BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Thesis Master of Science

An assessment of the predictive abilities of the yield curve: A multi-country study

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Start: 02.03.2018 09.00

Finish: 03.09.2018 12.00

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Hand-in date:
13.07.2017

Programmes:
Master of Science in Business - Finance
Master of Science in Business – QTEM Masters Network

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Abstract

In this thesis we assess the yield curve's predictive abilities for the eight countries in which OECD apply the interest rate spread as a part of their leading indicator index. We develop a dynamic model that uses the yield curve and a recession lag to predict recessions. The model is tested both in-sample and pseudo out-of-sample. Our findings indicate that the yield curve still serve as a leading indicator in some of the countries, but that OECD should revise its inclusion for some of the other countries. The study differentiates itself from other studies assessing the yield curve's predictive abilities by that we assess the relationship for different time periods, and we find that the yield curve's significance has weakened over the last two to three decades. The weakening of the yield curve's predictive abilities coincides with the growing awareness and focus on it as a leading indicator of recessions. Our research discusses an eminent, but little discussed, feature of research on the predictive abilities of the yield curve; that it fails to predict the onset of recessions. The thesis highlights the need for further research on several types of yield spreads and different types of recession indicators.

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1.0 Introduction

1.1 Motivation and contribution

Predicting different macroeconomic measures such as business cycles can be a challenging task. The Organization for Economic Co-operation and Development (OECD) publishes a Composite Leading Indicator (CLI) which is designed to provide early signals of turning points in business cycles. The CLI is published for all OECD countries, among them the United States, the United Kingdom, Germany and France, as well as the BRICS-countries. Each country has its own indicators, and for eight of them we find the interest rate spread as one of them. Previous research suggests that the interest rate spread, or more frequently cited, the yield curve is a leading indicator of business cycles. Especially the inversion of the yield curve has been found to precede recessions (please see Figure 1). The topic of this master thesis will be to investigate the relationship between the yield curve and recessions for the countries that OECD apply the interest rate spread for in their Composite Leading Indicator.

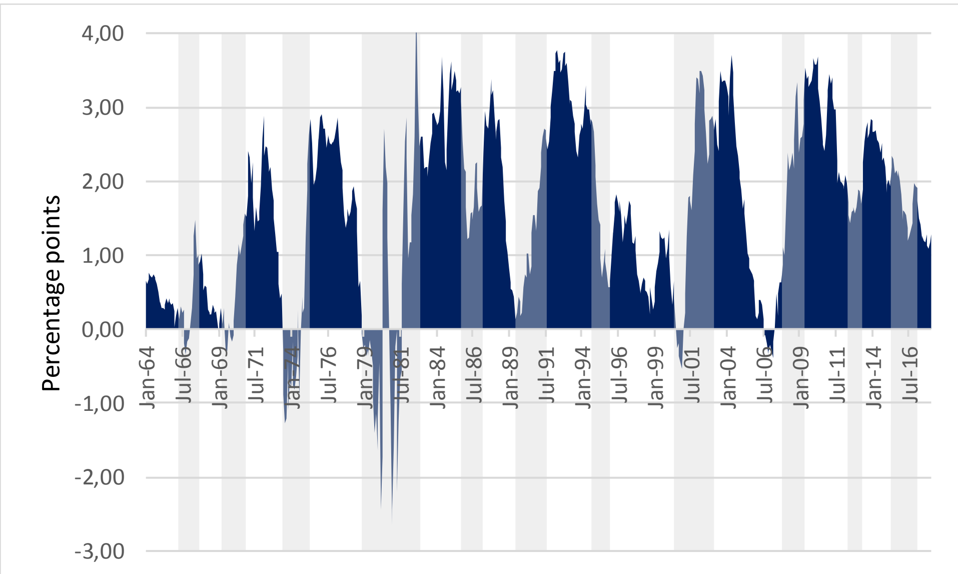

Figure 1: US recessions (shaded areas) and term spread between 10y government bonds and 3m treasury bills. Source: Federal Reserve Bank of St. Louis (FRED)

Recessions have several definitions, but all forms of recessions contain a contraction in the economic output, often measured through the Gross Domestic Product (GDP). A contraction in the economy leads to workers suffering job losses, investors losing capital and business owners shutting the doors of their businesses. Thus, it would be conducive if an inverted yield curve could predict these economic contractions. As we will address later, recessions often arise from unexpected shocks, which makes them inherently difficult to predict. However, the indicator can be useful as a signal of where we are in the economic cycle, that is if we are facing an upturn or downturn in economic activity.

We want to develop a model with the intention of predicting recessions with the inversion of the yield curve as our starting point. We choose to focus on recessions as applying a recession dummy, instead of GDP growth, are beneficial as *"A goodness-of-fit measure for a model of output growth would mix information on the predictability of the strengths of recoveries and expansions with information on the timing of recessions"* (Dueker, 1997, p. 42). As an indicator for recessions we apply the OECD Composite Recession Indicator. The relationship between yield curve inversion and recessions has been tested and proved earlier, by among others Wright (2006), Dueker (1997), Stock and Watson (1993), Estrella and Hardouvelis (1991), but research done after the financial crisis of 2008 are ambiguous to the predictive abilities of the yield curve. As such, we will not only test if the relationship between the yield curve and recessions hold applying data from the full sample, we will investigate how the relationship changes across different periods. The results can tell us if the yield curve's predictive abilities curtailed as the relationship amassed attention.

The topic of this thesis is highly relevant as the yield curve has flattened in several countries. The period after the economic crisis of 2008 has been a unique period as it has been one of the longest periods of continuous economic growth in modern times paired with an unprecedented level of low volatility. It is commonly accepted that this has been supported by governmental intervention in the markets. No prior period has seen such extensive public asset purchases, and the effectiveness and sustainability of these has been a highly debated topic among scholars and practitioners. Today, we are facing the end of these interventions, and with the recent flattening of the yield curve some economists fear that we are facing an imminent slowdown in economic activity. Some experts argue that there is reason to believe that a flattening of the yield curve could indicate an economic slowdown as it has been a reliable indicator in the past. Others believe that today's financial and economic environment is different and therefore question the signal effect of today's yield curve flattening. This motivated us to develop a profound understanding of the topic and hopefully be able to provide evidence if we should be worried about an upcoming recession or not.

1.2 Thesis question

Our thesis question is as follows:

Is an inversion of the yield curve still a leading indicator of recessions, and if not, when did the relationship cease to exist?

2.0 Theory description

This section will discuss the theoretical background of our topic and it will also provide a theoretical explanation of why inverted yield curves are a deviation from normal.

2.1 Expectations hypothesis

This hypothesis of the term structure of interest rates states that long-term rates are determined solely by the current and expected future short-term rates, so that the final expected value from an investment in a sequential combination of short-term bonds will equal the final value of an investment in long-term bonds. This is formulated as:

$$(1 + i_{lt})^n = (1 + {i_{st}}^{year\ 1})(1 + {i_{st}}^{year\ 2}) \ldots (1 + {i_{st}}^{year\ n})$$

The shape of the yield curve should thus depend on the expectations of the market participants with respect to future interest rates. The expectations theory therefore assumes that several short-term notes and bills can replicate a long-term bond. Due to the observation that yields don't always move in the same direction, this does not hold as a complete explanation.

2.2 Liquidity preference theory

Liquidity preference theory builds on the basic understanding that cash and other liquid assets are preferred over less liquid assets because they can more swiftly be traded for goods and services, corresponding to their full value.
This implies that long-term assets carry greater risk and should yield a higher rate of return, a premium, compared to short-term assets. This is consistent with an upwards-sloping yield curve, where investors are rewarded for holding the bonds with longer durations. However, as the yield curve is at times inverted, the liquidity preference theory cannot be a unifying theory of the yield curve.

2.3 Segmented market theory

In contrast to the expectations and the liquidity preference theory, the segmented market theory views short-term, intermediate, and long-term debt securities as separate markets. The core idea is that there is no inherent relationship between the levels of the varying maturities. However, as spill over-effects from a change in the yield on a certain maturity onto another maturity has been proven several times, this theory comes up short compared to the aforementioned theories.

2.3 Preferred habitat theory

This theory, which is a variant of the segmented market theory, suggest that different investors have their own preferences as to what maturity length they prefer to invest in. The investors are willing to invest outside of their maturity preference only if they are rewarded with a risk premium. If an investor prefers short-term bonds due to inflation impact on long-term bonds and the interest rate risk, he will only invest in long-term bonds if he is provided with a risk premium large enough to compensate for the investor leaving his preferred habitat. As with the previous theories, the preferred habitat theory is improbable as a complete explanation as an inversion of the yield curve would mean that most investors prefer long-term bonds and thus require a risk premium on short-term bonds.

2.4 Recession theory

Several definitions of recessions exist. One definition is that a recession is a business cycle contraction, which results in a general slowdown in economic activity. Another definition is two consecutive periods of real GDP contraction. However, the recessions addressed in this paper is in line with the definition provided by OECD. The organization use the growth cycle approach where business cycles and turning points are measured and identified in the deviation-from-trend series. This founds the basis for their published "Recession Indicators". This is a binary time series, which takes on a value of 0 or 1, depending on whether the economy is in a recession, or not. It highlights the period beginning at the peak and up until the trough. This might cause our recession indicator to signal more recessions than other recession definitions.

2.5 The slope of the yield curve

Considering both the liquidity preference theory and the expectations hypothesis, one has indications that the market participants' beliefs about the future market may be reflected in the slope and shape of the yield curve. This link between the yield curve and the drivers of the market implies that the yield curve may serve as a leading indicator of recessions.

Historically there are three main variations of the yield curve. Firstly, one has the traditional upwardly sloping yield curve, which is referred to as the normal yield curve. This yield curve has several interpretations if linked to the aforementioned theory, of which some involve expectations about higher future interest rates or strong current demand for shorter-term maturities, while another interpretation is a preceding inflation.

Secondly, one has the flat yield curve, which is not far from what we observe today. According to theory this can either imply that market participants expect interest rates to remain at the same level or that they are expected to decrease with an amount corresponding to the liquidity premium. Naturally, this can also be a temporarily occurrence as the yield curve shifts from normal to inverted.

Thirdly, there is the inverted yield curve. As previously mentioned this is a phenomenon that occurs when the short-term rates have a higher yield than the long-term ones. There are several possible explanations of this occurrence. One possible explanation is that market participants may want to shift consumption over to the future. The switch in investments could be caused by that the market expects poor economic sentiment in the short term. This will cause large investments in long-term bonds, which in turn drive the prices of these bonds up. Due to the inverse relationship between bond yields and prices, this will decrease the yield on long-term bonds. If one takes the sum invested in government bonds as more or less given, the increased investment in long-term bonds will decrease investment in short-term bonds, and thus decrease the slope of the yield curve. This explanation only holds if the poor economic times ahead is transitory as the default of a country would disincentivize investment in government securities of all maturities.

Another explanation is linked to the contra-cyclicality of monetary policy. As Figure 2 shows, the short-term rate tends to gradually decline in recessions to ease the monetary policy and stimulate the economy. According to Rudebusch (1995) and Haubrich and Dombrosky (1996), the public anticipates that this will happen until the economy improves. The low short-term rates in recessions could also reflect low real rates of return. According to the expectations hypothesis, the long-term rates need to decline immediately to equalize the holding period return of the bonds with different maturities. Depending on how much of their repayment will happen in the period with low interest rates, the rates on the different bonds will change by unequal amounts. Today's 3-month rate might not change if the low interest rate-environment is not expected to start for six months, but the 2-year rate will change. Hence, when a recession is impending, we expect the yield curve to dip.

