting and auditing framework. An advantage of using z-score is that it can be also used for companies for which more refined, market based data are not available. Furthermore, the z-scores allow matching the risk of default in different groups of institutions.

The bond credit ratings were extracted from the WRDS Trace Master database but were not used because ratings were annual and z-scores have proved to be one of the most reliable predictors of financial distress. Enron's Z-Score was equivalent to its BBB bond rating at year-end 1999. But in June 20012, Enron had a z-score equal to a B whereas the rating agencies had rated Enron as BBB just before it filed for bankruptcy.

To examine the predictive power of credit spread, Nonfarm payroll employment (EMP) and monthly index of industrial production (IP) published monthly by Statistics Canada are used to gauge the state of the economy.

4: Methodology and Results

4.1 Default Risk and Credit Spread

This Section focuses on the relationship between bond spreads and default risk. The cross-sectional heterogeneity of data has been examined by splitting into credit-spread portfolios sorted by the bond issuer's ex-ante projected probability of default (high, intermediate and low risk) and the bond's residual term-to-maturity. To control for maturity, the bond credit spreads were split into four maturity categories: (1) Short maturity: credit spreads of bonds with the remaining term-to-maturity of less than to 3 years; (2) Intermediate maturity: credit spreads of bonds with the remaining term-to-maturity of more than (or equal) 3 years but less than 7 years; (3) Long maturity: credit spreads of bonds with the remaining term-to-maturity of more than (or equal) 7 years but less than to 15 years; (4) Very long maturity: credit spreads of bonds with the remaining term-to-maturity of more than (or equal) 15 years.

Then, an arithmetic average of credit spreads in month t for each maturity portfolio and an arithmetic average of excess equity returns in month t for each maturity portfolio was computed.

The following time series regression between credit spread and expected default risk was estimated

$R_{it}=\alpha_i + \beta_i PD_{i,\,t-1} + \epsilon_{it}$

Where R_{it} denotes the average credit spread in month t and $PD_{i,\,t-1}$ denotes the expected probability of default at the end of month t-1.

As evidenced by the entries in Table 2, there is a strong positive relationship between measures of default risk based on the information from the corporate bond market. For non-financial firms, the estimates of the coefficients associated with the average PD in each maturity group are statistically significant at conventional levels for two out of four maturity based portfolios. For Financial firms, the estimates of the coefficients associated with the average PD in each maturity group are statistically significant at conventional levels for three out of four maturity based portfolios.

Table 2: Relationship between Credit Spreads and Expected Default Risk (By Maturity)

SHORT MATURITY (LESS THAN 3 YEARS) CORPORATE BONDS		
VARIABLE	NONFINANCIAL	FINANCIAL
CONSTANT	-.7764287	0.6369846
	(12.02)	(2.00)
PD t-1	.3601016	.0362435
	(2.85)	(6.73)
Adj R-squared	0.2371	0.0755
INTERMEDIATE MATURITY (3 to 7 YEARS) CORPORATE BONDS		
VARIABLE	NONFINANCIAL	FINANCIAL
CONSTANT	.2804909	-.1308427
	(0.45)	(5.35)
PD t-1	-.0002689	.0012613
	(1.0.1)	(2.19)
Adj R-squared	0.0000	0.0015
LONG MATURITY (7 to 15 YEARS) CORPORATE BONDS		
VARIABLE	NONFINANCIAL	FINANCIAL
CONSTANT	.98832225	-.0884604
	(6.27)	(3.82)
PD t-1	. 2011112	.0250413
	(2.87)	(26.67)
Adj R-squared	0.0014	0.3733
VERY LONG MATURITY (MORE THAN 15 YEARS) CORPORATE BONDS		
VARIABLE	NONFINANCIAL	FINANCIAL
CONSTANT	1.378309	.0630297
	(1.87)	(0.63)
PD t-1	-.1465656	.0162979
	(0.66)	(6.47)
Adj R-squared	0.0000	0.0763

Note: Sample Period Monthly data from July 2002 to August 2017 (T=205). Dependent variable in each regression is the average credit spread in month t. Absolute T-statistics are reported in Brackets. Breusch-Pagan / Cook-Weisberg test for heteroscedasticity Constant variance and Ramsey RESET test using powers of the fitted values of spread were used for robustness of the model.

With regards to expected probability of default, the bond credit spreads were split into three categories; high risk, intermediate risk and low risk. Lepetit and Strobe [2013] find that if z score>3, the firm is situated in the safe zone, it is financially healthy and the level of risk is low. If the score is between 1.8 and 3, the firm is situated in the grey zone and the level of risk is intermediate. A score of less than and equal to 1.8 involves high level of risk and the firm is situated in the distress zone. A higher z-score therefore implies a lower probability of insolvency. The sample had no observation with Z-score less than or equal to 1.8.

Table 3 contains the results of time series regression of monthly bond spreads in intermediate and low risk categories. In the credit-risk dimension, the PD explain the least variation in credit spreads of portfolios containing bonds issued by least risky firms, characterized by high Altman Z-scores. The explanatory power of the PDs also diminish somewhat for portfolios for longer maturity bonds. Although estimates of the coefficients associated with the average PD in each intermediate-risk portfolio are statistically significant at conventional levels for three out of four maturity based portfolios, they are economically small and movements in PD explain very less time-series variation in credit spread across the spectrum of credit quality.

This finding suggest that for the bonds under consideration the corporate spread is related to systematic movements in expected default risk within intermediate risk categories. The estimated coefficients, on average, are statistically significant; an indication the relationship holds across the cross-sectional distribution of credit risk as well the maturity of corporate debt instruments. However, the explanatory power of the PD diminish somewhat for portfolios for longer maturity bonds.

