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Credit Spreads Predictability on Norwegian business cycles

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Abstract

This thesis examines the predictability of corporate bond credit spreads on Norwegian business cycles. We provide evidence that credit spreads between investment-grade corporate bonds contain significant predictive information for Norwegian business cycles in the three- and six-month horizon. Further, we examine the forecast performance of corporate bond credit spreads over time and argue that their performance depends on the nature of the recessions. In sum, we confirm our hypothesis that credit spreads can be used as leading predictors for Norwegian business cycles.

Acknowledgments

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1 Introduction and research question

This thesis examines the predictability of Norwegian credit spreads on Norwegian business cycles. In particular, we look into debt securities issued by corporations and investigate how various credit spreads — the yield difference between debt securities of different rating classes, or government securities of comparable maturity — can explain fluctuations in economic activity. We find that they do contain information that is useful to forecast economic performance some periods ahead. More precisely, we find evidences that suggest that credit spreads of a BBB-AA and a BBB-A are useful as predictors for the business cycle. However, our analysis demonstrates that the predictive power of the spreads varies over time. We account for this, by assessing their forecast performance over time through the cumulative sum of squared error difference evaluation.

The motivation for this thesis is twofold. First, financial data is inherently forward-looking; thus, prices in the financial market should provide useful information about future expected economic outcomes. Their ability to predict future economic activity has been examined and shown for several financial markets, but to our knowledge, not yet for the Norwegian market. Second, the Norwegian bond market has experienced substantial growth over the last ten years, and according to the Nordic Trustee (2018), at an annual rate of 10% for the last decade, making the total outstanding amount of the market double in size. The Norwegian bond market reached its record year in 2018, comprising of almost NOK 2000bn in outstanding volume. Therefore, financial instruments in the bond market have become potentially more relevant in terms of forecasting, since they consist of an increasing part of Norwegian debt.

We conduct in- and out-of-sample forecast evaluation for investment grade credit spreads, to examine how they relate to business cycles of Norway. Specifically, we investigate which credit spread is the most reliable predictor of economic activity in Norway, by measuring the overall as well as the over-time performance. Our research question is as follows: *Can credit spreads predict Norwegian business cycles?*

Our present hypothesis, which is in line with international research, is that credit spreads are useful as predictors in forecasting business cycles.

The rest of the thesis is structured as follows. First, we give a brief introduction to the academic literature and theoretical framework related to credit spreads and the business cycle in Section 2 and Section 3. Next, we present an overview of the Norwegian bond market in Section 4. We further present our data and research methodology in section 5 and Section 6, followed by results and analysis in Section 7. After some robustness checks and analysis of forecast performance over time, we end with a conclusion in addition to suggestions for future research in Section 8.

2 Literature review

The usefulness of financial instruments as predictors of future economic activity has been thoroughly examined over the last decades. Early relevant studies focus on the paper-bill spread (see Friedman and Kuttner (1992) and Stock and Watson (1993)), and show that paper-bill spreads contain statistically significant information about future economic fluctuations. However, this indicator faces at least one challenge that deteriorates its forecast ability. Commercial bills and treasury bills are short-term debts, and are not affected by long-term credit risk; hence, these spreads may not reliably reflect investors' expectations about business cycles in the future (Zhang, 2002). These studies illustrate that the paper-bill spread failed to predict the 1990–91 recession, thus questioning its added predictive power beyond the Federal Funds rate.

In the last two decades, corporate bonds have undergone substantial growth and got much attention from studies related to business cycle forecasting. Gertler and Lown (1999) explore high-yield bonds in the US market from 1981 to 1999 and conclude that high-yield bond spread appears to have superior explanatory power for the business cycle (represented by GDP gap) than other leading financial indicators including term spread, paper-bill spread, and Federal Funds rate. This notion is also supported by Zhang (2002) for the sample period from January 1988 to November 2011, where the business cycle is represented by employment growth rate. However, Stock and Watson (2003) question the predictive power of high-yield spread when this indicator falsely predicted the US economic downturn in the autumn of 1998. After that, several studies were conducted to find more reliable predictors for the business cycle such as credit spreads on senior unsecured corporate debt (see Gilchrist, Yankov, and Zakrajšek (2009)), or a new high–information content credit spread index (see Gilchrist and Zakrajšek (2012)).

Being established as superior predictors for the business cycle, an increasing amount of academic research regarding the decomposition of its predictive power emerge. Gilchrist and Zakrajšek (2012) examine US credit spreads for US business cycles and decompose the predictive power of credit spreads into two components: first, a part that captures information about firms' probability of default, and second, a residual component that captures the bond premium. They find that shocks to the bond premium that are uncorrelated to the current state of the economy lead to a decline in asset prices and aggregate economic activity. Furthermore, they show that an increase in bond premiums is a sign of a reduction in risk-bearing capacity in the financial sector, leading to a contraction in the demand of credit and a decline in economic activity.

Although there are an increasing amount of studies regarding the relationship between credit spread and the business cycle, the relevant literature for countries other than the US is somewhat limited. Moneta (2005) finds that the yield spread between the 10-year government bond rate and the three-month interbank rate outperforms all other spreads in predicting recessions in the Euro area. De Santis (2016) shows that credit spread can forecast the growth rate of market sentiment, unemployment rate and industrial production in the Euro area at a twelve-months horizon, however, the predictive power of the spread is not convincing for short-term horizons.

Okimoto and Takaoka (2017) provide significant empirical evidence by investigating the predictability of credit spread and its term structure on the Japanese business cycle. They conduct both in-sample analysis and out-of-sample forecast evaluation, and find that 1-year credit spreads of BBB-rated bonds vs. government bond, and of A-rated bonds vs. government bond, provide significant predictions for one, three and six months ahead.

After reviewing the relevant literature on the relationship between credit spreads and economic activity, the paper of Okimoto and Takaoka (2017), as well as the extensive literature regarding the US corporate bonds market, inspired us to investigate the predictive power of corporate bond credit spreads for Norwegian business cycles. The next section aims to derive the theoretical framework and explain the mechanisms regarding credit spreads and business cycles.

3 Theoretical framework

3.1 The business cycle

The literature regarding the investigation of business cycles has primarily been focused on US data. It is defined by the National Bureau of Economic Research (NBER) as peaks and troughs in economic activity, where a recession takes place between a peak and trough, and expansion takes place between the trough and a peak. Recessions are said to occur if economic activity declines for more than a few months. Further, the NBER defines the average business cycle to last between 4-6 years. A more general definition comes from Burns and Mitchell (1947), who explain business cycles as fluctuations in the aggregate economy. An alternative way of defining business cycles is through the growth cycle. Stock and Watson (1993), define growth cycles to be periods of rising and falling activity relative to trend growth (Stock and Watson, 1993, 261).

Norway does not have any official dating of the classical business cycle turning points; however, Christoffersen (2000) have been exploring methods to define the turning points of the Nordic business cycles. He applies the Bry and Boschan algorithm [1] on monthly seasonally adjusted industrial production index to analyze business cycle turns in several Nordic countries. Bjørnland (2000) shows that although different detrending methods may suggest different cyclical behavior of quarterly national accounts, they can provide stylized facts of the business cycle in Norway. The author also concludes that the Norwegian business cycle behaves differently compared to other OECD countries, which may be due to more individual shocks a small oil-producing nation can experience.

As an economy recurrently experiences periods of booms and busts, different sectors

[1] Bry and Boschan algorithm is used to detect turning points of the business cycle. It identifies the cyclical turning points mainly by pointing out the local maximum and minimum of the selected series

and industries might be expected to vary in terms of profitability. Cyclical industries may behave and respond differently from defensive industries. Cyclical industries are producers of nonessential products, so when a recession hits the economy, these industries will face the highest risk of revenue losses first. Consumers are forced to prioritize consumption, and being rational agents, they will choose the necessities first. In contrast, defensive industries like production of food, utilities, and health care, will weather the storms of economic downturns better, as demands for such goods are universal necessities (Bodie, Kane, and Marcus, 2013). Even though industries react differently to the stages of business cycles, aggregate economic activity is affected as a whole. If a recession arrives, aggregate demand for labor is lower, due to fewer goods and services demanded by the market. In turn, employment growth is expected to decline. However, information about the future economic activity is not certain until it arrives; therefore, a measure to forecast stages of the business cycle is a vital tool for firms to base their investment decisions of the future.

3.1.1 Proxies for business cycles

The most common way to determine aggregate economic activity is to measure its total output, often represented as Gross Domestic Product (GDP). According to NBER (2019), it is the single best indicator of economic health. Other measures include the coincident index (CI), employment rate, unemployment rate, or the output gap. These variables are all used as proxies for aggregate economic activity and are closely related to the business cycle. However, the proxies vary in their ability to depict the business cycle between countries. Employment has been shown by several researchers to be a good proxy for depicting the business cycle. The NBER stated that at a monthly frequency, employment is the most reliable indicator of economic activity (Hall et al., 2001). Berridge (1922) concludes that employment is so "geared" to business cycles that it ranks particularly high as a proxy for business activity.

3.2 Economic performance indicators

Economic performance indicators are statistical variables that provide relevant measurements for evaluating the health of the economy and business cycles. Indicators can be of great importance to policy-makers, to be able to determine the health of the economy, as they can either directly or indirectly indicate economic performance.

The economic performance indicators can either be leading, coincident, or lagging. A leading indicator is one that changes before an economy as a whole change. Lagging indicators react after a shock hits an economy, and are often characterized by being easy to measure but hard to influence. Lagging indicator, therefore, cannot provide the prediction for future economic activity. Coincident indicators react simultaneously as a shock hits an economy and represent the current state. Thus, economic performance indicators can provide valuable information to policy-makers either for future states, in real-time or evaluating the aftermath of a shock to an economy. Various financial instruments are particularly good leading predictors for economic activity because they are inherently forward-looking. They are, to a great extent, driven by market expectations, meaning that they will convey future expected outcomes of aggregate economic activity.

Investors operating in the bond market take expected investment returns sometime in the future into consideration; thus, market prices will reflect the equilibrium expectation of future outcomes. Bond yields have been especially praised as being superior leading indicators of future economic performance, and their yield curve and spreads can provide useful information to predict future economic activity.