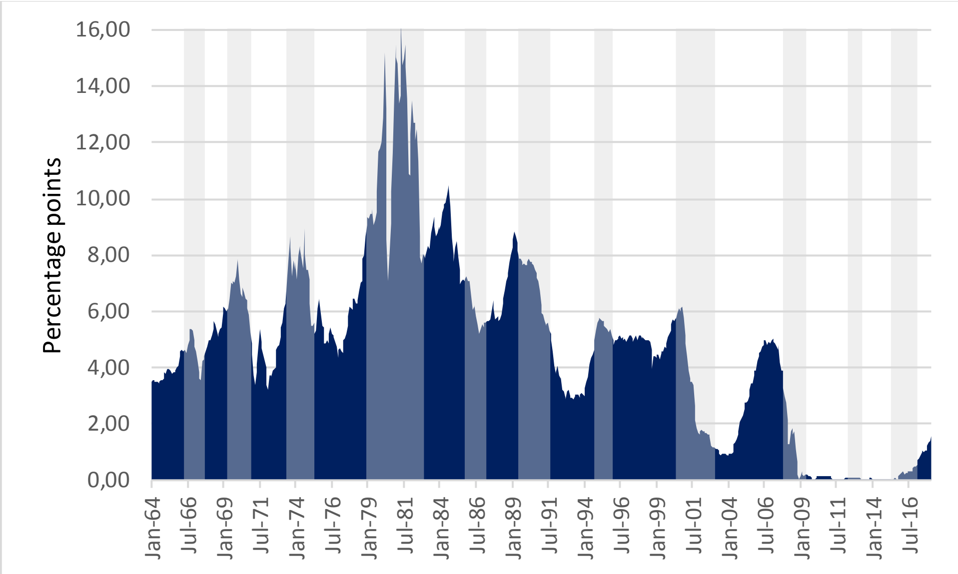

Figure 2: 3m US Treasury bills and US recessions (shaded areas)
Source: Federal Reserve Bank of San Francisco (FRED)

Depending on the size of the market participants' risk premia, and assuming that risk premia and liquidity premia are greater than, or equal to zero, there may exist expectations of an upcoming recession during a slightly upwards-sloping or flat yield curve as well. The rationale is that this risk premia can be high enough to offset an expected decrease in interest rates.

The theory discussed in this chapter gives a theoretical background of why the yield curve might give information regarding future GDP developments. We have discussed especially what an inversion of the yield curve might tell us about future economic sentiment. In the next section we will discuss what previous empirical research has to say about the relationship between the yield curve and recessions.

3.0 Literature review

3.1 Empirical research on the yield curve as a leading indicator

This thesis addresses whether an inversion of the yield curve serves as a predictor of a recession for the eight economies where it is included in OECD's index of leading indicators. We will also address the development of the relationship between the yield curve and recessions by checking the relationship for different time periods. As we will discuss below, historical findings indicate strong predictive powers of the yield curve. However, some more recent papers, for example Berganza and Fuertes (2018), indicate that the historical relationship might have been altered.

One of the first papers published on this topic was a paper by Kessel (1965), where he studied patterns rather than applying some of the more sophisticated models we have today. In the following years, several researchers addressed the same topic, and a study published by Estrella and Hardouvelis (1991) was one of the first to apply a nonlinear probit model, with interesting results. Later, Stock and Watson (1993) studied a composite index of leading indicators, which have been commonly cited in papers addressing the yield curve. In search of the predictive properties of the yield curve, Dueker (1997) tested both a nonlinear static and nonlinear dynamic probit model with a lagged recession variable and found interesting results for the last model. Estrella and Mishkin (1998) published a new paper, based on their previous (1995) paper and the research of Dueker (1997), which also addressed the yield curve as a predictor using a nonlinear probit model with a recession dummy, obtaining similar findings. Kim and Hamilton (2000) applied a two-factor affine pricing model, and their findings confirmed a relationship between the yield spread and real GDP. Among newer research, various methods have been applied by for instance, Ang, Piazzezi and Wei (2005), Wright (2006) and Ozturk and Pereira (2013), applying a dynamic model without arbitrage, probit models with independent factors, and unbalanced data panels, respectively.

Kessel (1965) links the yield on different government debt instruments to economic cycles, by applying models developed by Lutz, Meiselman and Hicks. His thesis was that one could better explain the term structure of interest rates by a combination of the expectations and liquidity preferences hypotheses than by either hypothesis alone. Although not the primary focus of his paper, Kessel found evidence that yield curves tended to be most upward sloping in the beginning of economic growth periods and most downward sloping pre-recession. His argument is that, when liquidity effects and incorrect expectations are disregarded, long-term rates should be higher than short-term rates when short-term rates are low and that the reverse should hold when short-term rates are high. This follows from the expectations hypothesis. As short-term rates are often counter-cyclical, that is, they are low near the troughs of the economic cycle and high near the peaks, one would expect a negative sloping yield curve at the peaks of economic cycles.

Kessel also addressed the effect of the liquidity premium. The liquidity premium refers to the fact that long-term assets are less liquid than short-term assets, and thus their yield should be higher (see chapter 2.2). He argues that near the troughs of the cycle, both expectational and liquidity forces push in the same direction and results in a positively sloping yield curve. However, at times near peaks, they have opposite effects. As always, the liquidity effect pushes the short-term rates below long-term rates. At the same time, as the market expects future short-term rates to be lower, the expectation effect pushes the long-term rate below the short-term. The slope of the yield curve near peaks will depend on the relative force between the liquidity and the expectational effect. Lastly, Kessel argues that as the two effects push in the same direction near troughs but work in opposite directions near peaks, short-term yields do not exceed long-term yields at peaks as much as they fall beneath long-term yields at troughs. Being one of the first papers linking the yield curve to economic cycles, Kessel's paper provides some evidence that the yield curve might be a leading indicator of recessions.

Estrella and Hardouvelis (1991) studied the relationship between the yield curve and real economic activity. Estrella and Hardouvelis first apply several basic regressions before they move on to a nonlinear probability model, which is estimated using maximum likelihood. They find that there is a positive relationship between the slope of the yield curve and increases in future real economic activity. The authors also find that, as a leading indicator, the yield curve outperforms survey forecasts. Interestingly, the study indicates that the yield curve does not only reflect the monetary policy of the economy, but also factors independent of the monetary policy. They conclude that the slope of the yield curve could provide useful information both to policy makers and private investors.

Although the study does not concern the inversion of the yield curve, it is useful as it concerns the relationship between the yield curve and economic output.

Especially the finding that the yield curve reflects factors other than monetary policy alone is interesting, as if it were only reflecting the monetary policy it would not provide any additional information. Estrella and Hardouvelis (1998) highlights that their findings may not hold in the future if the Federal Reserve were to adopt the slope of the yield curve as an information variable into its decision system.

Stock and Watson (1993) examined various leading indicators and composite indexes in their paper. They further addressed the 1990 recession and developed an experimental composite index with the purpose of forecasting how likely a US recession will be within six months. Despite exploring several explanations, they were not able to provide clear signals before each recession. The key take-away from this paper was the findings regarding forecast error. They found that the use of certain financial variables associated with a tight monetary policy was not fruitful. When attempting to predict contractions in US GDP this paper therefore focusses solely on the slope of the yield curve.

Dueker (1997) looks closer at the movements of the US yield curve before US recessions. Dueker first look at US history where the long-term rates have several times dropped below short-term rates, that is, an inversion of the yield curve. Following 1960, this phenomenon preceded each of the five following recessions. As Dueker mentions, the degree to which the slope of the yield curve is inverted, or differing from its conventional "normal" slope, is used by many researchers in this field as one of the most fruitful recession indicators. Dueker mentions the presence of term premiums, with the remark that yield curves do not need to be completely inverted to signal an upcoming recession, they simply must become flat relative to their "normal" slope. He looks closer into a quantitative approach involving a probit model, where he early mentions a weakness of simple static probit models. The weakness is that a simple static model lacks a dynamic structure which is suitable when working with time series data. A dynamic structure can take form as a lagged variable on data representing recessions. This drawback is not unique for this exact model, but common in several so-called limited dependent variable econometric models. The weakness arises because the predictor of recessions in this model is a time series variable, that has a unique autocorrelation structure, while the model does not consider any information from the autocorrelation structure of the left side variable to produce its predictions. He therefore extends his model to a dynamic probit model built on both the yield spread and a lagged variable of the recession indicator.

Several research papers and empirical results on univariate and multivariate time series modelling of different macroeconomic measures have proven the high relevance of including a variable's history when producing forecasts. To cope with this, Dueker highlights that one may follow the example set by Estrella and Mishkin (1995). That involves using a recession dummy variable as the left side variable to focus on recession timing. Dueker found that the slope of the yield curve still served as the most beneficial single predictor of recessions, having examined several extensions of the basic version of the probit time-series model. The robustness of his findings further strengthens the rationale of using the yield curve when attempting to predict recessions. Apart from the statistical reasons previously mentioned in this paper, the yield curve has other attributes that makes it useful as a recession indicator; it can be easily observed at the desired frequencies, and its signals can be easily interpreted. In addition, the expectations theory of interest rates' term structure founds a theoretical basis of its predictive power.

Lastly, Dueker (1997) address statistical issues that may arise when applying a probit model with time-series data. The statistically significant results he obtains when including a recession dummy indicates the noteworthy benefits of allowing for dynamic serial correlation. This serves as a compelling argument of extending the more basic probit model to a dynamic version.

Estrella and Mishkin (1998) have published one of the most frequently cited research papers on the predictive power of the yield curve, and among other things, they applied a nonlinear probit model with a recession dummy and the yield spread. Estrella and Mishkin study the relationships between the term structure of interest rates and various monetary policy instruments and tries to address potential links to observed real activity and inflation. They do this for both Europe and the US. Their findings indicate much of the same as other research papers on the topic, namely that the monetary stance serves as a strong determinant of the yield spread, and that real activity and inflation both have significant predictive power. Estrella, Rodrigues and Schich (2003) also test for a structural break between recession dummies and the yield spread, but do not discover any statistical significance.

Kim and Hamilton (2000) apply a two-factor affine pricing model, and first test the hypothesis of a relationship between the yield spread (3-month Treasury bill rates vs. 10-year Treasury bond rates) and future real GDP and find information beyond what you find in other measures. Although they confirm this relationship, it is not the primary objective of the article. Its focus is on why the yield curve can predict future economic output. Kim and Hamilton find that the spreads predictive power can be decomposed into two different effects by employing a model developed by Brenner, Harjes and Kroner (1996): the expectation effect and the term premium effect. The expectations effect refers to the expectations hypothesis that states that long-term rates are a projection of expected future short-term rates. The term premium is the premium one usually obtains by being willing to hold the additional risk that is associated with owning longer-term bonds. They also run a series of tests, including a Wald test for structural breaks, but find none. This article includes evidence that the short interest rate volatility is an important determinant of the yield spread.

According to Ang, Piazzesi and Wei (2005), the yield curve’s behaviour changes across the business cycle. The countercyclical premiums on long bonds and procyclical yield on short bonds is a key element, and the latter can be explained by the Federal Reserve lowering short yields during recessions in hope of stimulating economic activity. A prime example of this is Taylor’s (1993) rule, which states “For every 2-percentage point decline in GDP growth, the Fed should lower the nominal yield by 1 percentage point”. This serves as an example of the effects policy makers seeks to achieve from monetary policy.

The article uses a slightly different approach than many other research papers, as it applies a dynamic model that rules out arbitrage possibilities. The authors use the whole yield curve instead of two maturities to construct the spread. They argue that this may give more precise forecasts of GDP. A highlighted result is that the use of lagged GDP and the longest maturity yield allow their dynamic model to produce outstanding GDP forecasts out-of-sample compared to a more basic unconstrained OLS regression.

Wright (2006) provides a method for testing the probability of a recession by using first a basic probit model with the term spread between 3-month Treasury bills and 10-year Treasury bonds as the independent variable. He then augments his first model applying the nominal federal funds rate as well as a proxy for term premiums. The article is the first among the aforementioned articles that only tests what probability an inversion of the yield curve gives for a recession. It is highly relevant as it only focuses on the inversion of the yield curve, and not what the yield curve tells about future GDP growth. Interestingly, the article was written just before “The Great Recession” of 2008-2009. At the time, the yield curve was flat to inverted, and time would prove that this was indeed a predictor of the recession to come.