Table 3: Relationship between Credit Spreads and Expected Default Risk (By Credit Risk)

SHORT MATURITY (LESS THAN 3 YEARS) CORPORATE BONDS		
VARIABLE	Intermediate Risk	Low Risk
CONSTANT	.800781 (12.38)	(no observation)
PD t-1	.3180864 (2.57)	
Adj R-squared	0.2102	
INTERMEDIATE MATURITY (3 to 7 YEARS) CORPORATE BONDS		
VARIABLE	Intermediate Risk	Low Risk
CONSTANT	.066451 (1.05)	-.019979 (0.09)
PD t-1	-.0778496 (2.56)	. 0369288 (0.46)
Adj R-squared	0.086	0.0000
LONG MATURITY (7 to 15 YEARS) CORPORATE BONDS		
VARIABLE	Intermediate Risk	Low Risk
CONSTANT	.9819179 (5.26)	1.411852 4.92
PD t-1	.1557741 (1.83)	-.086167 (0.72)
Adj R-squared	0.07	0.0005
VERY LONG MATURITY (MORE THAN 15 YEARS) CORPORATE BONDS		
VARIABLE	Intermediate Risk	Low Risk
CONSTANT	2.596381 (4.70)	.9303818 (0.66)
PD t-1	-.6063996 (3.24)	.0305801 (0.08)
Adj R-squared	0.0964	0.0000

Note: Sample Period Monthly data from July 2002 to August 2017 (T=205). Dependent variable in each regression is the average credit spread in month t. Absolute T-statistics are reported in Brackets.

4.2 Credit Spreads and Economic Activity

This section studies the predictive power of credit spreads in the bonds sample with several commonly used credit spread indexes and compare their forecasting performance in-sample and out-of-sample.

First, the two measures of economic activity were projected the following bivariate Vector auto regression (VAR), supplemented with two sets of credit spreads:

$$\nabla EMP_{t+h} = \beta 0 + \beta 1i \nabla EMP_{t-i} + \beta 2i \nabla IP_{t-i} + \eta'_1 Z_{1t} + \eta'_2 Z_{2t} + \varepsilon_{1,\, t+h} \quad (1)$$

$$\nabla IP_{t+h} = \gamma 0 + \gamma 1i \nabla EMP_{t-i} + \gamma 2i \nabla IP_{t-i} + \theta'_1 Z_{1t} + \theta'_2 Z_{2t} + \varepsilon_{2,\, t+h} \quad (2)$$

In the VAR forecasting system given by equations 1–2, , Z_{1t} denotes a vector of standard credit spreads indexes, Z_{2t} denotes a vector of credit spreads associated with bonds in the sample and $\varepsilon 1$, $t+h$ and $\varepsilon 2$, $t+h$ are the forecast errors.

The vector $Z1t$ consists of four credit spread indexes which have been used considerably to forecast real economic activity. This set of standard credit spread indexes captures the information content of default-risk indicators at both short and long horizons by incorporating a paper-bill spread along with spreads on long-term corporate bonds. The four credit spread indexes used are as follows; (1) Paper-bill spread: the difference between the yield on 1-month nonfinancial AA-rated commercial paper and the yield on the Canada 1-month Treasury bill; (2) Aaa corporate bond spread: the difference between the yield on an index of seasoned long-term Aaa-rated corporate bonds and the yield on the Canada 10-Year Treasury note; (3) Baa corporate bond spread: the difference between the yield on an index of seasoned long-term Baa-rated corporate bonds and the yield on the Canada 10-Year Treasury note; and (4) high-yield corporate bond spread: the difference between the yield on an index of long-term speculative-grade corporate bonds and the yield on the Canada 10-Year Treasury note.

Table 4: Results of Panel VAR

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
emp_growth						
emp_growth						
L1.	-.0792092	.0079443	-9.97	0.000	-.0947797	-.0636386
ip_growth						
L1.	-.0211492	.002935	-7.21	0.000	-.0269018	-.0153967
pbillspread	.0028251	.0003361	8.41	0.000	.0021664	.0034838
AaaCBS	-.0075568	.0003997	-18.90	0.000	-.0083402	-.0067733
HighYieldCBS	-.0003782	.0000208	-18.16	0.000	-.000419	-.0003374
BaaCBS	.0018738	.0001036	18.09	0.000	.0016708	.0020768
spread	-.0005505	.0001102	-5.00	0.000	-.0007665	-.0003345
ip_growth						
emp_growth						
L1.	.9619566	.0197347	48.74	0.000	.9232774	1.000636
ip_growth						
L1.	.4238059	.0069606	60.89	0.000	.4101633	.4374485
pbillspread	.0154248	.0007318	21.08	0.000	.0139904	.0168591
AaaCBS	-.029651	.0008613	-34.42	0.000	-.0313391	-.0279628
HighYieldCBS	-.0014906	.0000426	-35.00	0.000	-.0015741	-.0014072
BaaCBS	.0027138	.000284	9.56	0.000	.0021573	.0032704
spread	-.0014115	.0001968	-7.17	0.000	-.0017971	-.0010258

Note: Each VAR specification includes 11 lags of ΔEMP and ΔIP. See Appendix A for Separate VAR for financial and nonfinancial firms. The results are consistent.

As evidenced by the p-values reported in Table 4, both the standard credit spread indexes and corporate spread are statistically significant predictors of Employment Growth and Industrial Production growth.

4.2.1 IN-SAMPLE FORECASTING

This section examines the in-sample predictive power of various credit spreads for the selected two measures of economic activity. Specifically, for each forecast horizon h, the forecasting VAR given in equations 1 and 2 is estimated using all available data. Then the h-month ahead growth rates of nonfarm payroll employment and industrial production and the associated forecast errors were calculated. To quantify the in-sample forecasting performance of the VAR specifications, the square root of the mean squared forecast error in percentage points (RMSFE) for each specification has been reported.

In both risk cases, Table 5 reports p-values associated with the Wald exclusion tests on the two sets of credit spreads along with the explanatory power of each forecasting equation as measured by the Adjusted R-squared.

Table 5: Predictive Content of Credit Spreads for Economic Activity

	Nonfarm Employment (EMP)		**Industrial Production (IP)**		**Credit Spreads**		**Overall**
	P>chi2	**Adj R2**	**P>chi2**	**Adj R2**	**Pr>W1**	**Pr>W2**	**Pr>W**
Low Risk	0.0001	0.9252	0.0000	0.9868	0.0000	0.0000	0.0000
Intermediate Risk	0.0000	0.9163	0.0000	0.9110	0.0000	0.0000	0.0000

Note: Each VAR specification includes 11 lags of ΔEMP and ΔIP. Pr > W1 denotes the p-value for the Wald test of the null hypothesis that coefficients on the set of standard credit spread indexes are jointly equal to zero; Pr > W2 denotes the p-value for the robust Wald test of the null hypothesis that coefficient on credit spreads in equal to zero. Pr>W denotes the p-value for the Wald Test of the null hypothesis that coefficients are jointly equal to zero.