3.3 Bonds and key concepts

A bond is a security sold by governments and corporations to raise money for investments today in exchange for a promised future payment (Berk and DeMarzo, 2016). Bonds are fixed-income securities because of the promise of a fixed stream of income that is predetermined by a specified formula. They are issued with a borrowing arrangement, which means that the borrower issues or sells a bond to a lender for some price. This arrangement obligates the issuer to make specific payments on predetermined dates to the bondholder. Semiannual payments of the interest rate are common and work as coupon payments. When bonds mature, the issuer pays the *par value*, which is defined as the nominal value of the bond when issued and the amount the bondholder is obliged to pay back at maturity, (typically 100), (Brealey, Myers, Allen, and Mohanty, 2012). In the following subsections, we will present several key concepts of bonds.

3.3.1 Pricing of bonds

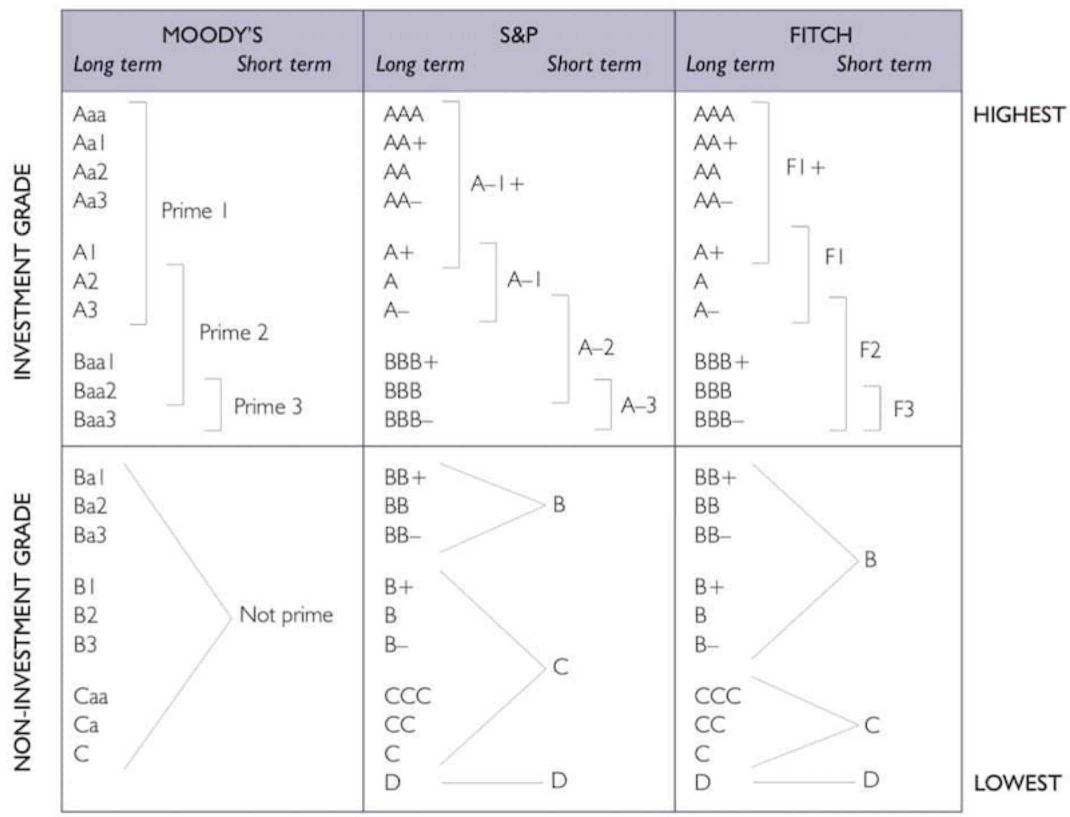
The price of a bond is fundamentally influenced by several factors. They are highlighted in the following.

Default risk

Default risk is the possibility that a bond issuer is not able to make the interest or principal payments when they are due. Government bonds are said to have a probability of default very close to zero, unlike corporate bonds where estimated income streams are not without risk of default. Investors trading in the market will consider default risk when evaluating a security.

The risk of defaulting of most corporate bonds are assessed by bond ratings provided by firms such as Moody's Investor Services, Standard and Poor's Corporation and Fitch, known as bond ratings. The rating is based on the overall financial situation of the borrower, and rating agencies emphasize both the ability and willingness of the borrower to meet their obligations. The rating firms assign letter grades to identify the probability of a bond default, see figure 1. The highest grade is AAA. Ratings above BBB are called investment grade bonds (IG), while those rated below are called high-yield bonds or junk bonds. The rating a bond receives reveals relevant information and is essential for issuing terms. A degrading from an investment grade to a high-yield rating, can impact the issuer significantly, and reduce its attractiveness in the secondary market.

Figure 1: Corporate credit ratings



Source: The Association of Corporate Treasurers

Embedded options

Embedded options are special conditions attached to a bond, specifying an action that bondholders or issuers can perform at a point of time in the future. An embedded option is an affixed part and cannot be sold separately. Thus, it can influence the value of the bond.

The most popular is call option, which allows the issuer to buy back or redeem bonds at a specified call price, before the expiration date (American) or at expiration date (European). In this case, investors must receive compensation for writing this call option to the issuer, due to the underlying risk for the bondholder. Thus, higher coupon rate must be offered, to sell the bond at par value (Bodie et al., 2013).

3.3.2 Consumption-based pricing model

In this section, we explain and elaborate the mechanics of corporate bonds, by considering the classical consumption model in asset-price theory.

An investor operating in the asset-market will evaluate how much to save and consume, and what portfolio of assets to hold. The price must equal the expected discounted payoff, using the investor's marginal utility to discount the payoff. Further, the price must account for the *delay* and the *risk* of the payments of the asset. The marginal utility loss of a small reduction in consumption today, to place it in some investment instead, should equal the marginal utility gain of selling the investment in the future, and gaining some payoff. The interest rate is connected to average future marginal utility, and to the expected path of consumption. High interest rates are associated with increased expected consumption, and investors are more likely to buy bonds (save) and increase future consumption. When recessions arrive, asset prices are most likely to fall, effectively causing the expected payoff of the portfolio to fall. The lower asset price reflects a discount for the riskiness of holding these assets (Cochrane, 2009, 13).

To define the price of a bond, we consider the consumption-based pricing equation from Cochrane (2009). We obtain the first-order condition for an optimal consumption choice at time t and is *the central asset-pricing* formula:

$$P_t = \mathbb{E}_t \left[\beta \left(\frac{u'(C_{t+1})}{u'(C_t)} \right) x_{t+1} \right] \tag{1}$$

where P_t is the asset's market price at time t, given C_t and C_{t+1} which is the consumption choice for the investor at time t and t+1 respectively, and given the payoff x_{t+1} at time t+1; β captures the consumer's impatience, and is called the *subjective discount factor*. If an investor buys a bond today, the payoff next period is the bond price plus coupon, $x_{t+1} = P_{t+1}$ + Coupon (ω).

Thus, the equation is transformed into:

$$P_t = \mathbb{E}_t \left[\beta \left(\frac{u'(C_{t+1})}{u'(C_t)} \right) (P_{t+1} + \omega) \right] \tag{2}$$

We define the stochastic discount factor as the rate at which the investor is willing to substitute consumption at time t+1 for consumption at time t:

$$m_{t,t+1} = \beta \left(\frac{u'(C_t)}{u'(C_{t+1})} \right) \tag{3}$$

Therefore, equation (2) will be expressed as:

$$P_t = \mathbb{E}_t \left[m_{t,t+1}(P_{t+1} + \omega) \right] \tag{4}$$

where P_t and P_{t+1} are the price of a bond at time t and t *+1* respectively; ω is the coupon; $m_{t,t+1}$ is *stochastic discount factor*, or the rate at which the investor is willing to substitute consumption at time t + *1* for consumption at time t, also known as the *marginal rate of substitution*.

The discount factor $m_{t,t+1}$ is a much debated variable by financial economists. Identifying the underlying risk and the so-called premium, theory tends to distinguish between two types of risks, namely systematic and idiosyncratic risk. In asset pricing, the classical idea is that systematic risk generates a premium on the asset, while the idiosyncratic risks are not priced in, meaning that investments do not carry any added interest rate for such risks. The reason behind this is due to the covariance between the payoff and the discount factor. If the covariance is zero, it means that the price is just the expected payoff discounted with a risk-free rate. This is the idiosyncratic part of the risk, and is associated with firm-specific risks, credit risks or liquidity risks. The systematic risk, on the other hand, is that part of the risk that perfectly correlates with the discount factor (Fama and French, 1993). These risk factors are discussed later.

3.3.3 Yield to maturity

For an observed price P_t, and a given *Par value* and *Coupon*, we can compute the yield to maturity (YTM) y, which is the estimated annual rate of return, given that the investment is held to maturity:

$$P_t = \sum_{t=1}^{T} \frac{Coupon}{(1+y)^t} + \frac{Par\ Value}{(1+y)^T} \tag{5}$$

YTM assumes that all coupon payments are reinvested at same rates as the current bond yield. Further, it takes into account the current market price, coupon payments and the term to maturity, and corresponds to the internal rate of return (IRR) of a bond. From equation (5), it is clear that bond prices and yield to maturity have an inverse relationship. A bond trading above its par value is said to be trading at a premium, due to lower interest rates in the market. Conversely, when bonds are trading below par value, they are trading at a discount, due to higher interest rates.

The coupon rate can either be a fixed rate or a floating rate note (FRN, floaters). A fixed rate is a fixed coupon over the lifetime of the bond, while a floater normally varies with the rate of the Norwegian Interbank offered rate [2] (NIBOR) of a short-term maturity. Here, the coupon rate is dependent on the default risk of the bond, where riskier bonds are given a discount to be able to attract investors. It is common to denominate coupon rates in basis point terms (bps). The coupon rate is calculated based on NIBOR of a short-term maturity, and is quoted as a spread in bps over NIBOR. Therefore, depending on the payments per year, the agreed-upon coupon fluctuates with changes in NIBOR.