Another important finding in Wright’s paper is that a model that use an independent factor, which reflects the level of the Federal Fund’s Rate, performs better both in- and out-of-sample. More specifically, Wright shows that a model with only the term spread as an independent factor more often gives a high probability of a recession than models using both the term spread and the level of the Federal Fund’s Rate. The best indicator of a recession, according to this paper, is an inverted yield curve with a high level of the Federal Fund’s Rate. However, this method also has some limitations. It is solely the model using only the term spread which at the time of the analysis, February 2006, predicted a probability of over 50% for a recession occurring within the next 6 quarters. The models using, among others, the level of the Federal Fund’s Rate, assigned a probability of around 20% of an imminent recession. Looking back, it was clearly the model with only the term spread that was the best in predicting a recession at the time. However, using the level of the Federal Fund’s Rate gave better results for the other recessions. Wright (2006) also runs a series of tests to identify structural breaks. Wright then addresses the weakness of certain tests. One weakness is the limited number of recessions in the US sample, which implies that some of these tests might fail. This is further underpinned by the instability between the yield curve and GDP development. However, Wright does not find significant evidence for time-variation in his chosen parameters in the relationship between the yield curve variables and GDP contraction. The sum of these findings implies both pros and cons for the use of basic and dynamic probit models.

Ozturk and Pereira (2014) also used the yield spread to empirically test whether the slope of the yield curve serves as a working predictor of recessions. Contrary to the conventional research on the topic, which applies time series, Ozturk and Pereira applies a framework based on unbalanced panel data for some thirty OECD countries, ranging from the 1990s until 2011. This alternative approach allows the application of their model for countries whose time series are shorter. In addition, they add four quarters of lagged GDP to ensure that the yield spread serve as a good predictor, while controlling for the changes in GDP. Their model, with a 25% type 1 error, produces decent results, and an explanative power of approximately 63%. This indicates that this method may be advantageous to predict recessions within the next 12 months, and that one may address a variety of models.

3.2 Recent evidence

The alteration of the relationship between the yield curve and recessions has been a topic of late as briefly mentioned above. As such, we want to address some of the most recent empirical research on the topic.

Papers by Liu and Moench (2016), Bauer and Mertens (2018), Johansson and Meldrum (2018) hold that the yield curve's predictive abilities prevail. However, other papers, such as Berganza and Fuertes (2018) argues that the current flattening are different from previous ones, "*…such that the inversion of the curve might not be anticipating a recession"* (Berganza and Fuertes, 2018, p. 10). None of the most-cited previous papers investigates the relationship across time periods as we will do. As such, our results will clarify the ambiguous results of recent papers.

4.0 Hypotheses and limitations

4.1 Possible hypotheses

Our main hypothesis is that an inversion of the yield curve is a reliable predictor of an impending GDP contraction for the countries in our sample. This hypothesis is grounded in the fact that OECD has found the interest rate spread to be a leading indicator for the eight countries we investigate the relationship between the yield curve and recessions for. The hypothesis is further based on the empirical research discussed in the previous chapter of this thesis. In the terms of our final dynamic probit model, this hypothesis can be represented in the following way:

$$\Pr(R_t = 1) = \varphi(\beta_0 + \beta_1 Spread_{t-k} + \beta_2 R_{t-k})$$

Based on the given model: H0: $\beta_1 = 0$, H1: $\beta_1 \neq 0$ for all countries of interest.

Our second hypothesis is that the relationship no longer holds in one or two of the economies, but that it holds in at least one of them. This could be true due to several reasons. One possibility is that some countries, but not all, have included the yield curve as an information variable in its decisions system. As Estrella and Hardouvelis (1998) discussed, this could weaken the predictive abilities of the yield curve. Another possibility is that one or more of the countries have experienced a shock to the economy, a Black Swan (Taleb, 2007), that were "impossible" to predict and caused a recession. We can represent this hypothesis followingly:

$$\Pr(R_t = 1) = \varphi(\beta_0 + \beta_1 Spread_{t-k} + \beta_2 R_{t-k})$$

H0: $\beta_1 = 0$, H1: $\beta_1 \neq 0$ for one or more of the countries. While, at least one country's beta coefficient is not statistically different from zero.

Our last hypothesis is that the yield curve cannot predict recessions anymore. If true, we will be able to analyse where the relationship ceased to exist through our different sample periods. The beta coefficients will in this case all be statistically insignificant different from zero.

4.2 Limitations

In this paper we are trying to predict recessions by using information from past data, including previous recessions. Previous research has shown that an inverted yield curve predicted US recessions with a remarkable accuracy. However, one of the problems with predicting recessions is that they often are unexpected, or to use the vocabulary of Nassim Nicholas Taleb, they are Black Swans (Taleb, 2007). Taleb used the term to describe rare events, often "six sigma events" which, if applying Gaussian models, are extremely unlikely to occur. In fact, the probability of such an event is twice in a billion. The Great Recession in the late 2000s came after a financial blow-up caused by complex derivatives with hidden tail risk very few were aware of. The recession in 2001 came in the aftermath of the "dot-com bubble" which was a bubble driven by the strong belief that internet and technological companies would change everything. These two events exemplify that forecasting can be strikingly difficult. As such, a limitation of our thesis lies in the inherently difficult approach of forecasting "Black Swans".

However, we believe that our approach somewhat copes with this limitation. Our model resembles a simple heuristic that only says something regarding the probability of a recession in the next months by using the markets' expectations implicit in the yield curve. This is our main motivation of not trying to predict GDP growth, but instead the probability of an economic slowdown. It is our belief that using heuristics-like indicators is more advantageous as recessions are highly difficult to predict. The way to predict highly complex events is not to build complex models, as the complexity of the event makes it near impossible to formalize specifically.

A problem connected to building statistical models that estimates the probability of a certain event occurring in the future is the problem of induction. The problem of induction is referring to the philosophical question of whether inductive reasoning leads to knowledge about the matter at hand. A typical example of inductive reasoning is to observe that a farmer feeds and cares for his domestic animals and induce from this that he is their friend. Thus, one infers a new claim based on a series of observations. The problem of induction arises when one day the farmer slaughters the animals, thus proving that he is not the domestic animals' friend. David Hume (1748), describes the problem and argues that one cannot determine that it is more probable that an induction is true even after a new positive observation. Bertrand Russell (1912) also discusses the problem, with Nassim Nicholas Taleb (2012) applying the same euphemism with the turkey believing that the farmer is his friend. The problem has received attention from financial researchers as well, with Eugene Fama noting: *"In an uncertain world, no amount of empirical testing is sufficient to establish the validity of a hypothesis beyond any shadow of doubt"* (Fama, 1965, p. 78). As such, we point to the fact that even though we may observe that our model is able to predict recessions, we cannot induce that an inverted yield curve necessarily precedes recessions.

Another problem that needs to be addressed is a frequent problem when working with economic and financial data. This type of data is often revised from its first estimate, and recurrently revised significantly. Diebold and Rudebusch (1991) discusses this problem in their paper on the forecasting ability of the Composite Leading Index (CLI). In the US, they include the interest spread as one part of this index, and they argue that the revisions: *"…suggests the possibility that the good performance of the CLI in previous forecasting exercises may be spurious, in the sense that the CLI data actually available in real time were substantially less helpful in forecasting changes in real activity than the evaluations that use final CLI data suggest"* (Diebold and Rudebusch, 1991, p. 603). They cope with this problem by analyzing the forecasting performance of the CLI by applying real time data. However, this would be hard to do as we only have access to the revised data when we collect historical data. Additionally, if we were to use real time data, it would limit the comparability of our study. As such, we choose instead to be aware of this limitation of our paper.

5.0 Methodology and data

5.1 Methodology

This paper sets out to test if the inclusion of the interest rate spread in the OECD's CLI is righteous. The interest rate spread is included in the index of leading indicators for Austria, Canada, Finland, Germany, Japan, Korea, South Africa and the United States. As discussed in the literature review, there have been several different methods of assessing the relationship between the yield curve and recessions. We have chosen to apply a probit model that uses the binary recession indicator we discussed earlier as the dependent variable. As such, our focus is on predicting when a recession is imminent. This implies that we will not address the magnitude of the GDP contraction, we will only address the likelihood of it happening within our forecast horizon.

Our baseline model is a simple static probit model. This is model A. Static refers to the fact that it does not include a lagged independent variable to control for a possible autocorrelation structure in the dependent variable. The autocorrelation structure could exist if there is a higher probability of a recession in the next period if there is currently a recession. However, we want to first use the static model as a baseline model. We specify our model as Dueker (1997):

$$\Pr(R_t = 1) = \varphi(\beta_0 + \beta_1 Spread_{t-k})$$

R_t is the recession indicator where $R = \begin{cases} 1, if\ the\ economy\ is\ in\ a\ recession \\ 0, else \end{cases}$.

φ is the cumulative standard normal density function while $Spread_{t-k}$ refers to the yield spread between 10-year treasury bonds and 3-months treasury bills in period t-k, where k refers to the forecast horizon.

In probit models our interest lies in modelling the probabilities of observing each possible outcome given the explanatory variables. For our thesis, this means that we are modelling the probability of a recession given the yield spread. The log-likelihood function for our probit model can be written:

$$L = \sum_t R_t\, lnPr(R_t = 1|Spread_{t-k}) + (1 - R_t) lnPr(R_t = 0|Spread_{t-k})$$

The log-likelihood function is solved by applying maximum likelihood estimation (MLE). MLE works by maximizing this likelihood function.

In standard linear regression models, one usually evaluates the fit of the model by computing the R^2. The interpretation of this measure of fit is that a high R^2 indicates that the variation in the model describes much of the variation of the dependent variable. For probit models, derivation of R^2 is impossible as MLE is not based on sum of squared residuals. Instead, we will use McFadden's (1973) pseudo-R^2. The measure is based on the estimated likelihood of unconstrained and constrained models, and is defined as:

$$McFadden's\ Pseudo - R^2 = 1 - \frac{\log \hat{L}_U}{\log \hat{L}_R}$$

Because we are dealing with a binary variable, we know that the likelihood is always between zero and one. When the model is well fitted, $\hat{L}_U$ is close to one, so $\log \hat{L}_U$ will be close to zero. Thus, the pseudo-R^2 will be close to one. For a poorly fitted model, $\hat{L}_U$ is close to $\hat{L}_R$, so the pseudo-R^2 will be close to zero. In other words, the interpretation of McFadden's pseudo-R^2 resembles the interpretation of R^2 in the linear regression model case.

Estrella (1995) proposed a slightly different pseudo-R^2 to measure the fit of probit models. Several of the most cited research papers within our field of study applies this measure of fit, among others Dueker (1997). The definition of Estrella's pseudo-R^2 is:

$$Estrella's\ pseudo - R^2 = 1 - (\frac{\log L_U}{\log L_R})^{-(\frac{2}{n})L_C}$$

As one can see, it is similar to McFadden's measure of fit for probit models. The data analysis in this thesis is done in MatLab, and as McFadden's pseudo-R^2 is a part of the LeSage toolbox we have applied, we have chosen to use McFadden's R^2 as the measure of fit for our models. As the interpretation of the two slightly different measures is the same, this choice will not severely affect the comparability of our study to the previous ones.

There is a need to inflate the T-statistics obtained through our regressions to account for heteroscedasticity and autocorrelation due to the issue of overlapping data. Our data overlaps as we use data with a k-month horizon, where k is between six and 18, and we do it every month. As such, the six-month forecast in January is using data from July to December the previous year. The same forecast for February is using data from August to January. Thus, we see that we must deal with the issue of overlapping data.

As Dueker (1997) and most of the other papers, we will test our model on different forecast horizons. Dueker (1997) and Estrella and Mishkin (1995) test several different variables and find that the yield curve becomes the dominant predictor of recessions at horizons beyond three months. Dueker (1997) finds that the nine-month lagged yield curve slope is the best predictor, while Estrella and Mishkin (1995) find that 12-month lagged yield curve is superior. The average duration of recessions in our sample is 22 months. Due to this and the findings of previous papers, we have decided to use 6-, 12- and 18-months as our forecast horizons.

We further develop our model by adding a lagged variable of the dependent variable. We use the notation of a dynamic probit model and specify the model as Dueker (1997):

$$\Pr(R_t = 1) = \varphi(\beta_0 + \beta_1 Spread_{t-k} + \beta_2 R_{t-k})$$

The lagged recession variable is added as time series regression is likely to violate the independent and identically distributed error term-assumption (iid-assumption) of the probit model. This is due to the serial correlation in the error terms. The proposed solution by Dueker which we follow here is to condition explicitly on the lagged dependent variable R_{t-k} and as such remove serial correlation in the error terms. This procedure is the probit equivalent of adding lags of the dependent variable in a linear regression model, such as one would do in an AR(p)-model.