The upper panel of Table 6 contains the results of this exercise for the short-run forecast horizon (3 and 6 months), whereas the lower panel contains results for the long-run forecast horizon (20 months). It reports RMSFE associated with each forecast along with the adjusted R2.

Table 6: In-sample Predictive Content of Credit Spreads for Economic Activity

Forecast Horizon h=3				
	Nonfarm Employment (EMP)		Industrial Production (IP)	
	RMSFE	***Adj R2***	***RMSFE***	***Adj R2***
Low Risk	0.01	0.9533	0.03	0.9954
Intermediate Risk	0.02	0.8531	0.1	0.9364
Forecast Horizon h=6				
	Nonfarm Employment (EMP)		Industrial Production (IP)	
	RMSFE	***Adj R2***	***RMSFE***	***Adj R2***
Low Risk	0.02	0.7087	0.07	0.9189
Intermediate Risk	0.04	0.6028	0.17	0.8320
Forecast Horizon h=20				
	Nonfarm Employment (EMP)		Industrial Production (IP)	
	RMSFE	***Adj R2***	***RMSFE***	***Adj R2***
Low Risk	0.07	0.5755	0.25	0.5211
Intermediate Risk	0.09	0.6815	0.32	0.5305

Note: Sample Period: Monthly Data from August 2014 to March 2017. Dependable variables in the VAR specification are ΔEMP t+h and ΔIP t+h, where h is the forecast horizon.

As evidenced by the MSFE reported in the Table 6, both the standard credit spread indexes and credit spreads are significant predictors of Employment Growth and Industrial Production Growth at that the short time horizon. The lower panel of Table 3 examines the in-sample explanatory power of credit spreads at the 20-month horizon. At this longer horizon, the information content of credit spreads for both measures of economic activity is considerable. In the case of nonfarm payroll employment, for example, standard credit spread indexes explain 68 percent of the variation in the 20-month ahead growth rate of nonfarm payroll employment. The results of these forecasting exercises indicate that the information content of credit spreads is concentrated in the low risk categories.

4.2.2 OUT-OF-SAMPLE FORECASTING

This section analyzes the out-of-sample predictive power of credit spreads for the selected two measures of economic activity using pseudo out-of-sample forecasts. To quantify the out-of-sample forecasting performance of the VAR specifications, the square root of the mean squared forecast error in percentage points (RMSFE) for each specification has been reported in Table 7.

Table 7: Out-of-sample Predictive Content of Credit Spreads for Economic Activity

Forecast Horizon h=6				
	Nonfarm Employment (EMP)		**Industrial Production (IP)**	
	RMSFE	***Adj R2***	***RMSFE***	***Adj R2***
Low Risk	0.04	0.6057	0.11	0.7547
Medium Risk	0.03	0.7378	0.11	0.8051
Forecast Horizon h=12				
	Nonfarm Employment (EMP)		**Industrial Production (IP)**	
	RMSFE	***Adj R2***	***RMSFE***	***Adj R2***
Low Risk	0.05	0.5354	0.17	0.7056
Medium Risk	0.06	0.7095	0.15	0.7776

Note: Sample Period: Monthly Data from August 2014 to December 2015. Dependable variables in the VAR specification are ΔEMP t+h and ΔIP t+h, where h is the forecast horizon.

The results reported in Table 7 signify that corporate spread have predictive power for the selected two measures of economic activity.

5: Robustness Checks

This cross-sectional analysis covers the time period from July 2002 to August 2017. The data set is ***weakly balanced*** if each panel doesn't contain the same time points. For instance, a company in the sample have issued first debt instrument in 2004. Panels are said to be *strongly balanced* if each panel contains the same time point. For example, if we did not have Debt instrument for firm for 2002 but have data for 2004 and onwards, xtset would indicate that the data have a gap. This limited the post-estimation testing in STATA as Hadri Lagrange, Levin-Lin-Chu Fisher-type test (based on augmented Dickey-Fuller tests) for unit root required strongly balanced data.

5.1 Stability test

Hamilton [1994] and Lutkepohl [2005] find that a VAR model is stable if all moduli of the companion matrix are strictly less than one. The stability condition of the estimated panel VAR was checked. The resulting table and graph of eigenvalues confirms that the estimate is stable.

Table 8: Stability Test Results

Eigenvalue stability condition

Eigenvalue Real	Eigenvalue Imaginary	Modulus
.4807623	0	.4807623
-.4423581	0	.4423581

All the eigenvalues lie inside the unit circle.
pVAR satisfies stability condition.

This stability implies that the panel VAR is invertible and has an infinite-order vector moving-average representation. Thus, it can impart interpretation to estimated impulse-response functions and forecasting.

5.2 Granger Causality Wald test

Table 9: Granger Causality Test Results

Equation \ Excluded	chi2	df	Prob > chi2
emp_growth			
ip_growth	51.924	1	0.000
ALL	51.924	1	0.000
ip_growth			
emp_growth	2376.028	1	0.000
ALL	2376.028	1	0.000

Results of the Granger causality tests below show that nonfarm payroll employment growth and other variable in the panel VAR Granger-causes industrial production. Likewise, industrial production and other variables Granger-causes nonfarm payroll employment growth at the usual confidence levels.

5.3 Lag Order Selection

The panel VAR lag order selection on estimation sample was ran.

Table 10: Lag Order Selection

Selection order criteria
Sample: 522 - 685

No. of obs = 6559
No. of panels = 201
Ave. no. of T = 32.632

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	.1515861	2919.942	0	2533.244	2831.942	2728.678
2	.1750516	2579.896	0	2228.353	2499.896	2406.02
3	.1760838	2357.373	0	2040.984	2285.373	2200.885
4	.1776352	1680.066	0	1398.831	1616.066	1540.965
5	.2346644	1261.513	4.8e-248	1015.433	1205.513	1139.8
6	.2108041	1094.044	9.1e-216	883.1177	1046.044	989.7181
7	.2447439	1099.421	2.4e-220	923.6496	1059.421	1012.483
8	.2772232	1163.037	1.3e-237	1022.42	1131.037	1093.487
9	.4548041	464.6241	7.39e-92	359.1609	440.6241	412.4612
10	.4757479	214.8046	4.82e-42	144.4958	198.8046	180.0293
11	.480916	139.5337	3.55e-29	104.3794	131.5337	122.1461
12	.5189633	.	.	.	.	.