3.3.4 Risk factors in bond yields

Bond returns fluctuate with market sentiments and the aggregate economic environment and are faced with different risk factors. After a bond is issued and trades on the secondary market, various risk measures will influence the interest rate, and in turn, the market price or the value of the bond change over time. Fama and French (1993) identifies two common risk factors in the fluctuations of bond returns. The first is related to time to maturity and unexpected changes in interest rates. The second is related to default risk, where shifts in economic conditions increase default risk. Changes in

[2] Norwegian Interbank Offered Rate reflects Norwegian money market rate at different maturities. The rate reflects the bank's interest rate requirement for unsecured loans in NOK to other banks, see Finans Norge (2019)

inflation expectations is a third common risk factor, which affects the market price of a bond. They are outlined below.

Duration

Price volatility is directly linked to time to maturity. The concept of the duration of a bond measures the sensitivity towards interest rate risk, which accelerates as the time to maturity lessens. Duration [3], measures the first derivative of the bond price P with respect to a change in yield to maturity, y.

$$\text{Duration} = -\frac{1}{P}\frac{dP}{dy} \tag{6}$$

Changes in interest rates have a more profound impact on long-duration bonds due to a higher risk of defaulting on payments some time in the future before maturity, and the more time there is for interest rate to change (Veronesi, 2010). To compensate for this added interest rate risk, long-term bonds must offer higher interest rates than short-term bonds, of the same credit quality.

Default risk

If the issuer enters financial difficulties or liquidity constraints, the credit quality might fall. This means the greater default risk of the bond, which in turn makes investors require higher YTM for holding the bond. The default risk of a particular bond is higher if time to maturity is high. Conversely, as time to maturity approaches, the default risk of a bond goes down.

Inflation expectations

The third risk factor is the changes in market expectations about inflation. Inflation expectations are linked with the inflation premium a bond must offer to be able to attract investors. The impact on rising inflation will make short-term interest rates go

[3] Often referred to as the modified duration or volatility, see Veronesi (2010)

up, which in turn will reduce demand for credit in the market. Long-term interest rates also tend to move up, but they tend to be less responsive to short-term fluctuations and market expectations. Normal yield curves have an upward-sloping curve, reflecting expectations of a healthy expansionary economy. Increased demand for short-term investments pushes yields further down, making the yield curve steep and upward-sloping. When yield curves are inverted, meaning that short-term rates are higher than long-term rates, it is a sign of a recession. Higher demand for long-term investments makes yields go down in the long-end and reduce demand for short-term bonds, which make yields go up in the short-term.

3.4 Credit spreads

3.4.1 Definition and characteristics of credit spreads

The difference in yield between two bonds of similar maturity but different credit quality is defined as a credit spread. Credit spreads vary based on the credit rating of the bond's issuer. High-quality issuers have lower probabilities of default, thus investing in their bonds are perceived as safer, hence giving lower yields. On the other side, lower-quality issuers must set a higher return on their bonds -a premium- to attract investors. As mentioned earlier, credit spreads fluctuate because of changes in market sentiments and future market expectations. In periods of higher uncertainty, investors tend to favor bonds with higher credit ratings, making traded price increase, thus reducing yields. Meanwhile, the price of the low rated bonds will decrease, meaning a higher return, leading to higher incentives for investors to take on higher risks. As a result, the credit spread between low-rated and high-rated bonds widens. Tang and Yan (2006), demonstrates that credit spreads are counter-cyclical, thus widening during recessions and narrowing during times of expansion for the US market.

3.4.2 Credit spread puzzle

Extracting information from the fluctuations of corporate bond spreads have been showed to be not straightforward. The literature has coined the expression *the credit spread* *puzzle*, referring to the phenomenon of spreads being wider than what would be explained by the expected financial health of the issuing firm. It is common to assume that such added default risk of a corporate bond portfolio can be diversified away and shake off any unexpected risk. However, Amato and Remolona (2003)[4] argues with evidence from the market of collateralized debt obligations (CDOs) that these portfolios are impossible to attain and that the losses are unavoidable. They conclude that credit spreads take the undiversified risk into account, thus making credit spreads wider than they would naturally be. This notion is counter-intuitive to the financial valuation theory of Black and Scholes (1973). It is fundamental in financial valuation even today and is widely used by traders and investors to correctly calculate the price of European options in financial markets. Debt securities like corporate bonds are essentially a combination of options; thus the Black-Scholes formula is used to derive the value of a non-callable corporate bond, given its probability of default. This was thoroughly researched by Huang and Huang (2012), which found that credit risk only accounts for a small fraction for the credit spread of corporate-treasury bonds. However, they conclude that features like illiquidity, call, conversion and asymmetric treatment of corporate and government bonds, play a role in determining the spread, and if taken into account *can* explain the yield spreads to a great extent.

4 The Norwegian bond market

4.1 Overview of the Norwegian Bond Market

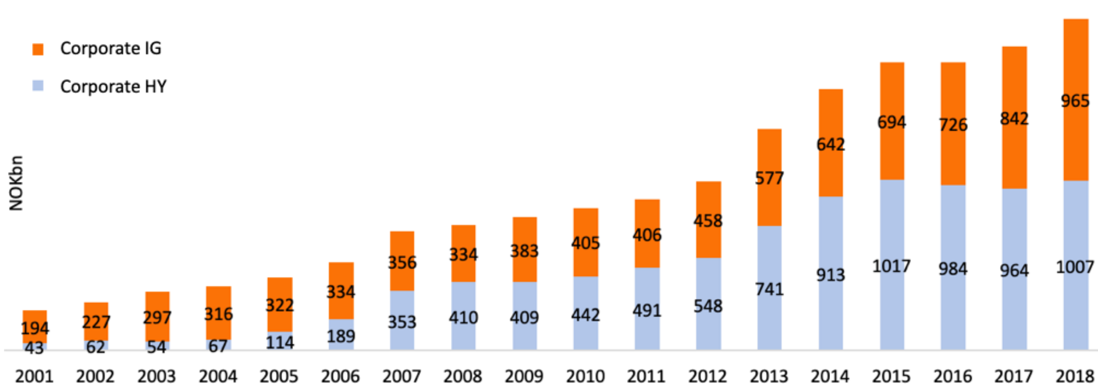
There are two fixed income marketplaces for issuers to list their bonds on the Norwegian bond market operated by Oslo Børs, namely Oslo Stock Exchange (Oslo Børs) and Nordic ABM (Alternative bonds market). Regulations and requirements for issuing bonds on the Norwegian marketplace are relatively easy to execute, which has been a contributory factor to the substantial growth of issued bonds in the past decade. In earlier years, only large corporations used the bond market as a source of debt fi-

[4] See also Collin-Dufresne and Goldstein (2001) for more discussion regarding the credit spread puzzle

nancing, as an alternative to financing through bank loans. Now, and especially after the financial crisis, small and medium-sized companies have entered the bond market as a source of financing debt capital and has become an integral part of issuers in the marketplace (Oslo Børs, 2018).

Figure 2 shows the development in the total outstanding amount of corporate bonds per year for Norway. There has been a change in the composition of the corporate bond market, from an almost nonexistent HY market in 2001, to a more even share of HY and IG today. The HY market has developed at a steady pace with the growth of capital-intensive industries like oil, steel, and telecommunication. Oslo Børs marketplace reports an increasing amount of foreign issuers in the HY market the recent years, reflecting the stronger position it has gained in an international context (Oslo Børs, 2018).

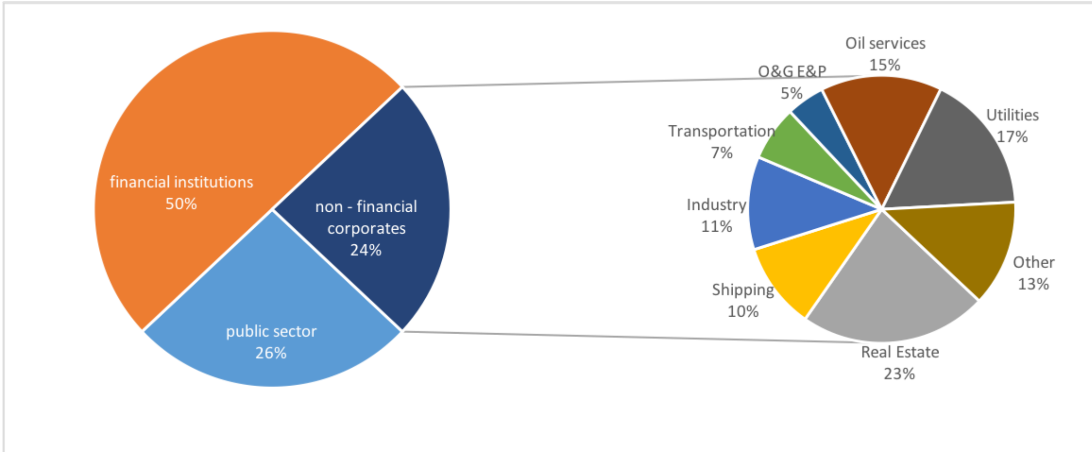
Figure 2: Total outstanding amount Corporate bonds per year (IG/ HY)



Source: Norway Bond Market Report 2018 (Nordic Trustee)

Figure 3 illustrates the distribution of issuers in the Norwegian bond market in 2018 in the outstanding amount. As can be seen from the figure, financial institutions are the main issuers in the bond market, consisting of nearly half of the total outstanding amount. Public sector follows with 26%, and the remaining 24% is non-financial corporates. Looking closer at the last sector, real estate, utilities, and oil services make up the most substantial part of the volume, with 23%, 17%, and 15% respectively.

Figure 3: Distribution of issuers in Norwegian Bond Market in 2018



Source: Norway Bond Market Report 2018 (Nordic Trustee)

4.2 Regulations

Issuing bonds in the Norwegian marketplace is more efficient and cheaper compared to many international markets. First of all, it requires relatively low costs and management resources: there are no rating-fees for issuers, and legal and trustee fees are minor compared to international bond markets. Second, it involves less documentation and procedures and there are no requirements to prepare a prospectus for a listing on the Nordic ABM. The process follows effective documentation with a standardized term sheet and loan agreement. Thus, the overall process normally takes 2 to 6 weeks, while it can take up to 3 months for other bond markets (Nordic Trustee, 2015). Third, there are no requirements for ratings from official rating agencies. Investment banks can assist issuers in proving shadow ratings based on public information about the company, although these ratings cannot be considered official, and this method has been omitted since 2017. As a result, Norway has the highest share of unrated bonds in Europe. The norm in Europe is that 10% of the total bond volume is unrated, whereas the Nordic market has a 40% share of unrated bonds (Schwartzkopff, 2016).