One known problem with regressions and probit models is the risk of overfitting the model. As McFadden's pseudo-R^2 does not penalize extra variables, one would always get better fit by adding new variables. To adjust for this, we want to perform both in-sample and pseudo out-of-sample analyses of our two models. Comparing the in- and pseudo out-of-sample fit are beneficial as adding additional variables frequently decrease the out-of-sample performance of the model. Additionally, by testing the model both in- and out-of-sample, we get to see if a model based on data including the Great Recession can be used to predict recessions in this decade.

Due to data availability, our in-sample period varies across the countries in our sample. For the US, we follow Wright (2006), Fama and Bliss (1987), Ang, Piazzesi, and Wei (2006) and start our in-sample period in 1964. The rationale behind the start date is according to Wright (2006, p. 5): *"…data on long-term yields before 1964 may be unreliable because at that time there were very few long maturity bonds that did not have prices distorted by being either callable or "flower bonds"* (redeemable at par in payment of estate taxes)". The out-of-sample period is from the beginning of 2010 until the beginning of 2018.

We will compare McFadden's pseudo-R^2 for the two sub samples, and for the pseudo out-of-sample period we will also compute the root mean square forecast error (RMSFE). A good model will have a low value of RMSFE. Lastly, we will evaluate the number of type 1 and type 2 errors of the model. Type 1 errors is often referred to as a "false positive", which in our setting translates to that the model predicts a recession that do not occur in the next k periods. Type 2 errors on the other hand is often referred to as "false negatives" and means that the model does not predict a recession that happens.

Post the analysis of in- and pseudo out-of-sample forecasts, we run the model for different time periods. Each window translates to a decade, such that we analyse the yield curve's predictive abilities in each decade of our sample. Our data does not always start at the beginning of a decade, such that for some countries, one of the windows will be shorter than the others. This analysis is performed to research the question of whether the yield curve's predictive abilities has deteriorated or not. We will report the same measures as discussed above for each of the time-windows.

5.2 Data

This paper applies data on the eight countries where OECD use the interest rate spread as one of the components in the CLI. These countries are Austria, Canada, Finland, Germany, Japan, Korea, South Africa and the United States. The data was collected from the Federal Reserve Bank of St. Louis (FRED) during May 2018. The different data series include 10-year government bonds, 3-month Treasury bills and OECD's recession indicator. The recession indicator is a binary time series. The frequency of our data is monthly. There are a limited number of recessions to be studied. The US for example, has had eleven OECD defined recessions since 1964. This limits the basis of our model.

Country	Type of spread	Recession data	Period	Frequency	Source
Austria	10y gvt. bond vs 3m/90d interbank rate	OECD based Recession Indicators from the period following the Peak through the Trough	1990-2018	Monthly	FRED
Canada	10y gvt. bond vs 3m/90d interbank rate	OECD based Recession Indicators from the period following the Peak through the Trough	1964-2018	Monthly	FRED
Finland	10y gvt. bond vs 3m/90d	OECD based Recession Indicators from the period	1988-2018	Monthly	FRED

	interbank rate	following the Peak through the Trough			
Germany	10y gvt. bond vs 3m/90d interbank rate	OECD based Recession Indicators from the period following the Peak through the Trough	1964-2018	Monthly	FRED
Japan	10y gvt. bond vs 3m/90d interbank rate	OECD based Recession Indicators from the period following the Peak through the Trough	2002-2018	Monthly	FRED
Korea	10y gvt. bond vs 3m/90d cert. of deposit	OECD based Recession Indicators from the period following the Peak through the Trough	2000-2018	Monthly	FRED
South Africa	10y gvt. bond vs 3m/90d interbank rate	OECD based Recession Indicators from the period following the Peak through the Trough	1981-2018	Monthly	FRED
United States	10y gvt. bond vs 3m bill	OECD based Recession Indicators from the period following the Peak through the Trough	1964-2018	Monthly	FRED

Table 1: Description of data

Estrella and Mishkin (1998) addressed the predictive powers of other yield spreads, such as the spreads compromised by using the 1-year or 10-year Government Bond spreads as the long-term interest rate and 3-month or 6-month Treasury Bills as the short-term interest rate. They found that the yield spread of the 10-year Government Bonds and the 3-month Treasury Bills performed best out-of-sample forecasts. Dueker (1997) applied the spread between 30-year rates and three-months rates but notes that studies needing internationally comparable data can take the spread between the 10-year and the three-month rates. Plus, as Knez et al. (1994) suggests, using several rates would not capture much additional information. The use of one rate would also minimize the data snooping problem as discussed by Lo and MacKinlay (1990). As such, we limit our research to the spread between 10-year government bond rates and three-month treasury rates.

6.0 Results

6.1 Discussion of results from different forecast horizons

Looking at Table 2 below, we see the pseudo-R^2 and log-likelihood values from our dynamic model. Generally, we observe that the model with six-month forecast horizon is the superior model. This is not the case for Japan, but as we will discuss later, the model with six-month horizon did not have any significant variables for Japan. These findings indicate that recessions are harder to forecast the longer the period you try to forecast for. To us, this is natural as time brings forth uncertainty. We thus recommend that it is the six-month forecast horizon which should be used as a leading indicator of recessions.

Forecast horizons	**6 months**	**12 months**	**18 months**
Austria	.265 (-111.5)	.025 (-148.0)	.040 (-145.7)
Canada	.280 (-259.4)	.081 (-330.7)	.081 (-331.0)
Finland	.327 (-113.8)	.058 (-159.2)	.046 (-161.2)
Germany	.331 (-265.1)	.114 (-351.4)	.104 (-354.2)
Japan	.086 (-42.6)	.263 (-34.4)	.327 (-31.4)
Korea	.181 (-53.2)	.002 (-64.9)	0.071 (-60.3)

South Africa	.372 (-143.9)	.112 (-203.3)	.034 (-221.2)
United States	.341 (-238.8)	.126 (-316.7)	.152 (-307.1)

Table 2: Pseudo-R^2 and log-likelihood from the dynamic model (Model B)

6.2 The significance of the interest rate spread

Following the discussion in the previous section, we will now discuss the results from the dynamic model with a six-month forecast horizon. As the tables in Exhibit 2 in the Appendix displays, we observe that the interest rate spread is statistically significant for Canada, Finland, Germany, South Africa and the United States. The p-values indicate that the statistical significance for these countries are high. Our results resemble the results in Gerlach and Bernard (1998) where they find that the domestic spread is significant for among others Canada, Germany and the United States. However, we do not find proof of significance for Japan as they do. An explanation of this could be that we have different sample periods. Our results are also equal to the ones of Khomo and Aziakpono (2007) where they find that Dueker’s (1997) dynamic model can predict South African recessions. As we do not observe that the yield is significant for Austria, Japan and Korea, we believe that OECD should revise the inclusion of the spread in their leading indicator index for these three countries.

6.3 The ability of the yield curve to correctly signal the beginning of recessions

Figure 3 displays the probability of recessions we obtain from our dynamic model with a six-month forecast horizon for the United States. The probability at a certain date is the predictions of the recessionary state of that date, based on information that was available six months earlier. Recession probabilities from the static and dynamic model for the rest of the countries in our study can be found in Exhibit 6 in the Appendix.

Primo, we observe that our model has its peaks during recessions. Hence, our model can capture information that coincides with recessions. However, we also observe that our model does not have a forecasted probability of recession above

50 percent prior to any of the recessions in our sample. If we turn to the results of Dueker (1997), we observe the same pattern except for in the 1978-1982 recession. In Exhibit 5 in the Appendix we find one plausible reason for the lacking ability of forecasting more than 50% probability of recession preceding the recession. The table in this exhibit demonstrates that OECD's recession indicator is more sensitive than NBER's, which is the one used in Dueker (1997), Wright (2006) and several others. Our model seems to better capture the severity, as measured by looking at how close to 100% probability the model displays, than both Dueker (1997) and Estrella and Mishkin (1997).

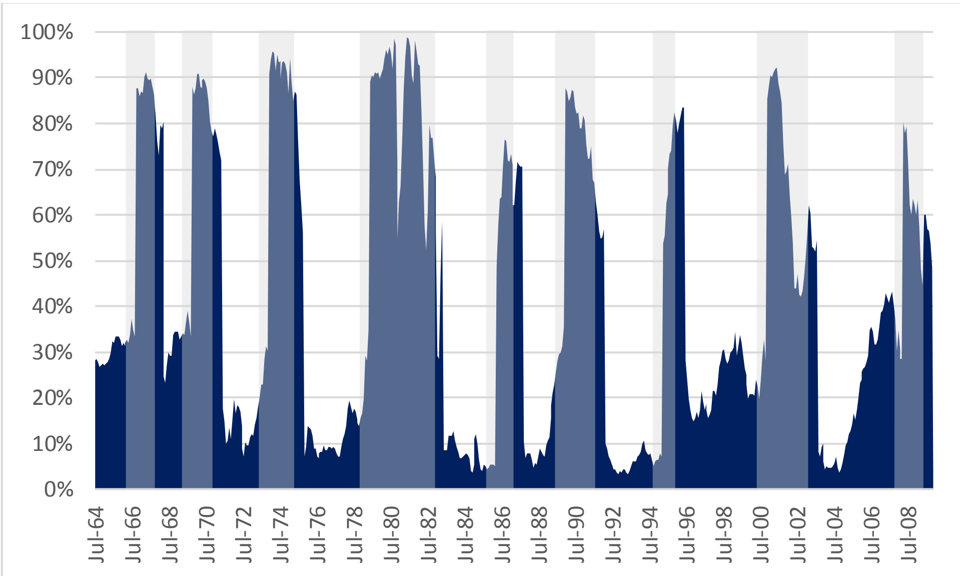

Figure 3: Recession probabilities and recessions (shaded areas) for the US

6.4 Out-of-sample performance

Table 3 displays the RMSFE of the models with different forecast horizons for all countries in our sample. If we compare these values to Wright (2006), we observe that our models generally perform worse out-of-sample than Wright's. One can also see the same pattern in the out-of-sample as in the in-sample period; our dynamic model performs worse with longer forecast horizons. The poor out-of-sample performance implicates that a change has occurred such that models based on information available before 2010 does not predict recessions post-2010 well. Interestingly, we observe the same pattern in our analysis of the yield curve's predictive abilities over different decades which we now will move on to discuss.

Country	6m	12m	18m
Austria	0.35	0.56	0.75
Canada	0.55	0.64	0.70
Finland	0.36	0.68	0.73
Germany	0.50	0.74	0.68
Japan	0.67	0.67	0.56
Korea	0.56	0.71	0.74
South Africa	0.38	0.54	0.67
United States	0.50	0.59	0.59

Table 3: Root Mean Square Forecast Error

6.5 The relationship between the yield curve and recessions across periods

Maybe the most remarkable finding in this thesis is evident when looking at the tables in Exhibit 3. The tables display which of the different time periods the yield curve is statistically significant at a 5% level for. Japan is the only country where the yield curve can be said to predict recessions in the present decade. The yield curve is statistically insignificant for the rest of the countries when using only data from this decade. This finding indicates that the relationship between the yield curve and recessions has diminished. Additionally, the significance of the yield curve was weakened in the period between 1990-2000. This coincides with the period where the yield curve's predictive abilities received the most attention. As such, consistent with conventional wisdom, the relationship cease to exist when it amasses attention.

7.0 Key findings

This thesis has investigated the yield curve's predictive abilities of recessions in the eight OECD-countries where the interest rate spread is included in OECD's leading index. Our results give insight to whether the yield curve should be used as a leading indicator. The main findings from our research are discussed below:

- The yield curve is a significant predictor of recessions for five of the eight countries in our sample. These countries are Canada, Finland, Germany, South Africa and the United States. The statistical significance is high for these countries.

