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An Evaluation of Leading Indicators in the Context of a Swedish Recession

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Abstract

The aim of this paper is to evaluate potential leading indicators of a recession in Sweden. To answer the question potential leading indicators are first identified with previous findings in literature and with the current state of the Swedish financial system as background. Then these variables will be included in a probit regression at different forecasting horizons. The horizons are one, two and four quarters ahead. The explanatory variables that are included in the regressions are Interest, Rate Spread, Credit, House Prices, OMX30 index, NYSE index, VIX, Inflation Gap, Current Account-to-GDP, and Unemployment rate, where the Spread is significant at all horizons and the stock price indices at a forecasting horizon of two quarters ahead. Finding that interest rate spread is significant in predicting the recession probability in Sweden confirms previous empirical findings. Also, from last the predicted recession probability in the models the interest rate spread does not have to decrease all too much to spur a recession probability over 50%. Furthermore, when performing a robustness check the results are somewhat inconclusive which implies that more contributions to evaluating leading indicators for small open economies like Sweden is needed in the literature.

Keywords: Probit, Financial Crisis, Recession, Sweden, Leading Indicators

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1 Introduction

With both the International Monetary Fund (2023) (IMF) and the Riksbank (2022) signalling that the risk of financial distress of Sweden have increased it becomes of interest to study what leading indicators could help detect the probability of a recession or a financial crisis. The probability of a financial crisis is something that have always been an interest in the economic literature. More recently, following the Global Financial Crisis (GFC) of 2008, the search for a numerical indicator that would provide early and reliable warnings of financial fragility. Furthermore, during the aftermath of the Covid-19 pandemic and because of the war in Ukraine high inflation have emerged which puts stress on the economy.

The stretched asset valuation and increase of debt following the pandemic is not a new concern, since the GFC *financial cycles* have gained more attention in the policy debate and economic literature. What the crisis made evident was that financial leverage boosts growth in the short run, while the downside risks to the real economy increases over the medium term. Furthermore, with the recent financial crisis and the fall of Lehman Brothers in mind policy that helped cushion the impact of the pandemic was implemented in form of quantitative easing mainly. However, this financial support also raised the historically high levels of financial leverage following the GFC (Chen & Svirydzenka, 2021). Furthermore, since the GFC there have been a response in strengthening the framework of Basel II and with the now implemented Basel III that have increased capital requirements for banks (Bank of International Settlements, 2017).

Sweden was not directly affected by the GFC but due to spill over effects the real economy and financial system in Sweden came under stress, the stock market fell over 40 percent for example (Österholm, 2009). Also, as Sweden was not affected by the subsequent house market crash that followed in several other countries the real house prices in Sweden instead continued to increase, leading to the question if the house market is overvalued, or even if there is a bubble (Ekeblom, 2014). With falling house prices in 2022 and an assessment of a continuous drop in prices in 2023 this is something that could pose as a threat to the financial system as well (The Riksbank, 2022).

One of the risks that the Riksbank have pointed out is the banks’ lending to non-financial corporation have experienced a large growth in recent years with property companies accounting for a significant proportion of the banks’ lending to the corporate sector. When firms increase their debt, it leads to a more interest rate sensitive corporate sector.

Furthermore, the capital market has been key for the increase in borrowing by property companies. Now with reduced access to wholesale funding and higher funding costs and lower rental income due to a weaker economy, could lead to a sharp fall in property prices. Another risk that makes the Swedish economy vulnerable is the high level of household indebtedness. As costs of living increases, because of both higher inflation and the higher interest rates, many borrowing households needs to adjust. However, most mortgagors are expected to meet their debt payments, some households may struggle to fulfil their obligation. The group of borrowers that this is mostly relevant for is the households with consumption loans, as they have a lower debt-servicing ability than mortgagors in general. Which could imply that consumer credit companies may suffer from increased loan losses. Moreover, there is a risk that consumption will reduce to an extent that could affect the profitability of the corporate sector, leading to an increase in the number of company bankruptcies (The Riksbank, 2022).