The efficient, relatively low-cost and few management resources needed to list bonds on the Norwegian bond market, has made it become an increasingly attractive marketplace for both domestic and foreign corporations.

5 Data Description

5.1 Dependent variable: Employment growth

Normally, GDP growth rate is the most reliable and preferred indicator for depicting business cycles. However, this variable is only available on a quarterly basis in Norway; thus, to acquire a broader range of data, we focus on monthly data. The dependent variable for this thesis is therefore employment growth.

We have retrieved employment level from Statistics Norway at a monthly frequency from the period November 2001 to January 2019. The employment level in Norway has been naturally increasing over time, due to increases in population, and greater social and economic conditions for labor. It also increases due to other factors not directly linked to business cycle fluctuations such as productivity shocks and labor-supply shocks. Since the variable is increasing over time, and might experience impulses not directly related to normal business cycle fluctuations, we need to transform the variable to become a reliable proxy for the business cycle. Therefore, we take log differential of the employment level to make the variable stationary and transform it into employment growth. Growth rates are favorable when comparing changes in a variable between different time periods, and they provide good intuition to the pace of the economic booms and busts. Besides, employment growth has been used by a substantial amount of papers to represent the business cycle that confirms its relevance, (see Gilchrist et al. (2009) and Zhang (2002)).

Our thesis focuses on the cyclical behavior of economic activity. Thus, we need to take away the long-term trend of the time series data, as well as other disturbances not related to normal business cycles fluctuations. We apply the Hodrick-Prescott (HP) filter, which is widely used in business cycle studies (see for example Bjørnland (2000) and Grünfeld (1996)). The indicator of economic activity in this thesis is thus the detrended employment growth, called *employment growth* hereafter. Details of methods used to transform this variable are thoroughly described in the methodology section.

5.2 Independent variable: Credit spreads

Credit spread is defined as the difference in yields between two bonds of the same maturity but different rating class. To formulate credit spreads, we use the yield to maturity of Norwegian corporate bonds in different SandP rating classes from Datastream.

With the limited rated bonds in Norway, it is challenging to analyze credit spreads of corporate bonds within all rating classes. For the HY market, very few of the corporate bonds are rated. Thus, the analysis is conducted based on the credit spreads of IG corporate bonds. We select the data available that consists of AA, A, and BBB rated bonds for all maturities from November 2001 to January 2019. Further, we use monthly data of Norwegian government bond yields from Bloomberg, and calculate the average yield from maturities 3Y, 4Y, 5Y, 8Y, and 10Y. There is a mismatch problem of data in terms of maturity between IG bonds and government bonds; thus, we proceed with the average of government bond yields. We define credit spreads as follows:

$$CS_i = YTM_i - YTM_{Gov} \tag{7}$$

$$CS_{i,j} = YTM_i - YTM_j \tag{8}$$

where i, j are SandP rating classes, namely AA, A and BBB; Gov is Norwegian government bonds; YTM is yield to maturity.

Equation (7) defines CS_i as the credit spread between i rated corporate bonds and government bonds. Equation (8) defines the $CS_{i,j}$ as the credit spread between i and j rated corporate bonds, where i $\neq$ j.

6 Methodology

To construct models for in- and out-of-sample testing, we use Ordinary Least Squares (OLS) regression. OLS is a type of linear least squares method for estimating the unknown parameters in a linear regression model. The OLS principle yields an estimator that minimizes the squared differences between the observed values of dependent variables and predicted values from the estimated model (Vogelvang, 2005, 55).

6.1 Assumptions for OLS

According to Wooldridge (2015), several criteria needs to be fulfilled in order for OLS to be a consistent estimator and the best linear consistent unbiased estimator.

1. Correct specification

   The model must be correctly specified, so that it contains valid information in estimation.

2. No perfect collinearity

   There should not exist any exact linear relationship between the independent variables.

3. Normally distributed errors

   The error u should be normally distributed with expectation equal to zero.

4. Homoscedasticity

   The error u must have a constant variance for all values of the dependent variable.

5. Autocorrelation

   The error u must not be correlated with itself.

If these assumptions are fulfilled, we say that OLS is the best linear, unbiased estimator (BLUE). There are several ways of testing OLS assumptions. An intuitive and easy approach is to plot the residuals, but there are also formal tests that can be applied. Since we are using time series data, this is relevant. To be able to use OLS correctly on time series data, the data need to be stationary. A stationary time series process is one where the expectation over time is constant in its mean, variance, and autocovariance. If we were to estimate a regression with non-stationary variables, it is likely to get *spurious regressions*. This means that the model can create false correlations between the variables.

6.2 Stationarity test

To check if the variables show signs of non-stationarity, we perform the Augmented Dickey Fuller test (ADF). The null hypothesis is that there is a unit root in the sample. We reject the null hypothesis if the t-statistics is smaller than the critical value for normal significance levels. An intuitive understanding of a variable with a unit root is that a lagged variable (y_{t-1}) will not give any relevant information to predict a present variable (y_t). For more details regarding the ADF-test, see Wooldridge (2015, 639-650).

All variables must be stationary to get consistent and unbiased estimates while conducting OLS. There are several ways to correct if some variables show signs of non-stationarity.

As mentioned earlier, the Norwegian employment level is increasing over time, thus clearly being a non-stationary variable. To transform this variable, we conduct two steps: First, we calculate the growth rate from employment level by taking log differential between the y_t and y_{t-12}. Second, we apply a linear filter called Hodrick-Prescott (HP), to remove the long-term trends from a time series variable. The series is filtered by the *smoothing parameter* known as λ. For monthly series it is common to use $\lambda = 14.400$. A challenge when using the HP filter is the end-point problem. Several papers [5] have raised concerns to using the filter, claiming that results can be nonsensical. It results from the fact that the HP-filtered series tend to be very close to the first and last observations in the estimation period. However, comparing the HP-filtered series with the observed data, the end-point problem does not seem to harm the usefulness of the proxy in our case; therefore we disregard it and move forward with the HP-filtered series of employment growth.

We can see from table 1 that the dependent variable, namely employment growth is stationary, after taking the difference and the log, and using the HP filter. All independent variables fulfill the claim of stationarity, as we can see, they all reject the null hypothesis at a 5% significance level in the ADF test.

To further evaluate whether variables are stationary, a graphical illustration of the variables is presented in figure 4. We see the relationship between the credit spreads and

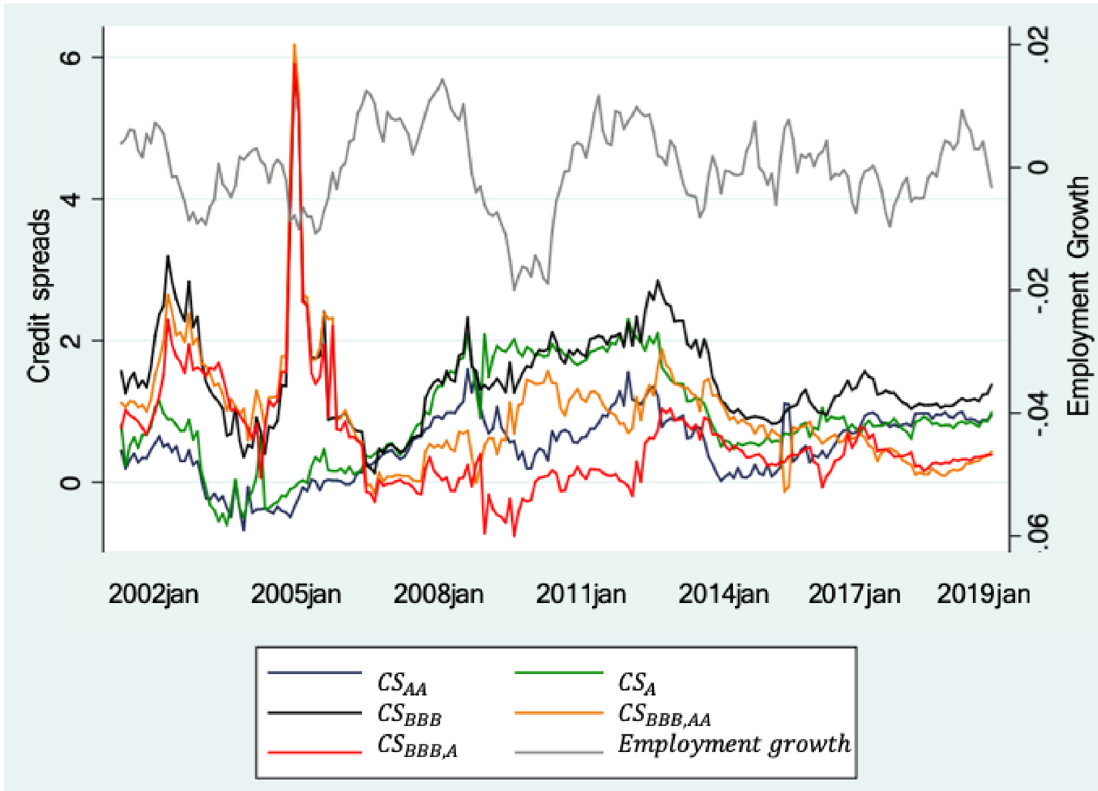
[5] see Baxter and King (1999) and Bruchez (2003)

Table 1: Augmented Dickey Fuller (ADF) test with drift and no lags

Variable	Test statistics	Pvalue
Employment growth	-2.908	0.002
CS_{AA}	-2.581	0.0053
CS_{A}	-2.036	0.0215
CS_{BBB}	-3.748	0.0001
$CS_{BBB,AA}$	-3.417	0.0004
$CS_{BBB,A}$	-3.541	0.001
1% critical value	5% critical value	10% critical value
-2.345	-1.652	-1.286

the employment growth from the period of November 2001 to January 2019. In the period of widening credit spreads, employment growth seems to be going down. Conversely, in periods of narrower credit spreads, employment growth appears to be going up. From a graphical point of view, there is a reason to believe that the spreads have a correlating effect on employment growth and that they appear to be counter-cyclical. In the period of the sample, FRED (2019) defines five recessions or busts for the Norwegian business cycle. The first is from the beginning of the sample, Nov 2001, until July 2003. At the same point of time, all credit spreads seem to increase, especially the $CS_{BBB,AA}$, $CS_{BBB,A}$ and the CS_{BBB}. Credit spreads related to the government bond, namely the CS_{AA}, and CS_{A} are stable and show only a small increase in the same period. The next bust is reported in the period between Oct 2007 and Aug 2010, when credit spreads related to the government bond increase, and somewhat surprisingly the $CS_{BBB,A}$ spread narrows. The third is between March 2012 and January 2014, when all credit spreads fluctuate upwards at the same rate. The fourth is between July 2015 and August 2016, where all credit spread makes a small incline upwards, with the exception of the CS_{A} which remains almost unchanged. The last reported recession started in July 2017 and is continuing; all credit spreads are moving slightly upwards. In the last two reported recessions, we observe that the differences between the credit spreads have narrowed, implying that the overall risk has gone down.