- We do not find a statistical significance at the 5%-level between the yield curve and recessions in Austria, Japan and South Korea. This indicate that OECD should revise the inclusion of the spread in their leading indicator index for these three countries. However, this finding may be due to our sample period and our choice of spread; between the three-month treasury bills and 10-year government bonds.
- Our results indicate that applying a six-month forecast horizon is superior to the 12- or 18-month forecast horizon.
- The inclusion of a recession lag in the model does not deteriorate the significance of the yield spread. This dynamic model performs better than the static model as measured by the McFadden's pseudo-R^2.
- Our model does not forecast a probability of higher than 50% before the onset of recessions. Dueker (1997) struggles with the same problem. This finding indicate that the yield curve does not properly function as a leading indicator. We encourage further research as to whether this problem arises from a sensitive recession definition or not.
- The out-of-sample performance of our model indicate that models built on information before 2010 does not predict recessions post 2010 well. This finding indicates a change in the relationship between the yield curve and recessions.
- This thesis indicates that the yield curve's predictive abilities have diminished over the last couple of decades. Interestingly, this change in the relationship seems to have changed in the period between 1990-2000, which coincides with the period where the relationship amassed attention from researchers and practitioners. The yield curve is not significant as a predictor of recessions after 2010, which suggests that today's flattening of the yield curve may not indicate an upcoming recession.
- We suggest further research which applies different yield spreads and less sensitive recession indicators than the one used in this thesis, OECD's recession indicator.

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Appendix

Exhibit 1 - Model A: The static model

Austria

k	β_0 **(p-value)**	β_1 **(p-value)**	**McFadden's pseudo-R^2**	**% correct predictions**
6	-0.03 (0.00)	-0.16 (0.32)	0.02	67%
12	-0.11 (0.00)	-0.09 (0.65)	0.01	57%
18	-0.11 (0.00)	-0.09 (0.66)	0.01	54%

Canada

k	β_0 **(p-value)**	β_1 **(p-value)**	**McFadden's pseudo-R^2**	**% correct predictions**
6	-0.05 (0.00)	-0.39 (0.00)	0.15	72%
12	-0.11 (0.00)	-0.27 (0.00)	0.08	68%
18	-0.18 (0.00)	-0.14 (0.12)	0.02	61%

Finland

k	β_0 **(p-value)**	β_1 **(p-value)**	**McFadden's pseudo-R^2**	**% correct predictions**
6	0.40 (0.00)	-0.51 (0.00)	0.21	75%
12	0.07 (0.00)	-0.23 (0.10)	0.06	70%
18	-0.02 (0.03)	-0.14 (0.32)	0.02	59%

Germany

k	β_0 (p-value)	β_1 (p-value)	McFadden's pseudo-R^2	% correct predictions
6	0.29 (0.00)	-0.42 (0.00)	0.16	67%
12	0.19 (0.00)	-0.35 (0.01)	0.11	67%
18	0.06 (0.00)	-0.23 (0.00)	0.06	63%

Japan

k	β_0 (p-value)	β_1 (p-value)	McFadden's pseudo-R^2	% correct predictions
6	0.47 (0.06)	-0.95 (0.26)	0.05	66%
12	1.09 (0.01)	-1.56 (0.04)	0.12	70%
18	1.76 (0.01)	-2.13 (0.04)	0.18	70%

Korea

k	β_0 (p-value)	β_1 (p-value)	McFadden's pseudo-R^2	% correct predictions
6	0.20 (0.00)	-0.29 (0.32)	0.02	53%
12	-0.16 (0.03)	0.09 (0.89)	0.00	62%
18	-0.31 (0.08)	0.25 (0.64)	0.01	61%

South Africa

k	$\boldsymbol{\beta_0}$ (p-value)	$\boldsymbol{\beta_1}$ (p-value)	McFadden's pseudo-$\boldsymbol{R^2}$	% correct predictions
6	0.15 (0.00)	-0.30 (0.00)	0.21	76%
12	0.09 (0.00)	-0.20 (0.00)	0.11	69%
18	-0.01 (0.00)	-0.06 (0.40)	0.11	56%

United States

k	$\boldsymbol{\beta_0}$ (p-value)	$\boldsymbol{\beta_1}$ (p-value)	McFadden's pseudo-$\boldsymbol{R^2}$	% correct predictions
6	0.42 (0.00)	-0.46 (0.00)	0.14	70%
12	0.37 (0.00)	-0.43 (0.00)	0.12	69%
18	0.21 (0.00)	-0.32 (0.00)	0.07	69%

Exhibit 2 - Model B: The dynamic model

Austria

k	$\boldsymbol{\beta_0}$ (p-value)	$\boldsymbol{\beta_1}$ (p-value)	$\boldsymbol{\beta_2}$ (p-value)	McFadden's pseudo-$\boldsymbol{R^2}$	% correct predictions
6	-0.69 (0.01)	-0.21 (0.24)	1.60 (0.00)	0.27	78%
12	-0.29 (0.01)	-0.08 (0.67)	0.43 (0.28)	0.03	57%
18	0.09 (0.02)	-0.08 (0.65)	-0.58 (0.21)	0.20	67%

Canada

k	β_0 (p-value)	β_1 (p-value)	β_2 (p-value)	McFadden's pseudo-R^2	% correct predictions
6	-0.59	-0.35	1.22	0.28	78%
	(0.00)	(0.02)	(0.00)		
12	-0.02	-0.29	-0.21	0.08	67%
	(0.00)	(0.00)	(0.43)		
18	0.15	-0.22	-0.80	0.08	69%
	(0.00)	(0.04)	(0.00)		

Finland

k	β_0 (p-value)	β_1 (p-value)	β_2 (p-value)	McFadden's pseudo-R^2	% correct predictions
6	-0.20	-0.44	1.16	0.33	81%
	(0.00)	(0.00)	(0.00)		
12	0.10	-0.23	-0.06	0.06	68%
	(0.01)	(0.08)	(0.92)		
18	0.24	-0.20	-0.51	0.05	60%
	(0.02)	(0.14)	(0.17)		

Germany

k	β_0 (p-value)	β_1 (p-value)	β_2 (p-value)	McFadden's pseudo-R^2	% correct predictions
6	-0.42	-0.38	1.41	0.33	79%
	(0.00)	(0.01)	(0.00)		
12	0.15	-0.34	0.08	0.11	66%
	(0.00)	(0.01)	(0.80)		
18	0.45	-0.31	-0.73	0.10	66%
	(0.00)	(0.02)	(0.01)		

Japan

k	β_0 (p-value)	β_1 (p-value)	β_2 (p-value)	McFadden's pseudo-R^2	% correct predictions
6	0.13	-0.81	0.59	0.09	71%

	(0.12)	(0.33)	(0.23)		
12	2.33	-2.46	-1.76	0.26	78%
	(0.00)	(0.01)	(0.04)		
18	2.59	-2.71	-5.83	0.33	78%
	(0.00)	(0.03)	(0.13)		

Korea

k	$\boldsymbol{\beta_0}$ **(p-value)**	$\boldsymbol{\beta_1}$ **(p-value)**	$\boldsymbol{\beta_2}$ **(p-value)**	**McFadden's pseudo-R^2**	**% correct predictions**
6	-0.61	-0.08	1.28	0.18	74%
	(0.15)	(0.81)	(0.01)		
12	-0.17	0.09	0.02	0.00	61%
	(0.11)	(0.84)	(0.97)		
18	0.14	0.12	-0.75	0.07	65%
	(0.01)	(0.81)	(0.14)		

South Africa

k	$\boldsymbol{\beta_0}$ **(p-value)**	$\boldsymbol{\beta_1}$ **(p-value)**	$\boldsymbol{\beta_2}$ **(p-value)**	**McFadden's pseudo-R^2**	**% correct predictions**
6	-0.63	-0.21	1.42	0.37	83%
	(0.00)	(0.00)	(0.00)		
12	-0.02	-0.18	0.19	0.11	67%
	(0.00)	(0.01)	(0.56)		
18	0.27	-0.10	-0.51	0.03	54%
	(0.00)	(0.15)	(0.21)		

United States

k	$\boldsymbol{\beta_0}$ **(p-value)**	$\boldsymbol{\beta_1}$ **(p-value)**	$\boldsymbol{\beta_2}$ **(p-value)**	**McFadden's pseudo-R^2**	**% correct predictions**
6	-0.32	-0.40	1.53	0.34	79%
	(0.00)	(0.00)	(0.00)		
12	0.26	-0.41	0.20	0.13	70%
	(0.00)	(0.00)	(0.47)		

18	0.79 (0.00)	-0.47 (0.00)	-1.01 (0.00)	0.15	68%

Exhibit 3 – Testing different time periods

Austria

Period	Intercept	Spread	Recession lag
1990-2000	Not significant	Not significant	Significant
2000-2010	Significant	Significant	Significant
2010-2018	Not significant	Not significant	Significant

Canada

Period	Intercept	Spread	Recession lag
1964-1970	Significant	Not significant	Not significant
1970-1980	Significant	Significant	Not significant
1980-1990	Significant	Significant	Not significant
1990-2000	Significant	Not significant	Significant
2000-2010	Significant	Not significant	Significant
2010-2018	Significant	Not significant	Not significant

Finland

Period	Intercept	Spread	Recession lag
1990-2000	Significant	Significant	Not significant
2000-2010	Significant	Significant	Significant
2010-2018	Not significant	Not significant	Significant

Germany

Period	Intercept	Spread	Recession lag
1960-1970	Not significant	Not significant	Significant
1970-1980	Significant	Significant	Significant
1980-1990	Significant	Significant	Not significant
1990-2000	Significant	Not significant	Not significant
2000-2010	Significant	Significant	Significant

2010-2018	Not significant	Not significant	Significant

Japan

Period	Intercept	Spread	Recession lag
2002-2010	Not significant	Not significant	Not significant
2010-2018	Not significant	Significant	Significant

Korea

Period	Intercept	Spread	Recession lag
2000-2010	Not significant	Not significant	Significant
2010-2018	Not significant	Not significant	Significant

South Africa

Period	Intercept	Spread	Recession lag
1981-1990	Significant	Significant	Not significant
1990-2000	Not significant	Not significant	Significant
2000-2010	Not significant	Not significant	Not significant
2010-2018	Not significant	Not significant	Not significant

United States

Period	Intercept	Spread	Recession lag
1964-1970	Significant	Significant	Significant
1970-1980	Significant	Significant	Not significant
1980-1990	Significant	Significant	Significant
1990-2000	Significant	Not significant	Significant
2000-2010	Significant	Significant	Significant
2010-2018	Not significant	Not significant	Not significant

Exhibit 4 - Periods with significant spread

Period	**Spread significant**
1960-1970	1/3 (United States)

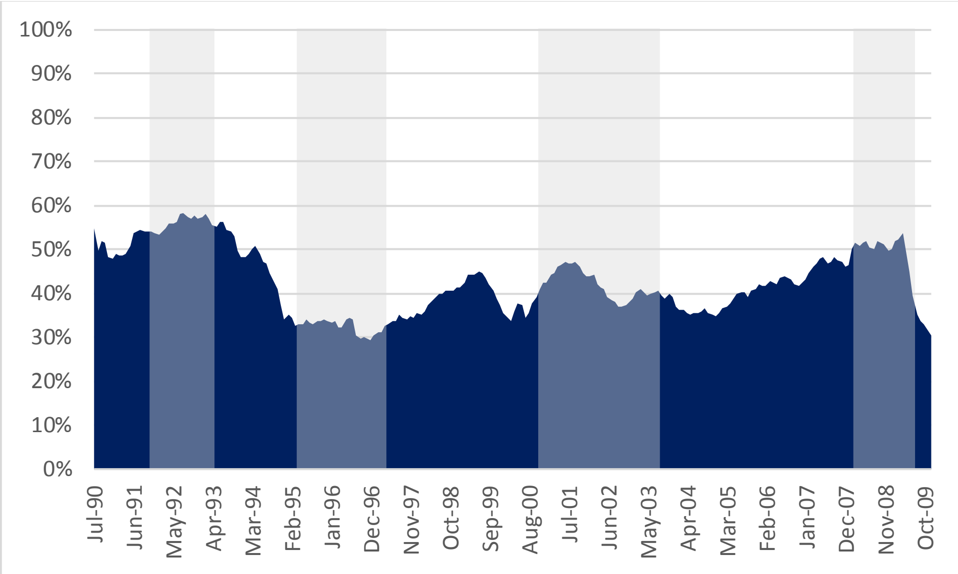
1970-1980	3/3 (Canada, Germany, United States)
1980-1990	4/4 (Canada, Germany, South Africa, United States)
1990-2000	1/6 (Finland)
2000-2010	4/8 (Austria, Finland, Germany, United States)
2010-2018	1/8 (Japan)