With the risks stated above for Sweden, the question is*: what leading indicators can help forecast the probability of a Swedish recession*? The factors that will be tested are inflation, unemployment, interest rate spread, financial volatility, asset prices, credit, and current account-to-GDP. In this paper a probit model will be used to test if the potential leading indicators have any explanatory power, and what the probability of a recession in Sweden is.

The rest of the paper is structured as follows. In the next section I will give more context and background to the subject and present results from previous literature that is relevant to test the potential indicators. The third chapter describes the mythological approach where the probit model is presented and how the estimations of the model will be conducted. The fourth chapter describes the data used in the paper. In the fifth chapter the results will be presented, both in-sample and out-sample results. The chapter will also present a robustness check for the in-sample results. The sixth chapter is where the results found are analysed. A conclusion follows in the last chapter of what leading indicators can be of used for forecasting recessions in Sweden.

2 Background

2.1 Definition and Features of a Financial Crises

Boom-bust cycles have been of interest for economists since John Stuart Mill wrote about the financial crisis of 1826. Already back then Mill implicated that a crisis typically went hand in hand with a credit boom. It is the work of previous economic historians that reminds us that financial crises have been the rule in capitalist economies, for as long as there have been data recorded at least. Furthermore, early work from Ludwig von Mises predicted the events of 1929 before the bust materialised, in which he stressed that the role of central banks and the banking sector was important. More specifically, Mises together with Minsky (1977; 1986) pointed out that the banking sector and leverage are factors that drive the fast credit expansions observed throughout history.

The first topic to deal with is the definition of a *financial crisis* in this paper. According to Giordani et al. (2017) a *recession* is easy and more precise to define as it is associated with an economic slowdown measured with GDP levels, while a financial crisis is more vaguely defined. Furthermore, financial crises can take various shapes and forms in terms of how they can be classified. Claessens & Kose (2013) distinguish between two types of crises: those classified using quantitative definitions (currency crises and sudden stops); and those that are largely dependent on judgmental analysis (debt and banking crises). Moreover, financial crises directly result in a loss of nominal wealth while the effect on the real economy is more indirect if this nominal loss cause a recession or depression to follow (Singh, 2011). For example, Schularick & Taylor (2012) define a financial crisis as an event where the banking sector of a country experience bank runs, default rate sharpy increases that lead to large losses of capital which results in public intervention, bankruptcy, or forced merger of financial institutions. They also point out that after World War II, public intervention by central banks and governments has resulted in financial crises with much less dramatic drops in credit aggregates, but with strong effects on GDP growth[1].

There have been several financial crises throughout the years that tend to occur cyclically (Kindleberger, 1996)[2]. Furthermore, financial crises come in many forms but occur in combination when economic fundamentals have deteriorated (Kaminsky & Reinhart, 1999;

[1] As this paper will focus on the real GDP growth as dependent variable in the empirical section, this definition suites the aim of this study.

[2] One historical example of an asset price crisis is the Dutch Tulip Mania from 1634 to 1637. And one example for a credit boom and bust could be the patterns before the East Asian financial crisis in the late-1990s.

Borio & Lowe, 2002). More specifically, a financial crisis is often associated with one or more of the following characteristics: i) large scale balance sheet problems (for companies, households, bank and soverigns; ii) large scale government liquidity and recapitalization support; iii) substantial change in asset prices and credit volume; iv) severe disruptions in financial intermediation and the supply of financing to various agents in the economy. These characteristics also implies that financial crises are multidimensional and using a single indicator would be a challenge to identify (Claessens & Kose, 2013). Moreover, characteristics that once again are appearing in the economy following the Covid-19 pandemic.