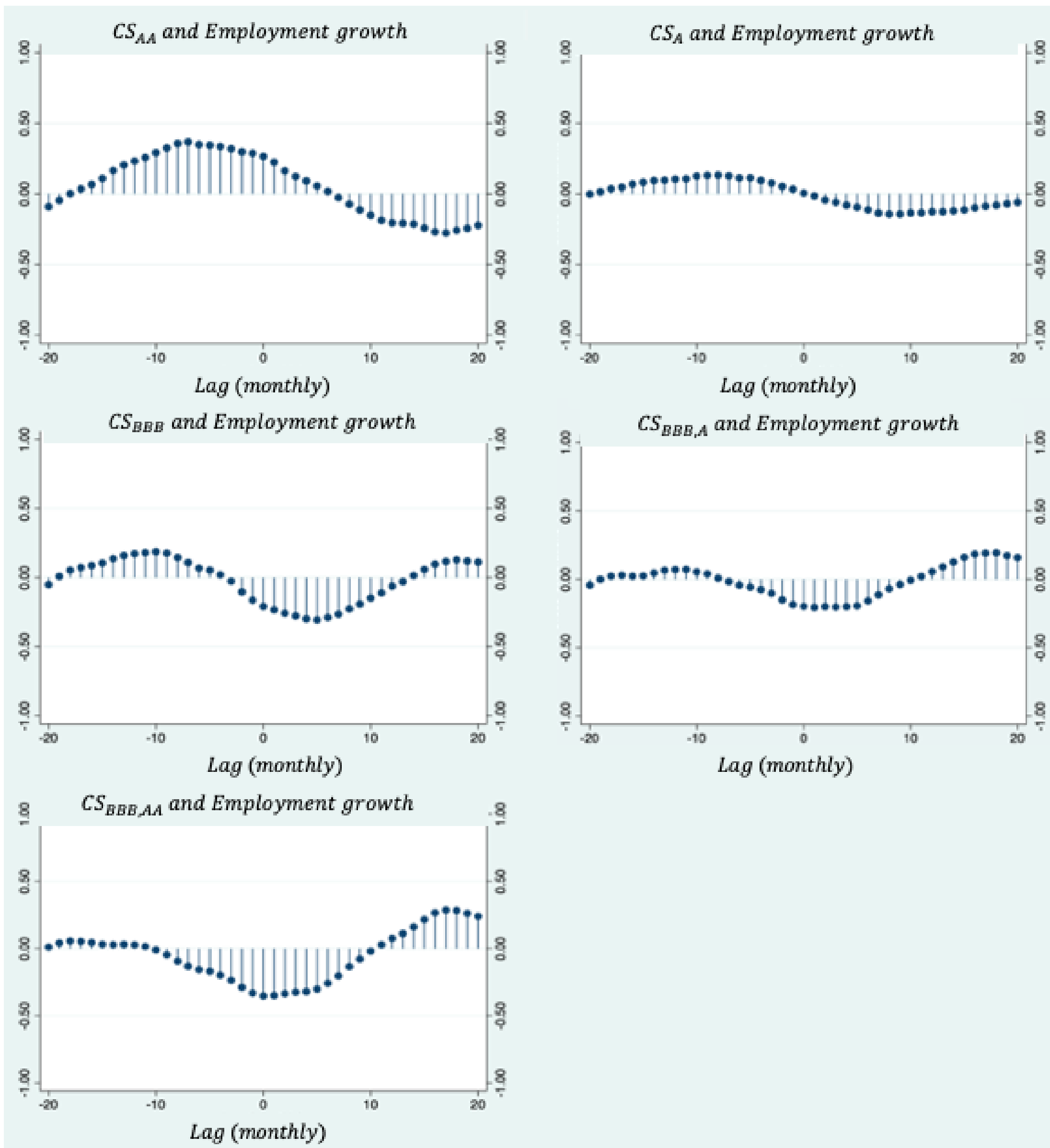
Figure 4: Plot of credit spreads and employment growth



6.3 Cross correlation

To further get an impression of how the two variables correlate, figure 5 shows a cross-correlation matrix of all variables against employment growth, with leading and lagging effect from -20 up to 20 monthly lags. A cross-correlation matrix measures the similarity of two series with different leading and lagging variations. The correlation values are standardized and range from -1 to 1, where 1 refers to a perfect positive correlation, and -1 is a perfect negative correlation, 0 means no correlation. From the figure, we see that $CS_{BBB,AA}$ and CS_{BBB} have the highest correlation with employment growth. The correlation is high from approximately 0-10 lags ahead, but the $CS_{BBB,AA}$ seems to correlate best at 0 lag with a correlation of -0.3526. While, CS_{BBB} have the highest correlation at 5 lags ahead, with a value of -0.3066. The implication of this result is particularly interesting, because, from the correlation plot of CS_{BBB}, it implies that this credit spread can fit as a leading predictor for Norwegian business cycles, while the correlation plot of $CS_{BBB,AA}$ indicates that this spread correlates contemporaneously with the business cycle, which is not in line with current theory. An observation by looking at the cross-correlation between CS_{BBB} and employment growth is that an increase in this spread might lead to a reduction in employment growth some periods ahead. However, without further analysis, we have to be careful when interpreting the correlation matrix. The correlation effect can exist due to a linear relationship amongst the variables, and fail to reveal the truth about other underlying effects. Nonetheless, this is a good foundation for further analysis.

Figure 5: Cross correlation between credit spreads and employment growth



6.4 Model selection

This thesis aims to check the predictability of the credit spreads on Norwegian business cycles. First, we conduct an AR model:

$$Y_{t+h} = \beta_0 + \beta_1 Y_t + \beta_2 Y_{t-1} + ... + \beta_p Y_{t-p} + \varepsilon_t \tag{9}$$

We decide the number of lags used in this model by conducting an Akaike Information Criterion (AIC). The challenge of selecting a correct specified model is crucial for robust results, and AIC serves as a benchmark of comparison and selection among different models (see Sakamoto, Ishiguro, and Kitagawa (1986) for more details). The model with the lowest AIC is considered the most suitable one.

Table 2: AIC test result

Number of lags	AIC
1	-11.8449
2	-11.8637
3	-11.8566

According to Table 2, the AIC test suggests to use the model with 2 lags, we therefore continue with the following benchmark model, hereafter referred to as Model 1:

Model 1:

$$Y_{t+h} = \beta_0 + \beta_1 Y_t + \beta_2 Y_{t-1} + \varepsilon_t \tag{10}$$

where Y_{t+h} is the employment growth at time $t+h$ months; Y_t is the employment growth at time t. Adding credit spreads to Model 1, we can answer the question whether credit spreads give more information to predict future employment growth. Therefore, we get 5 modified models that each represents a different credit spread. See description in table 3.

Table 3: Explanation of models

Model	Credit spread
Model 1	n/a
Model 2	CS_{BBB}
Model 3	CS_A
Model 4	CS_{AA}
Model 5	$CS_{BBB,AA}$
Model 6	$CS_{BBB,A}$

Notes: Model 1 is the benchmark model.

7 Results and analysis

In the following section, we will discuss and interpret the empirical results and the implications of our empirical results.

7.1 In-sample results

We estimate Model 1-6 with ordinary least squares (OLS) for the full sample with observations (from November 2001 up to January 2019) for one-, three-, six-, nine- and twelve-month horizons. Adjusted R^2 is used to compare the performance of the different models, and the results are summarized in Table 4-8.

We can see from the tables that all coefficients of credit spreads (β_3) for different horizon predictions have a negative sign. This implies that widening credit spreads predicts a decrease in employment growth in the future. More specifically, the results indicate that if the credit spread of either a CS_A, CS_{AA}, CS_{BBB} or $CS_{BBB,AA}$ increases 100 basis point[6], employment growth per month would theoretically decrease by between 0.06%-0.16% at the six-month horizon. The results confirm our theoretical hypothesis and are line with theory mentioned in Section 3, namely that credit spreads widen before recessions and tighten before expansions.

It can be drawn from Table 4 that Model 1 seems to be the better model to predict the Norwegian business cycle at the one-month horizon. The adjusted R^2 is high, and the two lags of the employment growth are significantly positive at the 5% level. Furthermore, adding credit spreads to the model does not yield any added information, at any

[6] 100 basis point = 1%

Table 4: One-month horizon

Model	β_0	β_1	β_2	β_3	Adjusted R^2
Model 1	0.0000	1.0735***	-0.1662**		0.8505
Model 2	0.0004	1.0610***	-0.1604**	-0.0003	0.8508
Model 3	0.0001	1.0717***	-0.1643**	-0.0001	0.8499
Model 4	0.0001	1.0738***	-0.1617**	-0.0002	0.8500
Model 5	0.0002	1.0651***	-0.1659**	-0.0002	0.8502
Model 6	0.0001	1.0690***	-0.1656**	-0.0002	0.8501

Notes: Significance levels: *10%, **5%, ***1%.

significance levels. Models 2 to 6 also have lower adjusted R^2 than Model 1.

Increasing the horizon to three- and six-month, we notice an improvement of the inclusion of credit spreads to all models and their forecast abilities, see Tables 5 and 6. Specifically, CS_{BBB} is significant at 1% level and the adjusted R^2 increases from 53% to 54%, and from 26.16% to 28.84% respectively, in comparison to Model 1. Table 6 indicates that credit spreads works best as indicators for the business cycle in a six-month horizon. CS_{BBB}, CS_{AA}, CS_A, $CS_{BBB,AA}$ are all significant at normal significance levels and contribute to an increase of the adjusted R^2.