Exhibit 5 - Different definitions of recessions

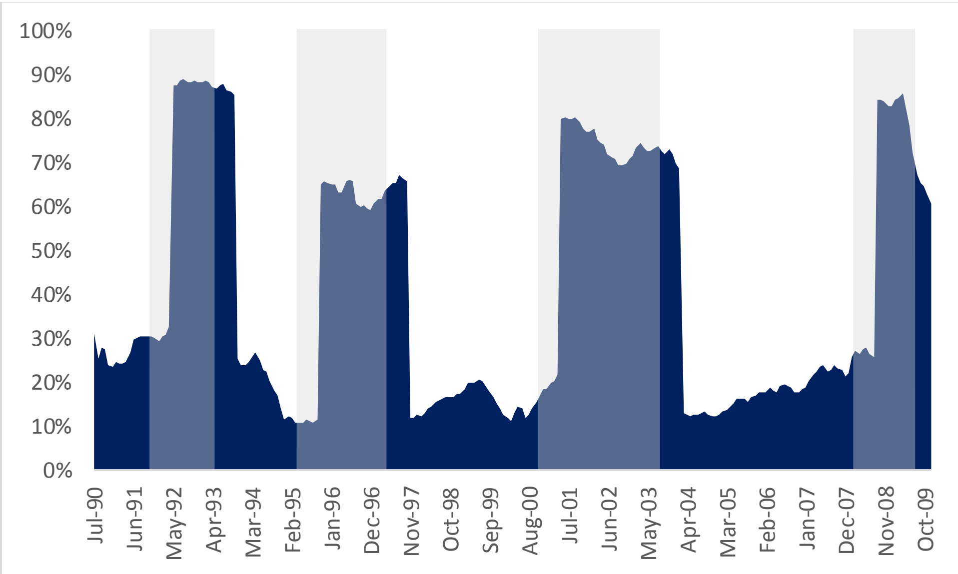
OECD recessions	NBER recessions
April 1966 – September 1967	January 1970 – November 1970
April 1969 – November 1970	December 1973 – March 1975
June 1973 – April 1975	February 1980 – July 1980
December 1978 – November 1982	August 1981 – November 1982
October 1985 – March 1987	August 1990 – March 1991
July 1989 – August 1991	April 2001 – November 2001
October 1994 – December 1995	January 2008 – June 2009
June 2000 – February 2003	
November 2007 – May 2009	
May 2012 – April 2013	
May 2015 – February 2017	