Eleventh-order panel VAR has the minimum Hansen's J statistic. Eleventh-order panel VAR is the preferred model, since it has the smallest MBIC, MAIC and MQIC, based on the selection criteria by Andrews and Lu [2001].

6: Limitations

There are four concerns, in this analysis and findings, regarding the predictive power of credit spreads for future forecast.

First, the analysis is based on data from 2002. One could argue that the lack of historical data limits the strength of the conclusion. A longer sample with more business cycles would make the conclusion more convincing. Nevertheless, that the importance of the credit spreads comes from their information content on expected long-term credit risks, which is not provided by other financial market indicators. This endorses its value to conventional leading indicators such as the term spread and the federal funds rate.

Second, Duca (1999) argues that the credit spreads occasionally transmit false signals when financial markets are under pressure. The Long-Term Capital Management (LTCM) hedge fund crisis is one example. The strained financial markets widened credit spreads in 1998, but economic growth did not decelerate in 1999. It would be interesting to carry out empirical research to determine that the predictive power of the credit spreads is strong even in the presence of false alarms.

Third, this paper doesn't completely replicate the Gilchrist et al. model.

Lastly, since there are several bonds issued by one firm, the firm-specific risk in error term doesn't account for this.

7: Conclusion

The useful predictive content of the credit spreads signify that they have the capability to help private investors and central bankers to convalesce their output forecasts. In comparison to non-financial leading indicators, credit spreads are accessible real-time on a daily basis. In comparison to information from the stock market, credit spreads are much less volatile.

Empirical results for Canada show that corporate spreads have predictive ability for economic activity. This inclines to reinforce the theory-based assertion that movements in credit spreads are successful in predicting near-term changes in real economic activity. The results show that the relationship between default risk and credit spread holds across the cross sectional distribution of credit risk as well the maturity of corporate debt instruments. The predictive content of corporate bond spreads in credit-risk portfolios for measures of economic activity, such as the growth of nonfarm payroll employment and industrial production, is considerable. Much of the predictive power of bond spreads for economic activity is embedded in securities issued by intermediate-risk rather than low-risk firms. The results imply that credit market shocks have contributed to Canadian Economic fluctuations during the June 2002– July 2017 period.

Appendices

Appendix A: Segregated PVAR

A1: PVAR for Financial Firms

```
Final GMM Criterion Q(b) =      .993
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                          No. of obs      =       415
                                          No. of panels   =        38
                                          Ave. no. of T   =    10.921
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
emp_growth						
emp_growth						
L1.	-.2526054	.0027018	-93.50	0.000	-.2579008	-.2473101
ip_growth						
L1.	.0174719	.0011055	15.80	0.000	.0153052	.0196386
pbillspread	-.0007327	.0000776	-9.44	0.000	-.0008849	-.0005805
AaaCBS	.0009906	.0001137	8.71	0.000	.0007677	.0012135
HighYieldCBS	.0004095	7.68e-06	53.36	0.000	.0003945	.0004246
BaaCBS	-.0039482	.0000397	-99.57	0.000	-.004026	-.0038705
spread	-.0000741	.0000349	-2.12	0.034	-.0001425	-5.65e-06
ip_growth						
emp_growth						
L1.	1.430739	.0177238	80.72	0.000	1.396001	1.465477
ip_growth						
L1.	.3090223	.0047968	64.42	0.000	.2996208	.3184238
pbillspread	.0107047	.000413	25.92	0.000	.0098953	.0115141
AaaCBS	-.0112047	.0007671	-14.61	0.000	-.0127082	-.0097012
HighYieldCBS	-.0004064	.0000367	-11.08	0.000	-.0004783	-.0003345
BaaCBS	-.0045428	.0001508	-30.13	0.000	-.0048383	-.0042473
spread	.0002069	.0000577	3.59	0.000	.0000939	.00032

Table 11: Results for PVAR of Financial Firms

A2: PVAR for Non-Financial Firms

```
Final GMM Criterion Q(b) =      .928
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                          No. of obs      =      1355
                                          No. of panels   =        66
                                          Ave. no. of T   =    20.530
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
emp_growth						
emp_growth L1.	-.4831573	.0042347	-114.10	0.000	-.4914571	-.4748576
ip_growth L1.	.0157609	.0027743	5.68	0.000	.0103233	.0211985
pbillspread	.0036352	.0001711	21.25	0.000	.0032998	.0039705
AaaCBS	-.0043491	.0001426	-30.51	0.000	-.0046285	-.0040697
HighYieldCBS	-.0002016	.0000193	-10.46	0.000	-.0002393	-.0001638
BaaCBS	-.0005632	.000048	-11.73	0.000	-.0006574	-.0004691
spread	-.0002668	.0000482	-5.53	0.000	-.0003614	-.0001723
ip_growth						
emp_growth L1.	1.242267	.0333357	37.27	0.000	1.17693	1.307604
ip_growth L1.	.4600406	.0074592	61.67	0.000	.4454209	.4746604
pbillspread	.0127424	.0007449	17.11	0.000	.0112824	.0142023
AaaCBS	-.0215614	.0009097	-23.70	0.000	-.0233443	-.0197784
HighYieldCBS	-.0006452	.0000535	-12.05	0.000	-.0007501	-.0005403
BaaCBS	-.008116	.0003301	-24.58	0.000	-.008763	-.0074689
spread	.0008	.000247	3.24	0.001	.0003158	.0012841

Table 12: Results for PVAR of Financial Firms

Appendix B: Forecast Error Variance Decomposition

Forecast horizon	Impulse variable emp_growth	ip_growth
emp_growth		
0	0	0
1	1	0
2	.9985778	.0014223
3	.9986216	.0013784
4	.9985659	.0014341
5	.9985673	.0014327
6	.9985647	.0014353
7	.9985647	.0014353
8	.9985646	.0014354
9	.9985646	.0014354
10	.9985646	.0014354
ip_growth		
0	0	0
1	.1431881	.8568119
2	.3328142	.6671858
3	.3279037	.6720963
4	.333334	.666666
5	.3331459	.6668541
6	.3333947	.6666052
7	.3333882	.6666118
8	.3333999	.6666
9	.3333997	.6666002
10	.3334003	.6665997

Table 12: Results for FEVD

Based on the FEVD (Forecast Error Variance Decomposition) estimates, we see that as much as 33 percent of variation in growth in Industrial Production can be explained by growth in nonfarm payroll employment. On the other hand, growth in Industrial Production explain only 0.14 percent of variation in growth in nonfarm payroll employment.