Table 5: Three-month horizon

Model	β_0	β_1	β_2	β_3	Adjusted R^2
Model 1	-0.0001	0.7292***	0.0000		0.5309
Model 2	0.0017**	0.6802***	0.0233	-0.0012***	0.5403
Model 3	0.0005	0.7201***	0.0098	-0.0006	0.5322
Model 4	0.0005	0.7314***	0.0197	-0.0011	0.5340
Model 5	0.0006	0.6985***	0.0016	-0.0007	0.5345
Model 6	0.0002	0.7147***	0.0020	-0.0005	0.5325

Notes: Significance levels: *10%, **5%, ***1%.

Table 6: Six-month horizon

Model	β_0	β_1	β_2	β_3	Adjusted R^2
Model 1	-0.0001	0.7978***	-0.3215**		0.2616
Model 2	0.0023**	0.7288***	-0.2876*	-0.0016***	0.2884
Model 3	0.0008	0.7825***	-0.3048*	-0.0010*	0.2680
Model 4	0.0007	0.8019***	-0.2946*	-0.0016*	0.2692
Model 5	0.0008	0.7547***	-0.3174**	-0.0010*	0.2691
Model 6	0.0002	0.7807***	-0.3188*	-0.0006	0.2632

Notes: Significance levels: *10%, **5%, ***1%.

At the nine-month horizon, $CS_{BBB,AA}$ and $CS_{BBB,A}$ are no longer significant, as can be seen from table 7. If we continue to a twelve-month horizon, all spreads, except CS_{AA}, lose their predictive power, see table 8. They are no longer significant and adjusted R^2 for all models are low.

Table 7: Nine-month horizon

Model	β_0	β_1	β_2	β_3	Adjusted R^2
Model 1	-0.0002	0.9385***	-0.7650***		0.1324
Model 2	0.0013	0.8955***	-0.7436***	-0.0010*	0.1399
Model 3	0.0008	0.9218***	-0.7467***	-0.0011*	0.1400
Model 4	0.0009	0.9401***	-0.7240***	-0.0023**	0.1513
Model 5	-0.0001	0.9324***	-0.7645***	-0.0001	0.1285
Model 6	-0.0002	0.9371***	-0.7648***	-0.0001	0.1280

Notes: Significance levels: *10%, **5%, ***1%.

Table 8: Twelve-month horizon

Model	β_0	β_1	β_2	β_3	Adjusted R^2
Model 1	-0.0003	0.1567	-0.3054*		0.0194
Model 2	0.0007	0.1287	-0.2912	-0.0007	0.0194
Model 3	0.0007	0.1395	-0.2863	-0.0011	0.0271
Model 4	0.0010	0.1568	-0.2561	-0.0028**	0.0471
Model 5	-0.0007	0.1712	-0.3065*	0.0003	0.0157
Model 6	-0.0005	0.1639	-0.3065*	0.0003	0.0152

Notes: Significance levels: *10%, **5%, ***1%.

The result thus far demonstrates that credit spreads contain information useful to predict Norwegian business cycles. Specifically, comparing Models 1-6, the results indicate that CS_{BBB} seem to be better than CS_{AA} and CS_A as predictors for business cycles, especially in the short-run horizons. For longer horizons like nine or twelve months ahead, CS_{AA} can add more information, although the low adjusted R^2 indicates that the models are no longer reliable for forecasting at the twelve-month horizon.

However, the results up to now are based on an in-sample analysis, and to be able to assess whether credit spreads can predict business cycles of Norway, we conduct out-of-sample forecast evaluation of Models 2-6. Before we go ahead with the out-of-sample analysis, we run several robustness checks to assess the strength of the statistical models and to make sure the benchmark model fulfills the assumptions for OLS explained earlier in the methodology section.

7.1.1 Robustness check

The robustness checks aim to measure the reliability of our in-sample analysis. First, we assume that model specifications are in line with the OLS assumption. To test formally if the other OLS assumptions hold, we have conducted several tests. The first test is the Breusch-Pagan (BP) test. It is commonly used to ensure that the residuals produced have constant variance. If this is not the case, OLS should not be efficient, and the biases in the estimated residuals may lead to invalid inference (Breusch and Pagan, 1979).

The results from the BP-test is reported in Table 9. We fail to reject the H_0 of no heteroscedasticity on the benchmark model for all horizons (1, 3, 6, 9 or 12 months) in the in-sample forecast. This implies that the residuals are unbiased and consistent and should not cause any spurious correlations.

Table 9: Breusch-Pagan test for homoscedasticity

h-month horizons	chi2(1)	pValue
1	1.87	0.1719
3	1.70	0.1929
6	1.70	0.1919
9	1.60	0.2054
12	1.46	0.2269

Notes: The table reports the p-values against the test statistics that has a chi-squared distribution with 1 degree of freedom. The H_0 is that there is constant variance of the residuals. h = 1, 3, 6, 9 and 12.

The second test we run in the in-sample analysis on the benchmark model is the Breusch-Godfrey (BG) test. It tests for the presence of serial correlation, or autocorrelation in the error terms. If the errors suffer from serial correlation, we say that when $u_{t-1} > 0$ will, on average, cause the error one period ahead, u_t, to be positive (Wooldridge, 2015). The results of the BG-test is reported in Table 10. It assumes that the residuals are not heteroscedastic, which we have confirmed is not the case, as illustrated in Table 9. The results indicate that we cannot reject the null hypothesis of no serial correlation for almost all horizons for both 1 and 2 lags of the dependent variable, except for three- and nine-month horizon with 2 lags. This result implies that we find no reason to doubt the validity of the benchmark model and are safe to move onto the out-of-sample forecast evaluation.

Table 10: Breusch-Godfrey test for autocorrelation

h-month horizon	lags	chi2(1)	pValue
1	1	0.053	0.8175
	2	2.539	0.2809
3	1	0.125	0.7241
	2	5.619	0.0602
6	1	0.208	0.6482
	2	1.795	0.4076
9	1	0.102	0.7494
	2	4.914	0.0857
12	1	0.195	0.6585
	2	1.517	0.4684

Notes: The table reports the p-values against the test statistics that has a chi-squared distribution with 1 degree of freedom. H_0 is that there is constant variance of the residuals. h = 1, 3, 6, 9 and 12.

7.2 Out-of-sample results

We have computed a 5[7], 9 and 12-year rolling window in the one-step-ahead forecast evaluation. A good forecasting model should give a forecast not far away from what turns out to be the outcome. We explain the details of our procedure using the one-month-ahead forecast for a 9-year rolling window as an example. First, we estimate Models 1-6 in-sample, using data from November 2001 to October 2010 and evaluate the one-month ahead forecast based on the estimation results. Next period, the rolling window continues to forecast one-month ahead. The procedure is repeated until we reach the end of the sample. To evaluate the forecast performance of Models 1-6, we compute mean squared forecast error (MSFE). MSFE is a frequently used measure of the difference between values predicted by a model and the values actually observed. The model with the smallest MSFE is expected to be the better predictor in forecasting out-of-sample. MSFE is calculated by the following formula:

$$MSFE = \frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n} \tag{11}$$

[7] Model 2-6, using 5 year rolling window, does not yield any lower MSFE than the benchmark model. Further details can be found in table A.1 in the Appendix

where $X_{obs,i}$ is observed values; $X_{model,i}$ is predicted values at time i; and n is the number of forecast values.

To compare the forecast performance of the models, we calculate the MSFE of the alternative model relative to the MSFE of the benchmark model. If the ratio is smaller than unity, the forecast performance of the alternative model is better than the benchmark model. Thus, the smaller the ratio, the better the forecast performance.

Further, we determine whether MSFE differences between Model 1 and Models 2-6 are significant through the Clark-West test. The Clark-West test was introduced with the aim of comparing a parsimonious null model to a larger model that nests the null model (Clark and West, 2007). The null model is represented as Model 1 and the alternative model is Models 2-6, sequentially. The null hypothesis is that MSFEs of the two models are the same, i.e., two forecasts are similar when it comes to predictive accuracy. The alternative hypothesis implies that the MSFE of the alternative model is lower, and provides a significantly better prediction.

Table 11 reports the results of the relative MSFE for Models 2-6, using a 9-year rolling window. Our first observation is that none of the models have lower MSFE than Model 1, at the one-month horizon. This is consistent with our findings in the in-sample analysis and table 4 where none of the estimates were statistically significant. Our second observation regarding table 11 is that the predictive power of almost all models in the three- and six-month horizon seem to outperform Model 1. Model 2 yields a significantly better forecast for the twelve-month horizon at a 5% level, while Model 3 outperforms Model 1 at the six- and nine-month horizon, significant at a 10% level. Further, Models 4, 5 and 6 report lower MSFE than Model 1 for the three-month horizon, all significant at a 1% level. Model 5 also outperforms Model 1 at the six-month horizon at a 10% level.

So far, our observations are in line with the general view of the usefulness of credit spreads as predictors of business cycles. We continue the analysis with a 12-year rolling window, to see if any of the models improve their forecast performances.

Our first observation regarding Table 12 is that the 12-year rolling window offers more significant results for all models. Model 2 still does not yield any significantly lower

Table 11: Relative MSFE: 9-year rolling window

	Horizon 1	Horizon 3	Horizon 6	Horizon 9	Horizon 12
Model 2	1.020	1.051	1.012	1.010	0.941**
Model 3	1.021	1.022	0.972*	0.994*	1.079
Model 4	1.013	0.997***	1.096	1.473	1.906
Model 5	1.004	0.957***	0.949*	1.120	1.331
Model 6	1.002	0.983***	0.996	1.043	1.090

Notes: The table reports the mean squared forecast error (MSFE) of the Model 2 to 6 relative to Model 1 from a period of one to twelve months. Horizon refers to the forecast horizon h. MSFE is computed using a 9-year rolling window. The stars represent on which significance level, the alternative models outperform the benchmark model (Model 1), based on the Clark-West test. Significance levels: *10%, **5%, ***1%.