Exhibit 6 – Probability of recessions, six month forecast horizon

Austria

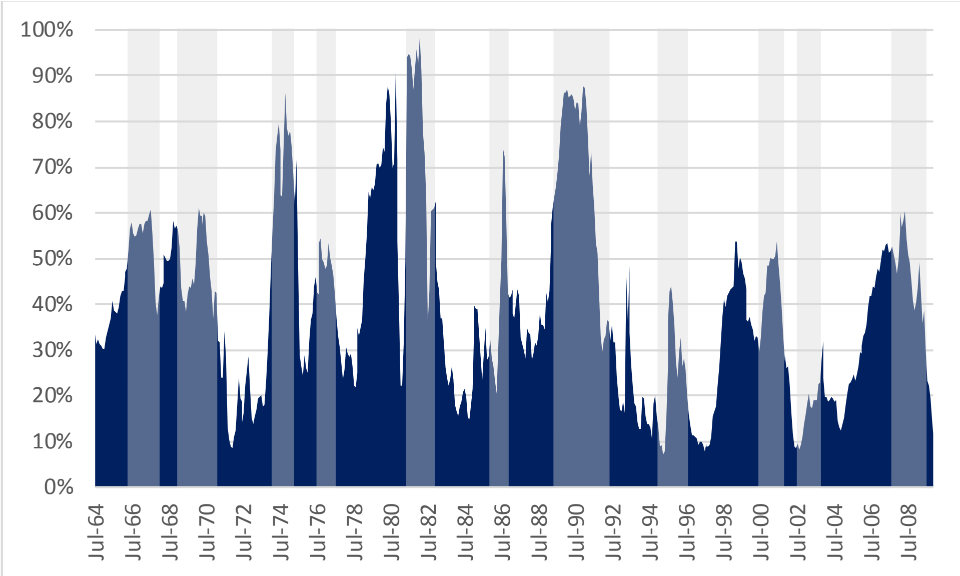


Austria: Static model

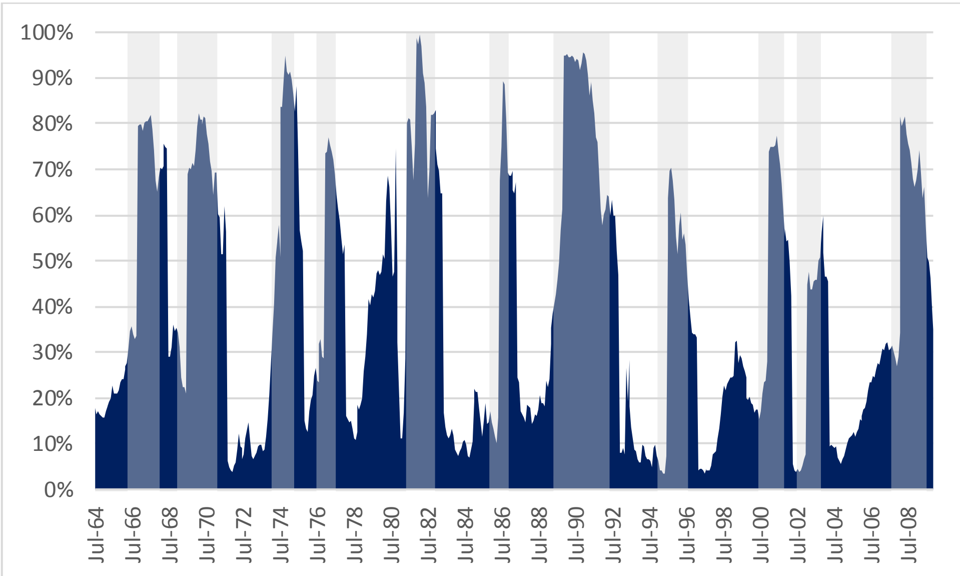


Austria: Dynamic model

Canada

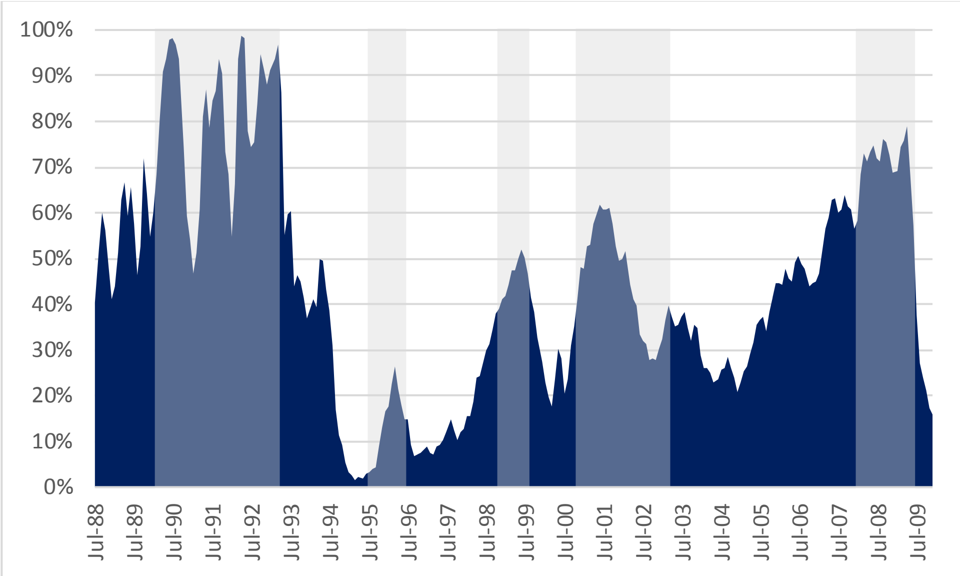


Canada: Static model

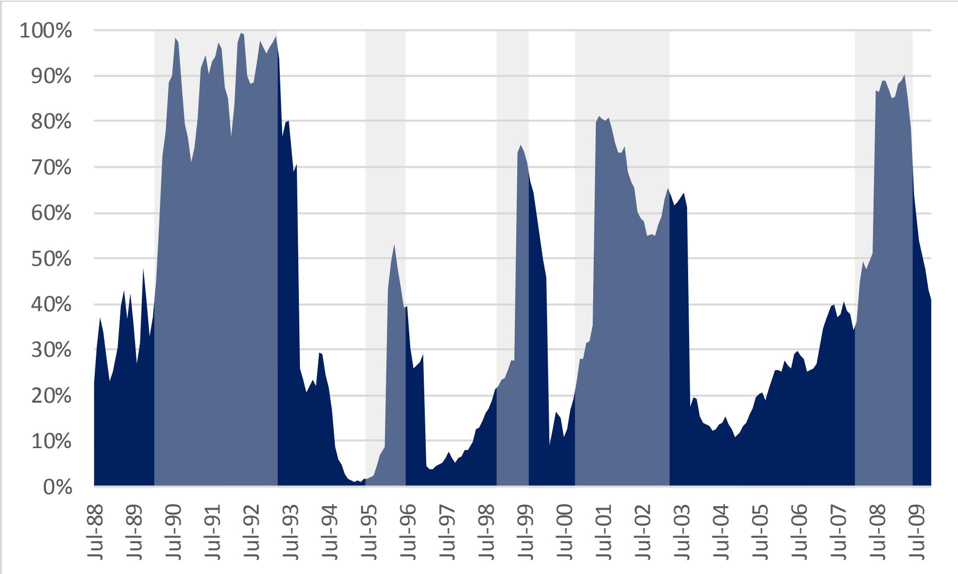


Canada: Dynamic model

Finland

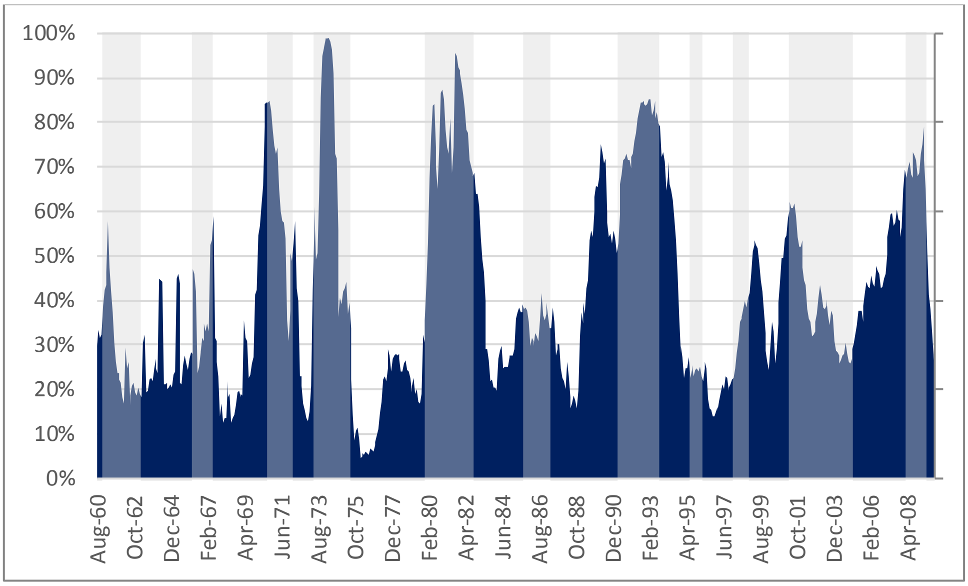


Finland: Static model

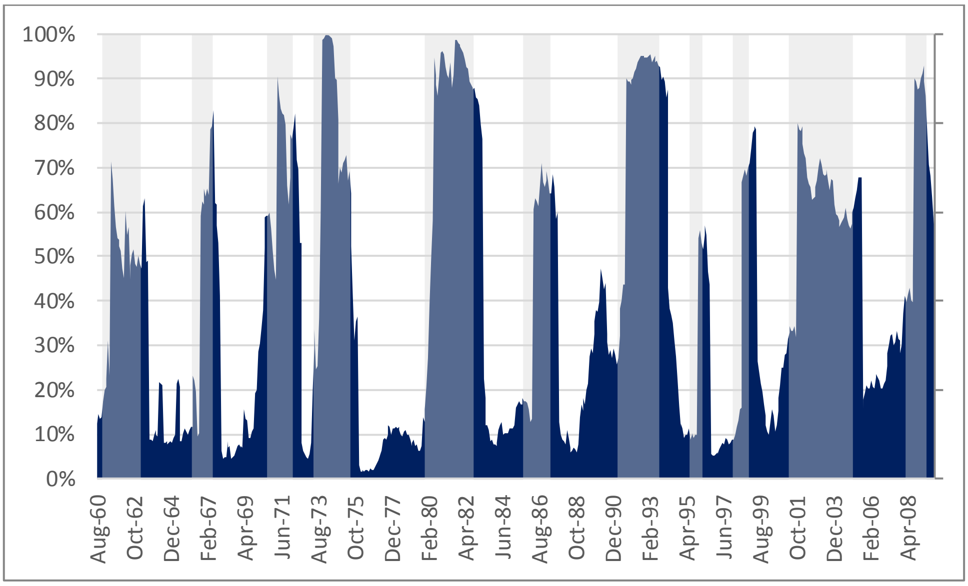


Finland: Dynamic model

Germany

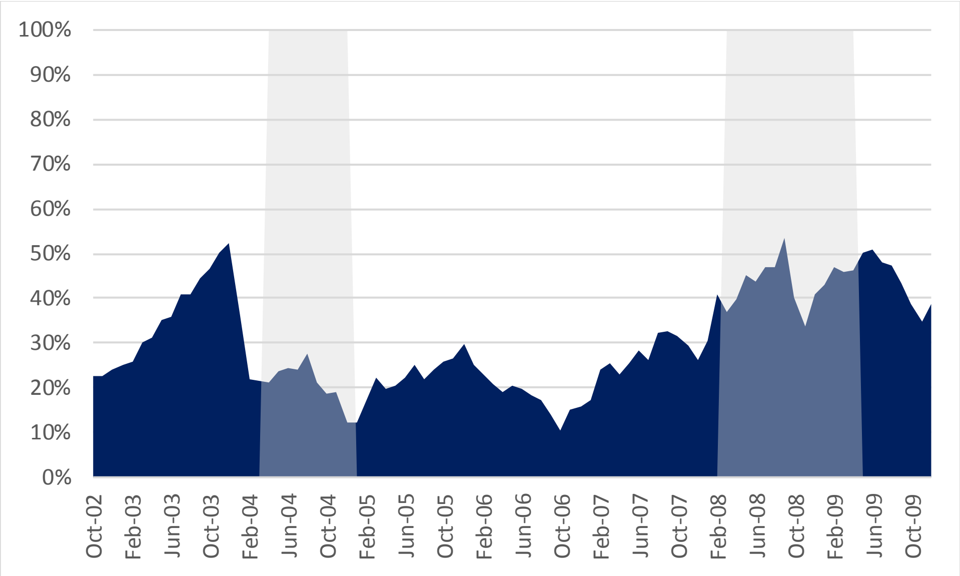


Germany: Static model

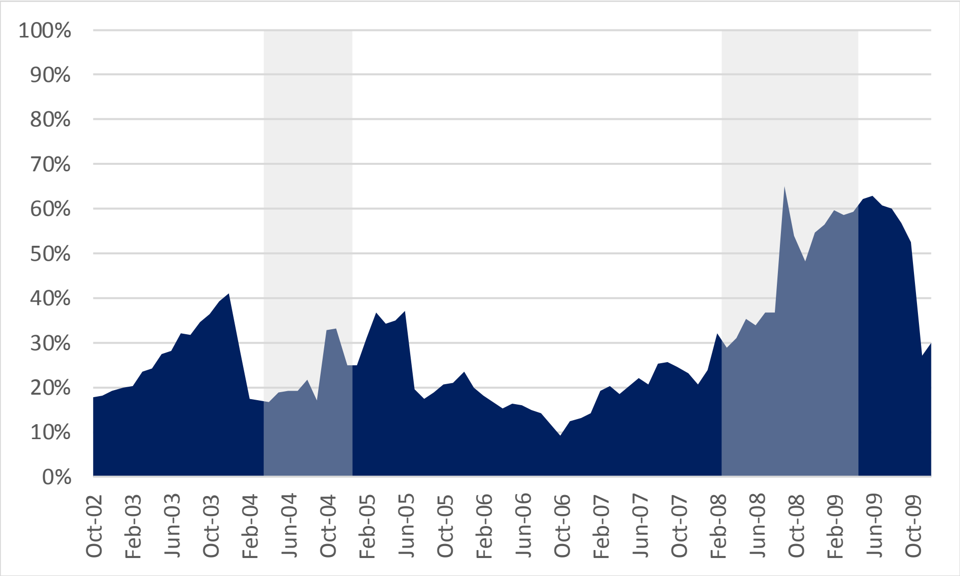


Germany: Dynamic model

Japan

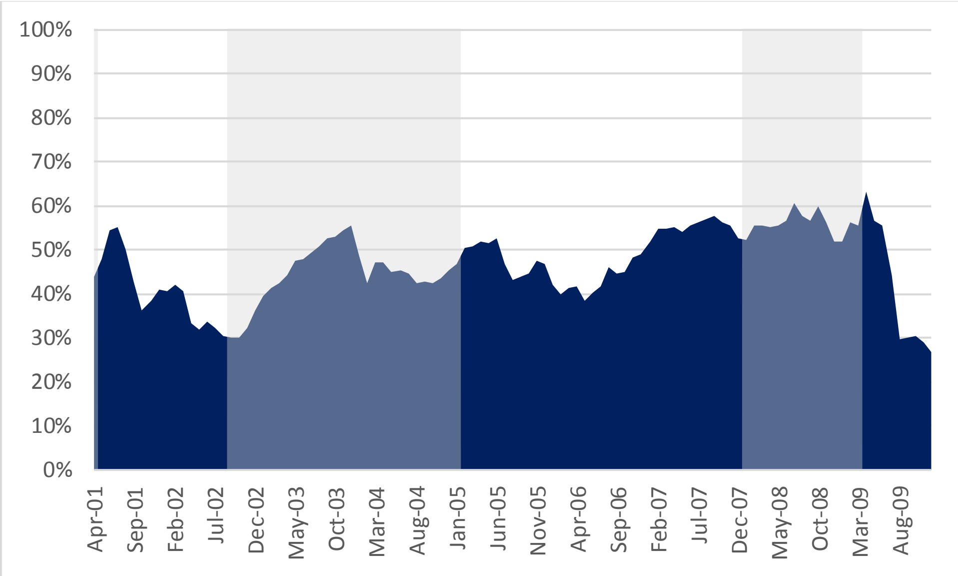


Japan: Static model

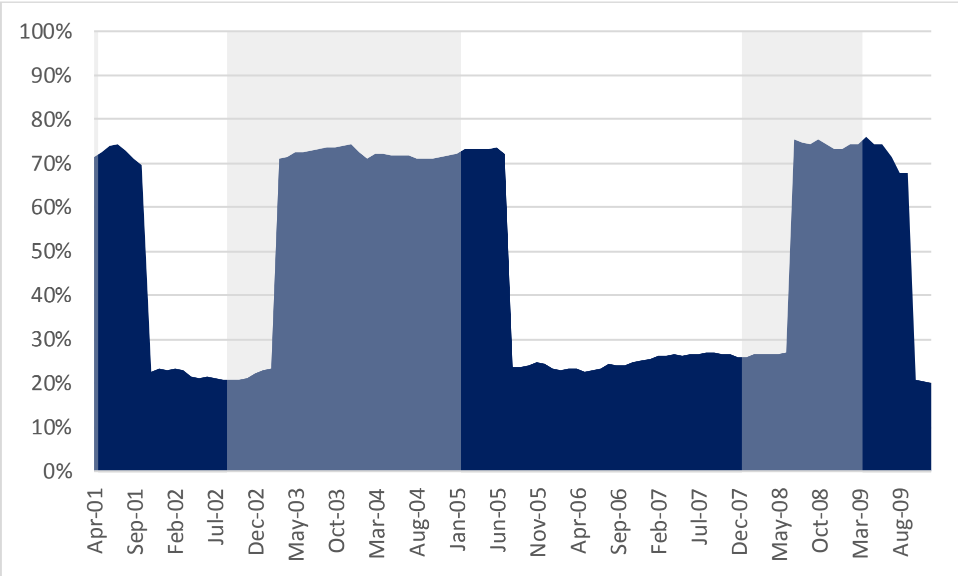


Japan: Dynamic model

Korea

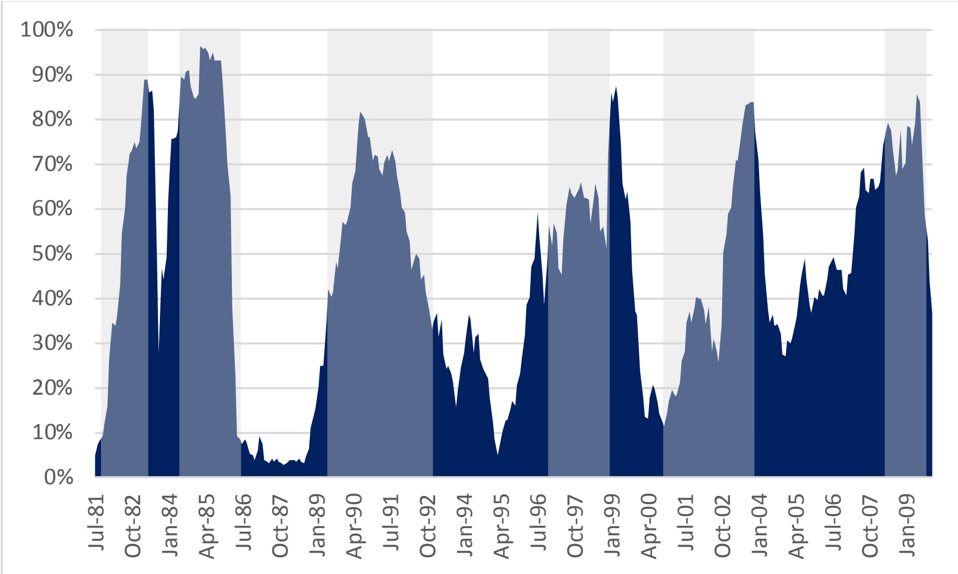


Korea: Static model

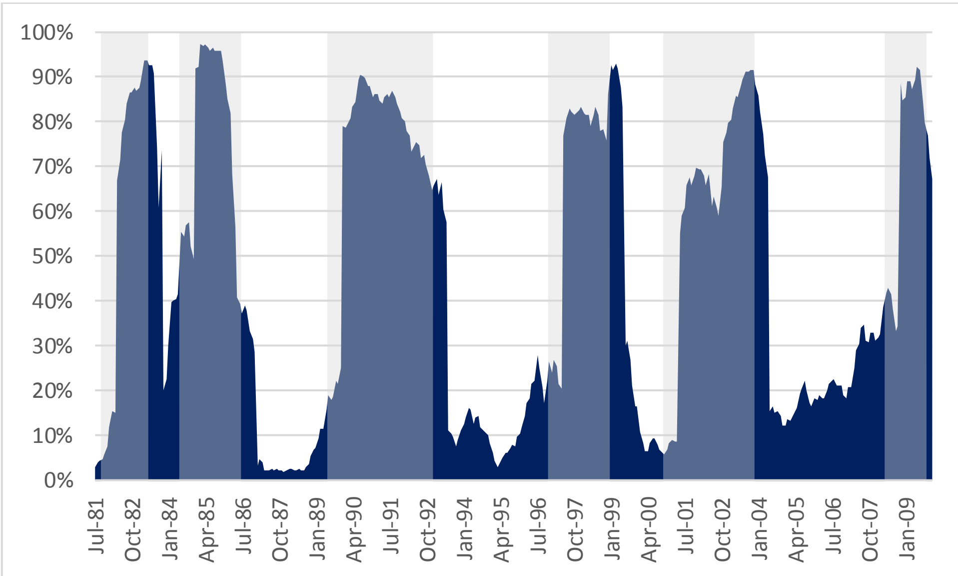


Korea: Dynamic model

South Africa

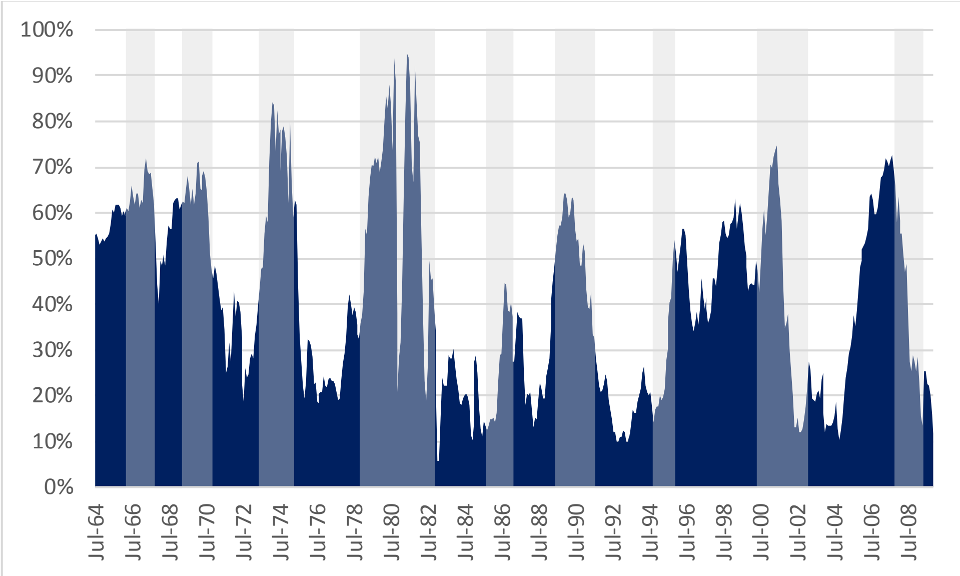


South Africa: Static model

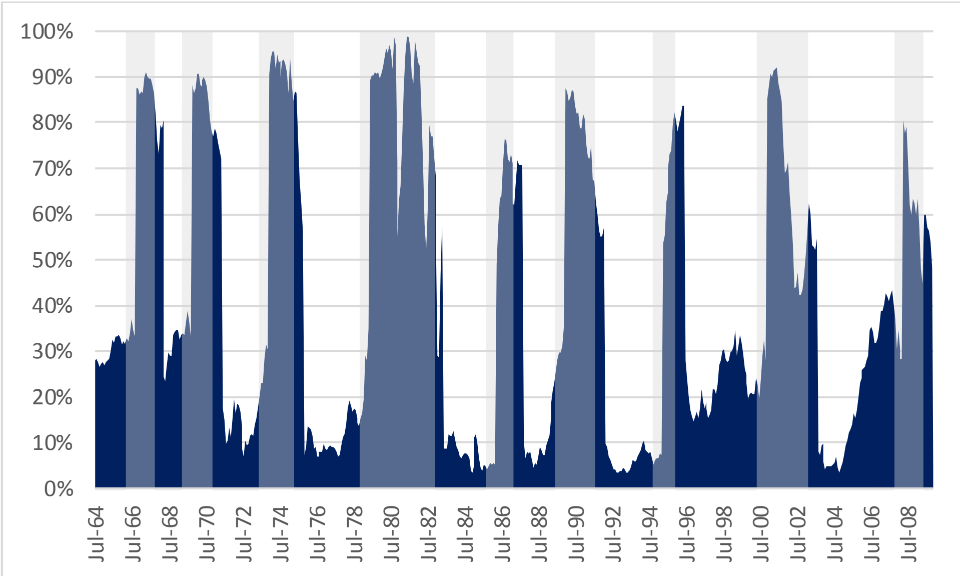


South Africa: Dynamic model

United States



United States: Static model



United States: Dynamic model

Exhibit 7 – Marginal effects at different horizons

This exhibit reports the marginal effects of the interest rate spread, i.e. yield curve, and the recession lag variable for Model B. The interpretation of the marginal effect is similar to the interpretation of the coefficients in the ordinary linear regression model. If the interest rate spread changes one percentage point, then the marginal effect of the spread displays how much the probability of a recession changes. The marginal effect of the recession lag is the change in the probability of a recession if the economy is already in a recession.

Six-month forecast horizon

Please notice that the interest rate spread is not significant for Austria, Japan and Korea. The recession lag is not significant for Japan. The marginal effects for these countries might be spurious.

Country	Interest rate spread	Recession lag
Austria	-0.05	0.41
Canada	-0.10	0.35
Finland	-0.13	0.36
Germany	-0.09	0.35
Japan	-0.23	0.17
Korea	-0.03	0.40
South Africa	-0.06	0.41
United States	-0.10	0.39

12-month forecast horizon

Please notice that the interest rate spread is not significant for Austria, Finland and Korea. The recession lag is only significant for Japan. The statistical insignificant results may be spurious.

Country	Interest rate spread	Recession lag
Austria	-0.03	0.16
Canada	-0.11	-0.08
Finland	-0.09	-0.02
Germany	-0.13	0.03
Japan	-0.85	-0.60
Korea	0.04	0.01
South Africa	-0.07	0.08
United States	-0.15	0.08

18-month forecast horizon

Please notice that the interest rate spread is not significant for Austria, Finland, Korea and South Africa. The recession lag is only significant for Canada, Germany and the United States. The statistical insignificant results may be spurious.

Country	Interest rate spread	Recession lag
Austria	-0.03	-0.23
Canada	-0.09	-0.32
Finland	-0.08	-0.21
Germany	-0.12	-0.29
Japan	-0.87	-1.87
Korea	0.05	-0.29
South Africa	-0.04	-0.20
United States	-0.18	-0.40

Exhibit 8 – Pseudo-R^2 and log-likelihood values at different horizons for the static model

Forecast horizons	6 months	12 months	18 months
Austria	.017 (-149.2)	.005 (-151.3)	.005 (-151.3)
Canada	.146 (-307.4)	.077 (-332.3)	.023 (-351.7)
Finland	.213 (-133.0)	.058 (-159.2)	.022 (-165.2)
Germany	.156 (-334.5)	.113 (-351.6)	.056 (-373.2)
Japan	.053 (-44.1)	.125 (-40.8)	.180 (-38.2)
Korea	.023 (-63.5)	.002 (-64.9)	0.013 (-64.1)
South Africa	.215 (-179.8)	.109 (-204.1)	.012 (-226.4)
United States	.138 (-312.4)	.122 (-318.1)	.070 (-336.9)

Exhibit 9 – Root Mean Square Forecast Error

Country	6m	12m	18m

Austria	0.35	0.56	0.75
Canada	0.55	0.64	
Finland	0.36	0.68	0.73
Germany	0.50	0.74	0.68
Japan	0.67	0.67	0.56
Korea	0.56	0.71	0.74
South Africa	0.38	0.54	0.67
United States	0.50	0.59	0.59

Exhibit 10 – MATLAB code

Below is the MATLAB-code for the 12-month forecast horizon dynamic model for the United States. The code for the different forecast horizons and countries are similar to this code.

```
%============================================================
===============

% Requirements:
%   - LeSage toolbox
%   - Recession indicators all countries dataset
%   - Yield curve
%============================================================
===============


%% Initial setup

clear all;
close all;
clc;

%% Load data

%============================= NOTE:
=============================
% Please do the following:
%   - Set working directory to the same folder as the
dataset is saved in.
============================================================