The dynamics of financial and macroeconomic variables around crises have been extensively studied in the literature. Financial crises have previously been preceded by bubbles in asset prices and/or credit booms that eventually turns in to busts (Claessens & Kose, 2013). Furthermore, studies on asset and credit bubbles implies that the higher the growth rate is in the boom phase, the more severe the contraction will be in the bust phase of the crisis (Gavin & Hausman, 1996). Asset price bubbles have been observed for centuries where sharp increases makes the asset prices deviate from what economic fundamentals would suggest. Patterns of sharp increases in asset prices, often followed by a crash, is one of the most prominent figures for the account of financial instability, not just in advanced countries but for emerging countries as well. Furthermore, various types of models have been attempting to explain why asset bubbles appear considering how rational individual behaviour can lead to collective misprising while other models assume irrationality (Claessens & Kose, 2013). [3]

Another aspect preceding a financial crisis is the build-up of leverage and greater risk-taking through expansion of credit. Both distant and more recent financial crises experience significant growth of credit before going bust, which also lead to sharp contractions of asset prices. The growth of credit can be triggered by factors such as shocks and structural market changes. These shocks that lead to a credit boom include positive changes in productivity, economic policies, and capital flows (Claessens & Kose, 2013). A study by Dell'Ariccia et al. (2013) finds lagged GDP growth is positively associated with the probability of a credit boom. Furthermore, sharp increases in international financial flows amplify credit booms and making most national financial markets affected by global conditions[4]. Moreover, financial liberalization and innovations, specifically if they encourage excessive risk-taking can trigger

[3] See Garber (2000) for a more extensive review of these models.

credit booms. Empirical studies have shown that crises are often preceded by financial liberalization (Kaminsky & Reinhart, 1999). And lastly, expansionary monetary policies have been linked with credit booms. As interest rates affect asset prices and the net worth of borrowers, this in turn affects lending conditions (Claessens & Kose, 2013).

Asset price busts and credit crunches typically have adverse effects on the real economy. If asset prices go bust this can affect bank lending other investment decisions, affecting the real economy through two channels. First, borrowing and lending can be collateralised and if the market price of collateral falls, the ability of companies to rely on asset prices as collateral for new loans and financial institutions' ability to extend new credit becomes reduced adversely affect investments. Second, large dislocations that arise from financial turmoil, such as fire sales, distort decisions of financial institutions to lend or invest, prompting these institutions to hold cash among other effects. Through these two channels a credit crunch can be triggered and cause contractions in the real economy (Claessens & Kose, 2013). However, those asset price booms that does not involve a financial intermediary or financed through leverage does not entail large risks for the economy. The burst of the internet bubble in the late 1990s early 200s only involved equity markets. On the other hand, when banks or other financial institutions are involved in financing these asset price booms, the adverse consequences following the bust are typically much higher. This becomes evident when observing the GFC as it was financed by banks (and shadow banks), involving the housing market and was very costly for the economy. Abiad et al. (2011) report that in a 21 out of 23 countries that experienced a boom in the real estate and credit markets during the GFC suffered a crisis or a severe drop in GDP growth.

2.2 The Swedish Experience of Financial Fragility

In the beginning of the 1990s, Sweden faced a deep financial crisis, where real income declined, unemployment increased, and large budget deficits could be observed. The boom-bust cycle could mainly be explained by the deregulation of Sweden's financial system during the mid-1980s which integrated Sweden with the global financial markets.[5] Some of the characteristics preceding the financial crisis during the 1990s, as increase in house prices, and the utilization the increase in asset prices as collateral for further borrowing, fuelled by a rising inflation rate (Jonung, 2009a) is something that could also be observed in other

[5] The interested reader can get a much richer description of the Swedish financial crisis in Jonung (2008) and Jonung (2009b).

countries prior to the GFC. House prices increased rapidly, which also could be observed in Sweden in the years following the GFC (see Figure 2.1), raising concerns about an increase in the probability of a future financial crisis (Andersson & Jonung, 2016). Furthermore, this is a pattern that also can be observed today as house prices have almost doubled in value since 2008. Also, in Figure 2.2 and 2.3 the observed movement in relation to the 1990s financial crisis is quite similar to the movement of the same variables in more recent time.