Appendix C: Impulse-Response Function

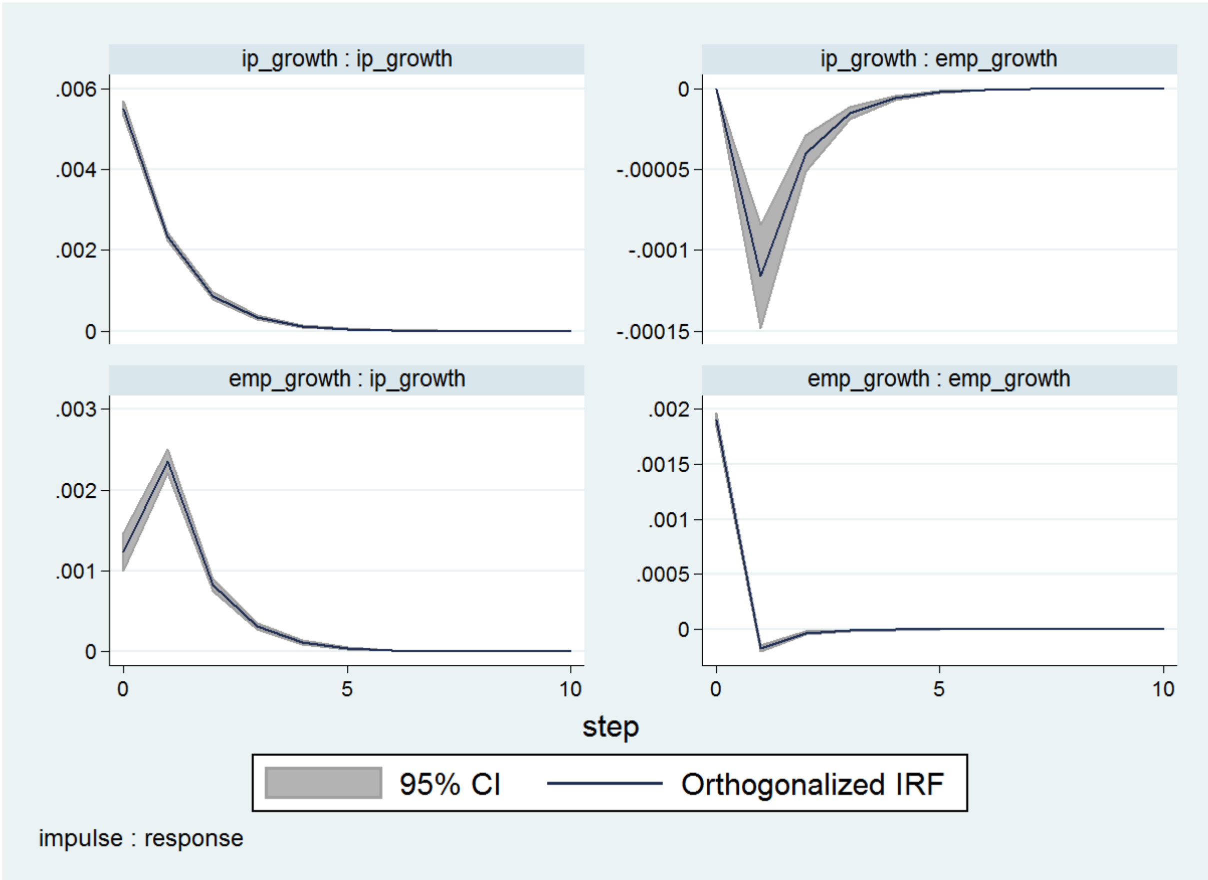
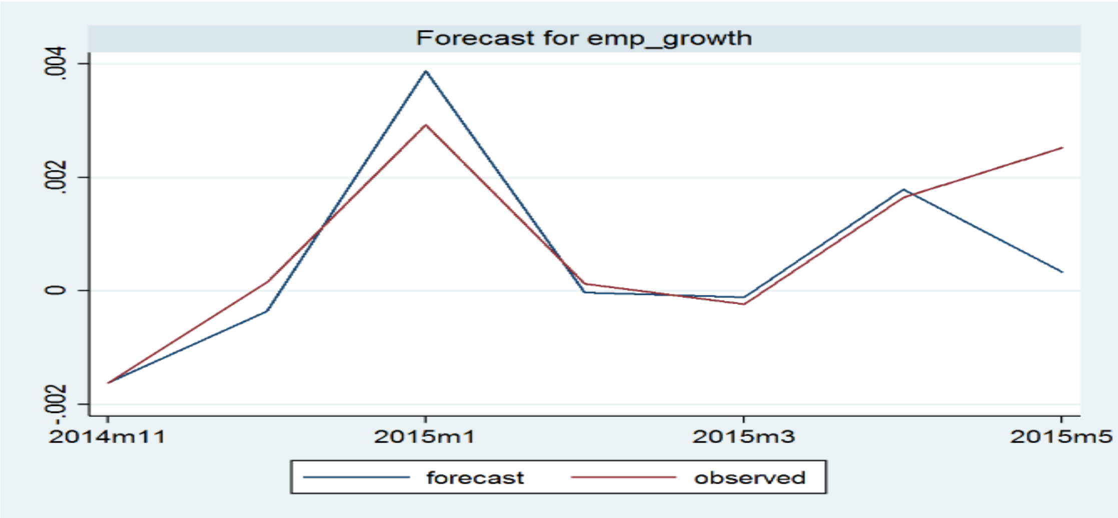


Figure 1: Results for Impulse-Response Function

Confidence bands are estimated using Gaussian approximation based on Monte Carlo drawn from the estimated panel VAR model. In terms of levels, the IRF plot shows that a positive shock on employment growth leads to increased industrial production. A positive shock on industrial production leads to decreased employment growth.