MSFE than Model 1 at any horizon. Model 3 now significantly outperforms Model 1 at both the six- and the twelve-month horizon at 1% and 5% level, respectively. Further, Model 4 significantly outperforms Model 1 at both the three- and twelve-month horizon, both at a 1% level. Model 5 is still significantly better than Model 1 at the six-month horizon, and Model 6 outperforms Model 1 at three-, six- and nine-month horizon, all at a 1% level.

Table 12: Relative MSFE: 12-year rolling window

	Horizon 1	Horizon 3	Horizon 6	Horizon 9	Horizon 12
Model 2	1.032	1.102	0.953	1.231	1.232
Model 3	1.022	1.014	0.974***	0.989	0.897**
Model 4	1.020	0.998***	1.041	1.013	0.870***
Model 5	0.985	0.952	0.966***	1.186	1.529
Model 6	0.999	0.990***	0.964***	0.994***	1.044

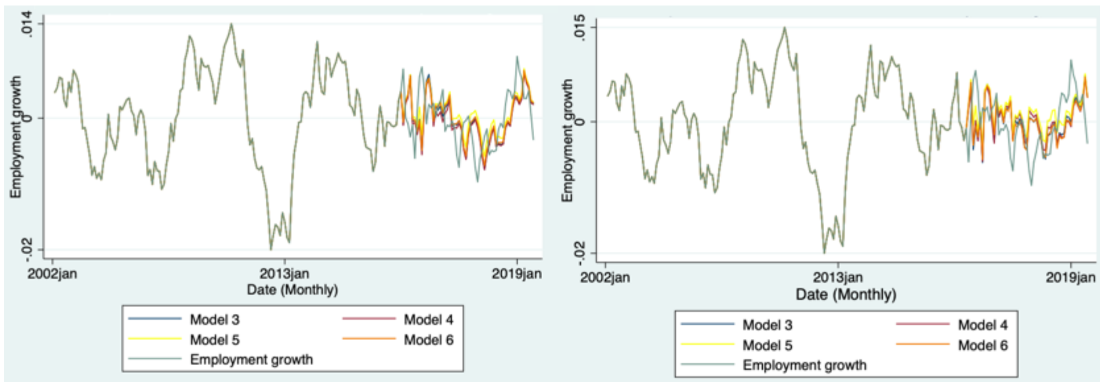
Notes: See description in Table 11. MSFE is computed using a 12-year rolling window.

The in-sample and out-of-sample result for both rolling windows indicate that all models, with the exception of Model 2, provide better forecast performance compared to Model 1. In other words, adding either CS_A, CS_{AA}, $CS_{BBB,AA}$ or $CS_{BBB,A}$ offer forecast gains for Norwegian business cycles[8]. In addition, we conclude that these credit spreads can provide the most significant forecast gains for the three- and six-month horizon, although some of these spreads also offer satisfactory predictions for a longer horizon of twelve months.

[8]Detailed forecast plots of the three- and six-month horizon can be found in A.1 and A.2 in the Appendix

Figure 6 plots the predictive performance of Models 3-6 at the three- and six-month horizon. The solid line shows the actual employment growth whilst the dotted lines present the prediction performance of Models 3-6 starting from November 2014. We notice that all models seem to confirm our observations from Table 12 for the three- and six-month horizon. The performances of the various spreads seem to differ, to a small extent. Overall, the plot shows that the model predictions are quite close to what turned out to be the actual data.

Figure 6: Forecast plot of Models 3-6 at three- and six-month horizon



Notes: Predicted values are computed using a 12-year rolling window.

According to the MSFE ratios in Tables 11 and 12 in addition to the result of the Clark-West test, we may conclude that the 12-year rolling window seems preferable for the overall forecast performance of the sample. The intuition behind why 12-year rolling window performs better is that the number of observations used in the forecast period is greater; hence, the number of predicted values are fewer. More precisely, we forecast a period from May 2011 to January 2019 when applying the 9-year rolling window, and from May 2014 to January 2019 when using 12-year rolling window (for three-month horizon). Models using a 9-year rolling window forecast a longer time period, thus more predicted values. This leads to more uncertainties in the forecast period, as we can see that the relative MSFEs are not less than unity. Figure 6 shows a sudden drop hits employment growth, before it smooths out at the end of the sample. The 12-year rolling window overcomes the potential concern of such abnormal fluctuations in employment growth, by using more observations than the 9-year rolling window. However, smaller rolling window forecast evaluation can still yield interesting information useful to predict business cycles. Credit spreads might vary in forecast performance over time. Therefore, we continue our assessment of the credit spreads forecast performance over time, by using the 9-year rolling window.

7.3 Forecast performance over time

In this section, we show that the predictive powers of the credit spreads vary over time, by computing the cumulative sum of squared error forecasts difference (CSSED), formerly introduced by Welch and Goyal (2007).

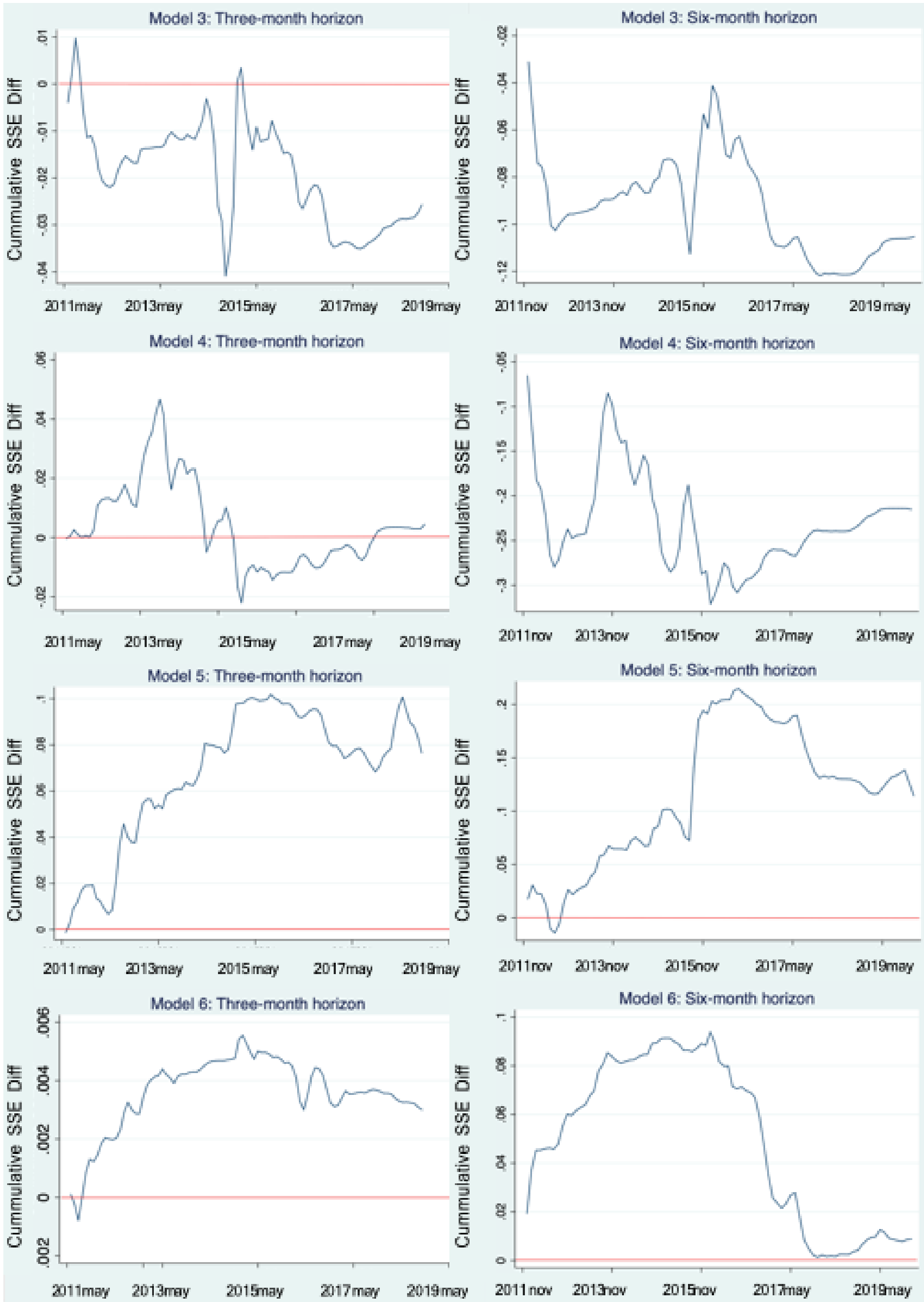
$$CSSED_{m,\tau} = \sum_{i=R}^{\tau} (\hat{e}_{1,i}^2 - \hat{e}_{m,i}^2) \tag{12}$$

where $\hat{e}_{1,i}$ is the forecast error of model 1, $\hat{e}_{m,i}$ is the corresponding error of alternative models (Model 2-6), at time i. R refers to the beginning of the forecast period. $CSSED_{m,\tau}$ represents the cumulative sum of squared error forecasts difference between Model 1 and Model m, from time R to time τ. According to equation (12), increases in CSSED indicates that the alternative model outperforms Model 1, while a decrease means the opposite, namely that the benchmark model outperforms the alternative model. Referring to the results from the in-and out-of-sample analysis, we will consider the CSSEDs of Model 3-6, each compared to Model 1. The forecast values of the models are extracted from a 9-year rolling window estimation, testing for three- and six-month horizon.

Figure 7 illustrate our findings. First, we notice that Model 3 only outperform the benchmark model at shorter periods of time at both the three- and six-month horizons, more precisely from the beginning of 2012 to the beginning of 2014, and from the beginning of 2015 until the middle of 2015. For the remaining part of the sample, Model 3 does not outperform Model 1. Overall, Model 3 does not seem to offer any forecast gains, as CSSEDs for neither three- or six-month horizon sums up to zero for the estimation period.

Model 4 provides forecast gains for the three-month horizon from the period from mid-2011 to the mid-2014. After this period, Model 4 offers no added forecast gains until

Figure 7: Cumulative SSE Differences for Models 3-6 at three-month and six-month horizons. 9-year rolling window



mid-2015, before the CSSED steadily increases until the end of the estimation period. Since the CSSED of Model 4 at the end of the forecast period is net positive, it provides forecast gains for the three-month horizon. This is not true for the six-month horizon, as the net CSSED is negative.