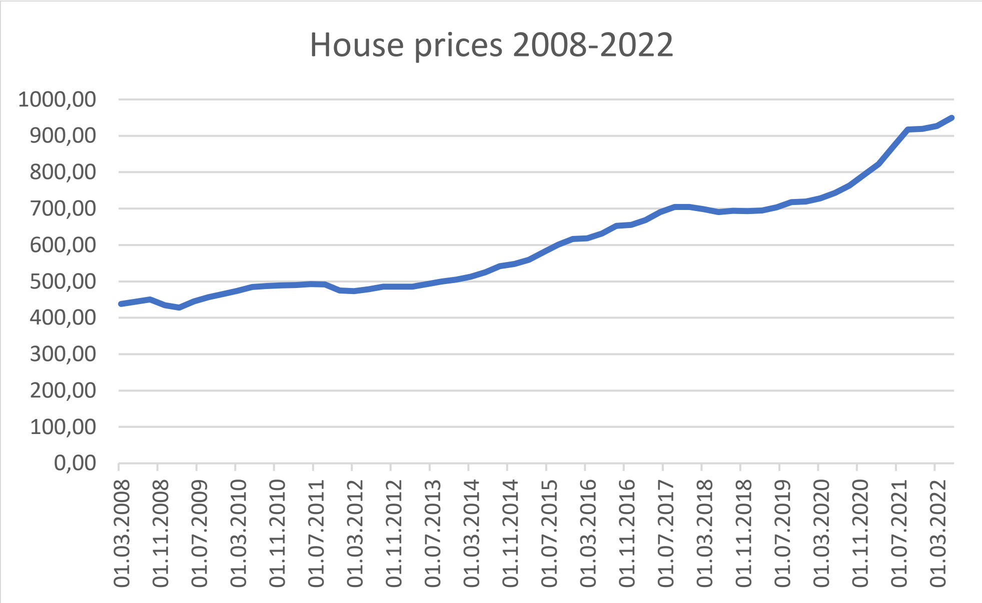

Figure 2.1: House price index from 2008Q1-2022Q2 (base year 1986Q1=100)

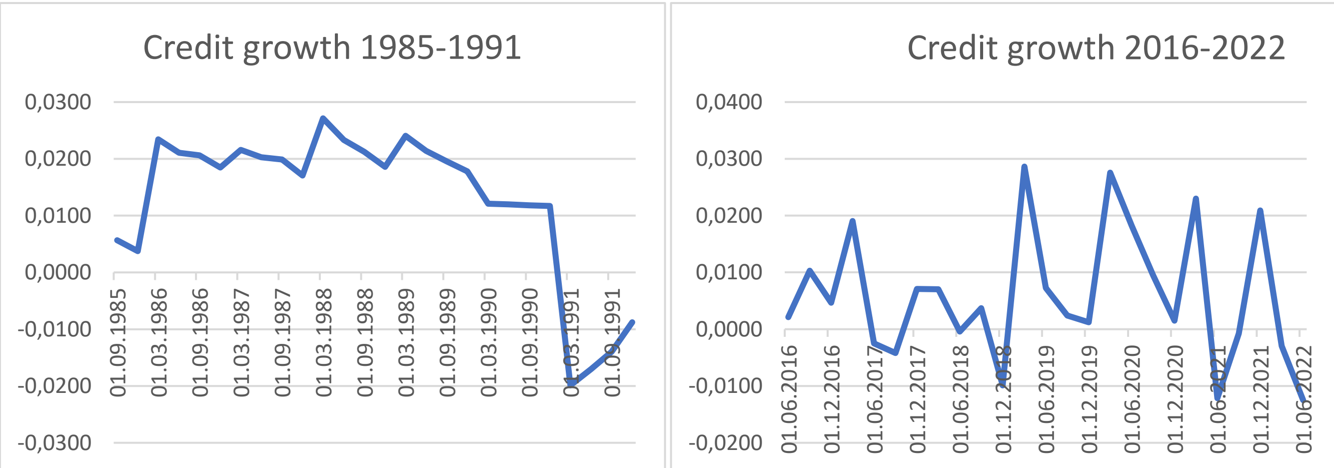

Figure 2.3: Inflation rate before the 1990s financial crisis (left) and credit growth from 2016 to today (right)