Appendix D: In-Sample Forecasting



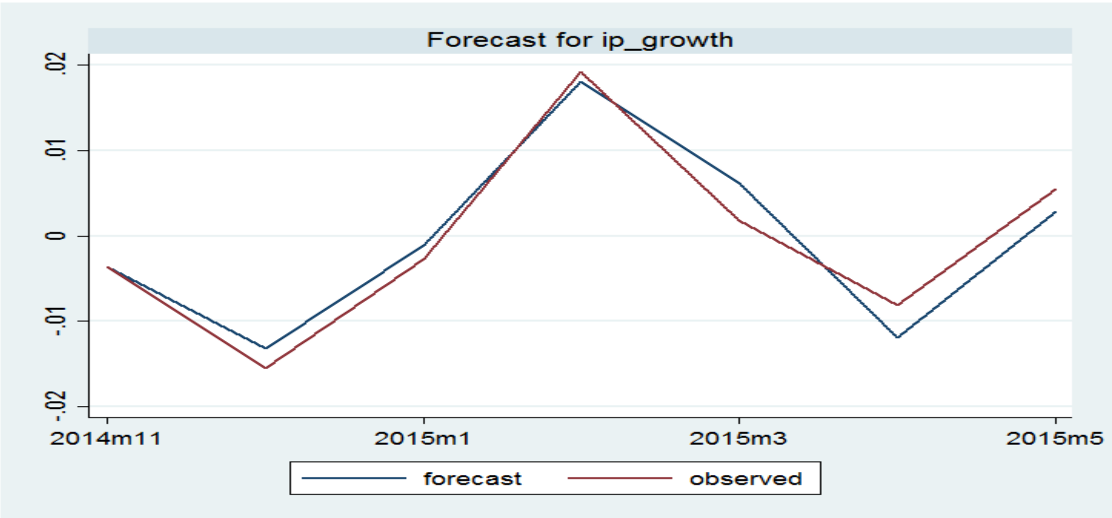


Figure 2a and 2b: In-Sample Forecasting (h=6 months and low risk category)

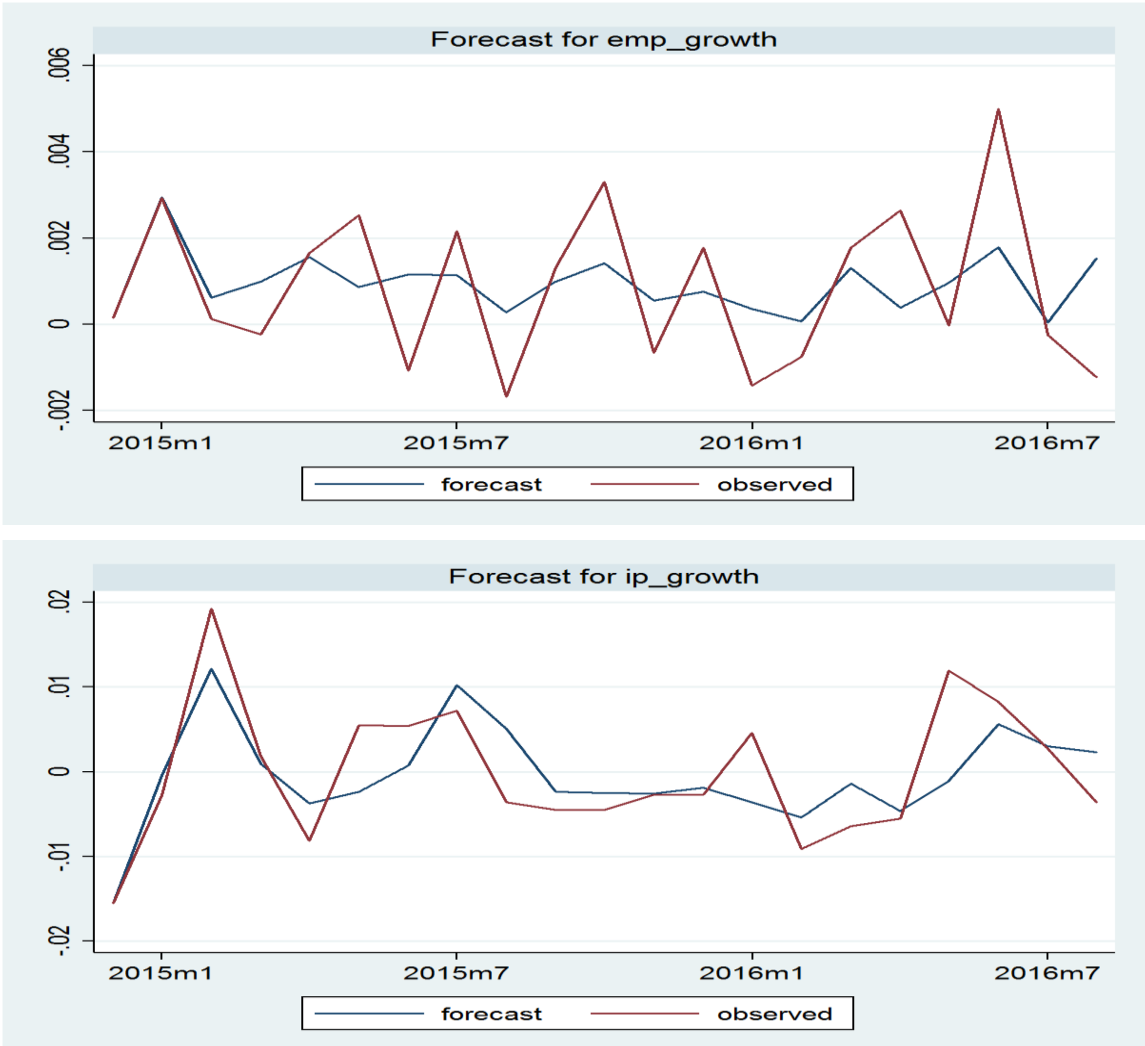
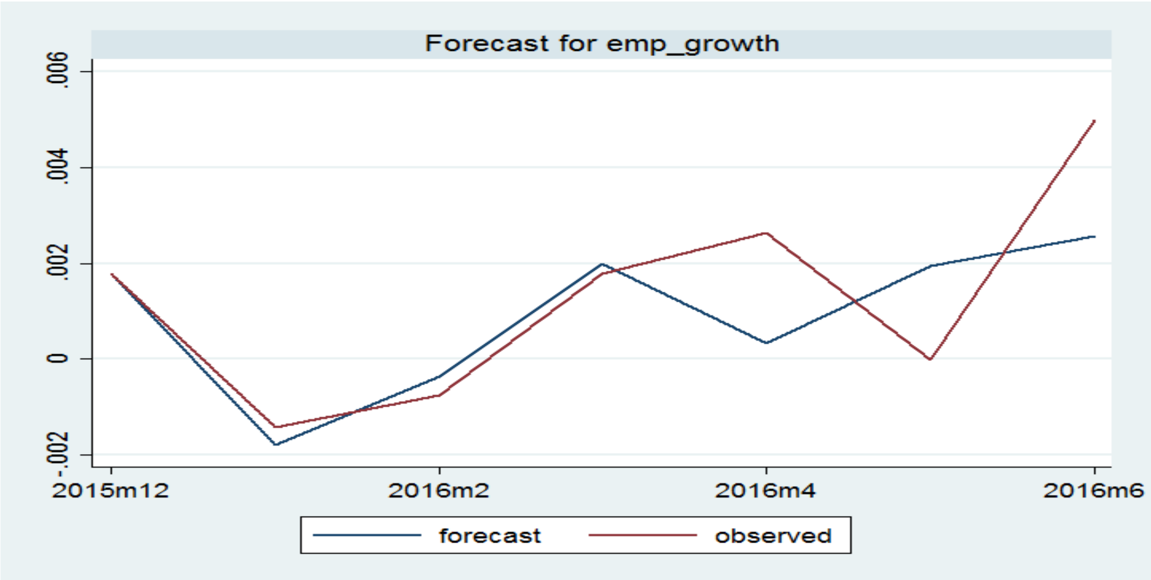