Model 5 and 6, in contrast to Model 3 and 4, seem to outperform Model 1 at both horizons. Furthermore, they both outperform the benchmark model in the first half of the sample, specifically from May 2011 to May 2015, for both the three- and six-month horizon. Although they deteriorate in forecast performance for the remaining part of the prediction period, the CSSEDs of both models are net positive at the end of the estimation period.

To give an explanation for the varying forecast performance over time, we look back at Norwegian business cycles during the estimation period. From May 2011 to January 2019, Norway experienced three recessionary periods. More precisely from April 2012 to February 2014, from August 2015 to September 2016, and from August 2017 up to now. The nature of these recessions is different. The downturn of the Norwegian economy in 2012 is likely to relate to financial turmoil in other countries in Europe, with the bailout of Spain, Italy, and Greece from the European central bank and the increased uncertainty of financial markets in the region. Aggregate demand for banks fell, and they experienced reduced lending and liquidity. This, in turn, made interest rates rise, and spreads to widen. Asset-prices fell and the labor market experienced lower employment growth after some lags. For this period, all models show increases in CSSEDs, proving a stronger predictive power than the benchmark model.

On the other hand, for the recession in August 2015 to September 2016, all models lose their forecast ability. This recession is said to originate from the downturn of the oil price and international oil demand. Norway, as a small and oil-producing economy, suffered negative effects of the petroleum sector crisis, leading to particularly high inflation and decreasing employment rates in 2016.

We interpret these findings in the following way. Credit spreads closely follow fluctuations in financial markets; therefore, it is a sensible argument that they can predict the up-and-downs in economic activity driven by changes in sentiments in the financial sector (such as the recessionary period from 2012 to 2014). However, other disturbances not originated by changes in the financial sector (such as sudden negative changes in the oil price, which are most likely to affect aggregate economic activity), credit spreads do not seem to correctly interpret these signals of an approaching downturn in the market, to predict business cycles of Norway. Although $CS_{BBB,AA}$ or $CS_{BBB,A}$ may fail to predict some types of recessions for Norway, they provide significant forecast gains to business cycles in Norway, overall.

8 Conclusion

This thesis examines the predictive power of Norwegian credit spreads for Norwegian business cycles from the period of November 2001 to January 2019, a sample size of about 18 years. We conduct in- and out-of-sample analysis to find evidence to the existing literature such as Okimoto and Takaoka (2017), Moneta (2005) and Faust, Gilchrist, Wright, and Zakrajšsek (2013), that credit spreads offer forecast gains for business cycles. More precisely, we show that the $CS_{BBB,AA}$ and $CS_{BBB,A}$ are the most useful credit spread for the three- and six-month horizon.

Our empirical results support the theoretical framework about credit spreads: widening before economic recessions and narrowing before expansions. However, the credit spreads can provide more accurate prediction in some periods, but do not consistently outperform the benchmark model. The analysis of forecast performance over time shows that the $CS_{BBB,AA}$ and $CS_{BBB,A}$ are useful as predictors for business cycles from the middle of 2011 to the beginning of 2016. However, the predictive power deteriorates after this period. We attribute the differences in forecast performance over time to be partly due to the nature of the recessions and where they originate from.

An evident limitation of this thesis is the lack of data foundation of the Norwegian bond market. Only a fraction of the bonds on the Norwegian market are rated, thus making the data sample somewhat limited in terms of information and robustness, compared to the literature which examines other markets like the US or Japan.

To the best of our knowledge, our thesis is among the first studies to examine the

Norwegian credit spreads and Norwegian business cycles, demonstrating its usefulness in forecasting abilities. Interesting future work would be to investigate the predictive power of the term structure of credit spreads, which has been done by several papers, but to our knowledge, not for the Norwegian bond market.

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10 Appendix

Figure A.1: Forecast plot of Models 3-6 at six-month horizon. 12-year rolling window

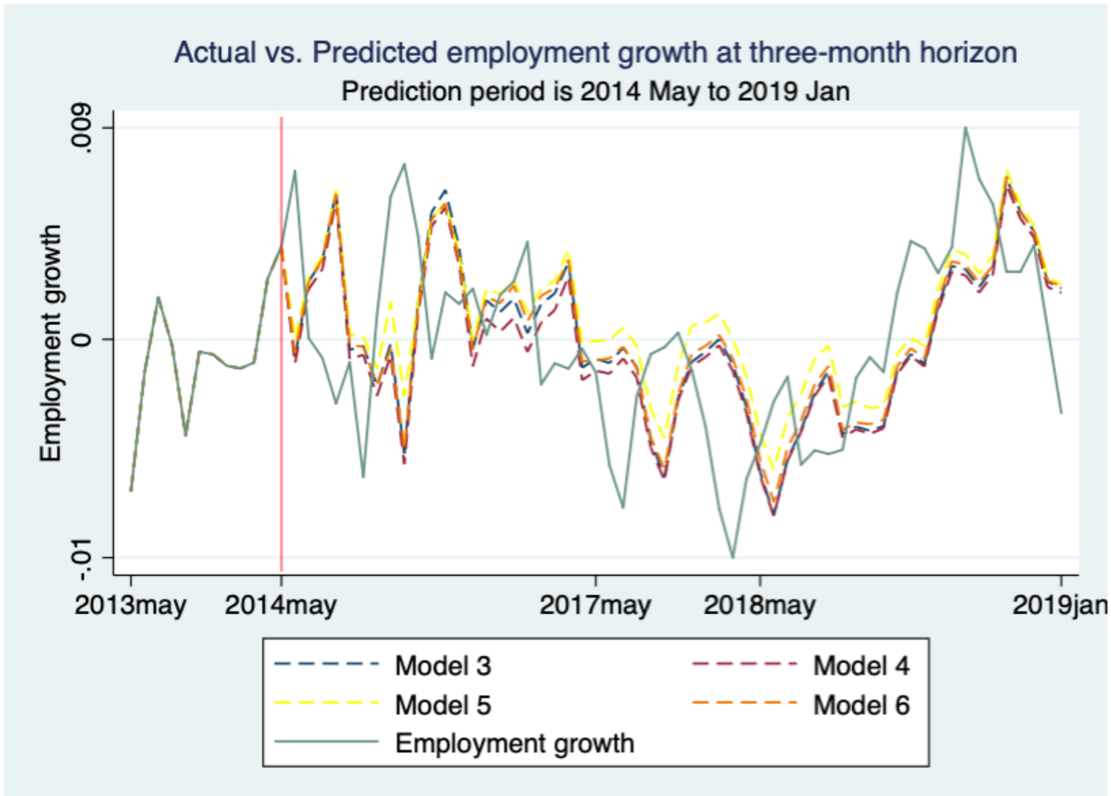

Figure A.2: Forecast plot of Models 3-6 at six-month horizon. 12-year rolling window

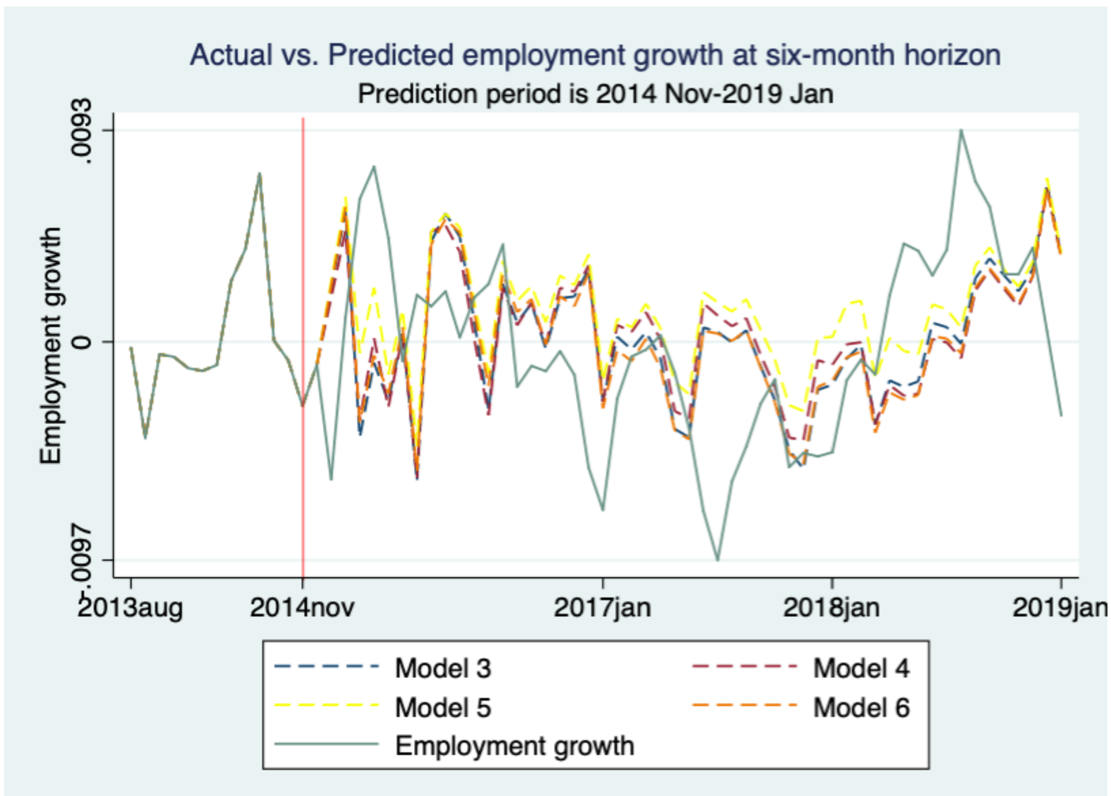

Table A.1: Relative MSFE: 5-year rolling window

	Horizon 1	Horizon 3	Horizon 6	Horizon 9	Horizon 12
Model 2	1.048	1.080	1.044	1.239	3.151
Model 3	1.055	1.146	1.263	1.415	3.694
Model 4	1.053	1.120	1.264	1.535	4.159
Model 5	1.053	1.171	1.136	1.367	3.358
Model 6	1.088	1.335	1.609	1.896	4.702

Notes: See description in Table 11. MSFE is computed using a 5-year rolling window.