=====

data = importdata('Interest rates CLI-countries with
interest rate spreads.xlsx');
data2 = importdata('Results and POOS CLI countries.xlsx');
%% Create variables
```

```
Recessions_US = data.data.US(19:553,10);
Recessions_US_actPOOS = data.data.US(554:650,10);
Recessions_US_POOS_6m = data2.data.US(23:120,7);

Spread_US = data.data.US(7:541,7); % The spread has to match
the lagged recession indicator

Lag_US = data.data.US(7:541,10); % The lag of the recession
indicator lags the recession indicator by 12 months i.e. the
forecast period

N = 535; % number of observations
constant = ones(N,1); % a Nx1 vector of 1s, used for probit
regression


%% Probit model

%============================= NOTE:
=============================
% Please download the LeSage toolbox and change the path to
the
% location of the saved toolbox.
%============================================================
======

addpath(genpath('C:\Users\Jan Nylund\Downloads\LeSage
Toolbox'));

% a probit model with Recessions_US as the dependent
variable and the
% spread and the lagged recession indicator as independent
variables
model = probit(Recessions_US, [constant, Spread_US,
Lag_US]);


% finding standard errors
model.NWSE = nwest(model.y,[constant, Spread_US,
Lag_US],12);

model.NWSE.SE = model.beta ./ model.NWSE.tstat

% finding p-values
model.NWSE.pValue = NaN(numel(model.NWSE.beta),1);

for i = 1 : numel(model.NWSE.beta)
    if model.NWSE.tstat(i,1) >= 0
        model.NWSE.pValue(i,1) = 2 * ( 1 -
tcdf(model.NWSE.tstat(i,1),N-numel(model.NWSE.beta)) );
    else
        model.NWSE.pValue(i,1) = 2 *
tcdf(model.NWSE.tstat(i,1),N-numel(model.NWSE.beta));
    end
```

```
end
clear i % deleting counter-variable i

%% Display regression table
model.NWSE.Coefficients = [model.beta, model.NWSE.SE,
model.NWSE.tstat, model.NWSE.pValue; model.lik, NaN, NaN,
NaN];
model.NWSE.Coefficients =
mat2dataset(model.NWSE.Coefficients,...
    'VarNames',{'Estimate','StError','tStat','pValue'},...
    'ObsNames',{'Intercept','Spread','Recession lag','LR'});
format short % makes sure we only get 5 digits in our
answers
display(model.NWSE.Coefficients)


%% Question 2 - marginal effects

% creating input variables
input_Spread = median(Spread_US);
input_Lag = median(Lag_US)

% calculating yhat = x'ÃŸ  for the specifit input variables
marginal_effect_index = [1 input_Spread input_Lag] *
model.beta;

% creating empty matrix for marginal effects
marginal_effect_table = NaN(1,2);

% fill in matrix
for i = 2:numel(model.beta)

    marginal_effect_table(1,i-1) =
normpdf(marginal_effect_index)*model.beta(i,1);

end
clear i % deleting counter-variable i

% create dataset from matrix
marginal_effect_table = mat2dataset(marginal_effect_table,
'VarNames', {'Spread', 'Recession Lag'},...
    'ObsNames', {'Marginal effect'});

% display marginal effect table
display(marginal_effect_table)

%% Question 3 - a) likelihood ratio test

% Using the LeSage toolbox:
display(mat2dataset(model.lratio,'VarNames',{'Lratio'}))

%% Question 3 - b) pseudo-R2

% We obtain the McFadden pseudo-R2 using the LeSage toolbox
```

```
display(mat2dataset(model.r2mf,'VarNames',{'R2mf'}))

%% Question 3 - c) Percentage of correct predictions

% Yhat will be the model's predictions. If Yhat is 0.5 or
above, the model
% predicts Recessions_US to be 1, and if not, 0.
predictions = model.yhat;
    predictions(predictions>=0.5,:) = 1;
    predictions(predictions<0.5,:) = 0;

% We compare the real value of USRecessions and the
predicted value. Since the
% comparisson gives us 1s for correct, and 0s for wrong
predictions, we can
% sum the 1s and divide it by the number of recessions to
get the fraction of
% correct predictions.
fraction_correct_predictions = (sum(Recessions_US ==
predictions))/numel(Recessions_US);

% display result
display(mat2dataset(fraction_correct_predictions,
'VarNames', {'Percentage_correct_predictions'}))


%% Question 4 - a) unconditional probabilities

% The unconditional probabilities is the number of 1s in the
two dependent
% variables over the number of observations (recessions).
I.e. the probability
% of y = 1 if one were to pick randomly a time period.

display(mat2dataset(sum(Recessions_US)/numel(Recessions_US),
'VarNames', {'Unconditional_prob_recessions'}))


%% RMSFE
% Computes the Root Mean Square Forecast Error
pred12m = data2.data.US(23:120,7);
    pred12m(pred12m>=0.5,:) = 1;
    pred12m(pred12m<0.5,:) = 0;

DD_12m = ((Recessions_US_actPOOS(1:97,1) - pred12m(1:97,1))
.^ 2);

POOS12m = sqrt(mean(DD_12m(1:97,1)))

%% Resetting to defaults

% Restore default path for MatLab
Restoredefaultpath
clc
```