Figure 3a and 3b: In-sample forecasting (h=20 months and Intermediate-Risk Category)

Appendix E: Out-of-Sample Forecasting



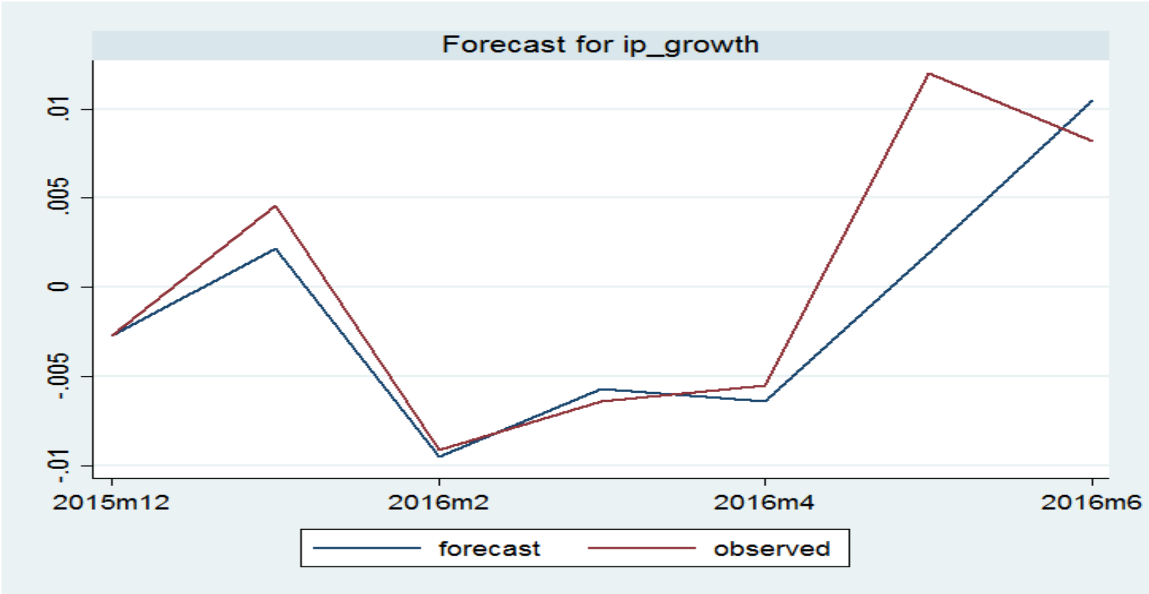


Figure 4a and 4b: Out-of-sample forecasting (h=6 months and Low-Risk Category)

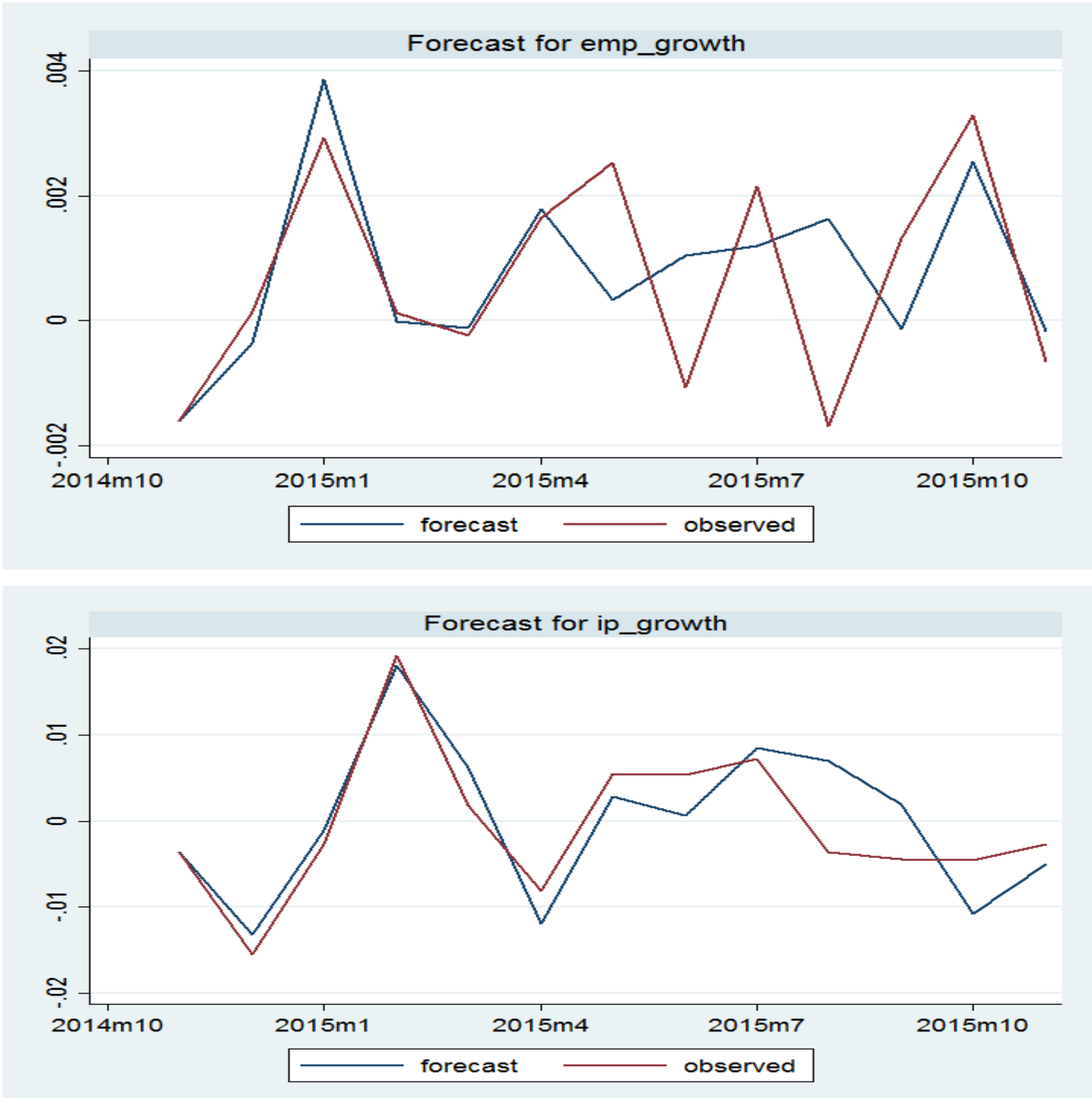


Figure 5a and 5b: Out-of-sample forecasting (h=12 months and Low-Risk Category)

Appendix F: PVAR with exclusion of set of credit indexes

Equation	Parms	RMSE	R-sq	chi2	P>chi2
emp_growth	24	.001922	0.3832	45.35078	0.0036
ip_growth	24	.006176	0.3829	45.28978	0.0037

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
emp_growth						
emp_growth						
L1.	-.1311745	.1148486	-1.14	0.253	-.3562737	.0939247
L2.	-.0206757	.1114652	-0.19	0.853	-.2391436	.1977921
L3.	-.037716	.109774	-0.34	0.731	-.2528691	.1774372
L4.	-.2018096	.1041756	-1.94	0.053	-.4059901	.0023709
L5.	.0688945	.1082702	0.64	0.525	-.1433112	.2811002
L6.	-.0259774	.1116156	-0.23	0.816	-.24474	.1927851
L7.	-.0667129	.1119744	-0.60	0.551	-.2861788	.152753
L8.	.0205787	.1108796	0.19	0.853	-.1967412	.2378987
L9.	.3220372	.1020381	3.16	0.002	.1220462	.5220282
L10.	-.2732473	.1030668	-2.65	0.008	-.4752544	-.0712401
L11.	-.1066047	.1079348	-0.99	0.323	-.3181531	.1049436
ip_growth						
L1.	-.0263874	.034524	-0.76	0.445	-.0940533	.0412784
L2.	.0521923	.0344327	1.52	0.130	-.0152946	.1196792
L3.	.0157745	.0321265	0.49	0.623	-.0471923	.0787412
L4.	-.0300617	.0329968	-0.91	0.362	-.0947341	.0346108
L5.	.0411944	.0333993	1.23	0.217	-.0242671	.1066558
L6.	.0288924	.0341198	0.85	0.397	-.0379811	.095766
L7.	-.0161887	.0334706	-0.48	0.629	-.0817898	.0494124
L8.	.0343271	.0318428	1.08	0.281	-.0280837	.0967378
L9.	.0400719	.0317393	1.26	0.207	-.0221359	.1022798
L10.	-.0388526	.0317977	-1.22	0.222	-.1011749	.0234696
L11.	.038794	.0311361	1.25	0.213	-.0222316	.0998197
spread	-.0004155	.000514	-0.81	0.419	-.0014229	.000592
_cons	.0015679	.0004923	3.18	0.001	.000603	.0025329
ip_growth						
emp_growth						
L1.	.1637743	.3690085	0.44	0.657	-.5594691	.8870177
L2.	-.2379523	.3581377	-0.66	0.506	-.9398893	.4639846
L3.	-.3204777	.3527038	-0.91	0.364	-1.011764	.370809
L4.	.3937024	.3347162	1.18	0.240	-.2623293	1.049734
L5.	.4121598	.347872	1.18	0.236	-.2696568	1.093976
L6.	.4384311	.3586207	1.22	0.222	-.2644526	1.141315
L7.	-.0108881	.3597737	-0.03	0.976	-.7160317	.6942554
L8.	-.3439929	.3562559	-0.97	0.334	-1.042242	.3542557
L9.	-.1769318	.3278482	-0.54	0.589	-.8195025	.465639
L10.	-.0571883	.3311534	-0.17	0.863	-.706237	.5918604
L11.	-.1524134	.3467944	-0.44	0.660	-.8321179	.5272912
ip_growth						
L1.	.2637334	.1109257	2.38	0.017	.0463231	.4811437
L2.	.0069979	.1106323	0.06	0.950	-.2098374	.2238332
L3.	-.0398549	.1032224	-0.39	0.699	-.2421671	.1624572
L4.	.1200043	.1060185	1.13	0.258	-.0877882	.3277968
L5.	.2546398	.1073119	2.37	0.018	.0443123	.4649673
L6.	-.1021774	.1096268	-0.93	0.351	-.3170421	.1126872
L7.	-.0824142	.1075409	-0.77	0.443	-.2931905	.1283621
L8.	-.131432	.1023109	-1.28	0.199	-.3319577	.0690936
L9.	-.1814026	.1019783	-1.78	0.075	-.3812763	.0184712
L10.	.0435961	.1021658	0.43	0.670	-.1566452	.2438375
L11.	.1833807	.1000402	1.83	0.067	-.0126945	.3794558
spread	-.0006131	.0016515	-0.37	0.710	-.00385	.0026238
_cons	.0014101	.0015818	0.89	0.373	-.0016902	.0045104

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