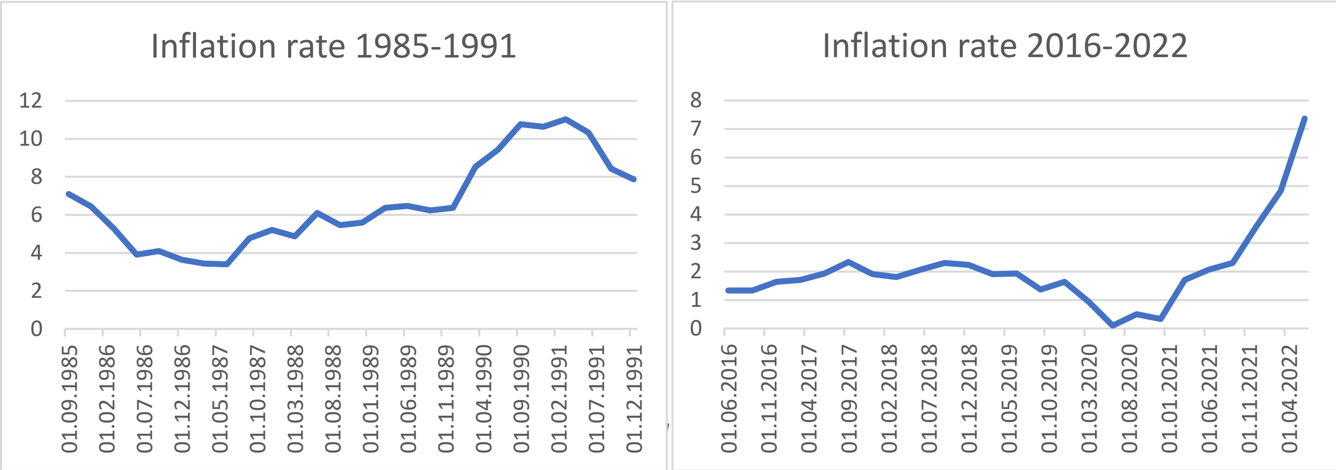

Figure 2.3: Inflation rate before the 1990s financial crisis (left) and credit growth from 2016 to today (right)

Since the 1990s a growing number of countries have adopted inflation targeting, including of course Sweden. This was initially deemed a success and is presently the approach best considered to adopt monetary policy as consumer price inflation became more stable at lower levels. However, in the years after the GFC, inflation targeting has been criticised for causing credit and debt to grow excessively (Jonung, 2022). Moreover, even before the onset of the GFC the household indebtedness was increasing rapidly towards the levels of the 1990s crisis (Persson, 2009) (see Figure 2.5). Furthermore, as implemented in the US, inflation targeting contributed to the growing imbalances that resulted in the GFC. Moreover, the expansionary monetary policy that have been adopted after the crisis and during the Covid-19 pandemic have also helped raised asset prices further and thus made the probability of a new financial crisis in the future more likely. The Riksbank even going to a further extent, as inflation was below the inflation target of 2 percent following the GFC, decreased interest rates even below zero (see Figure 2.4). Keeping negative policy rates in the 2014-2019 period, while other major central banks such as the FED kept rates above but close to zero (Jonung, 2022). However, Sweden as a small open economy with exports and imports that amount to around 50 percent of GDP at the time of the GFC was mainly affected by the collapse of global trade (Ingves, 2011). Also, the Riksbank have been conducting quantitative easing as a policy tool, which been more commonly used as a tool following the GFC. It has been found that quantitative easing affects the spread between interest rates and can thus work to prevent the spread from increase or decrease (Hörmann & Schabert, 2011).

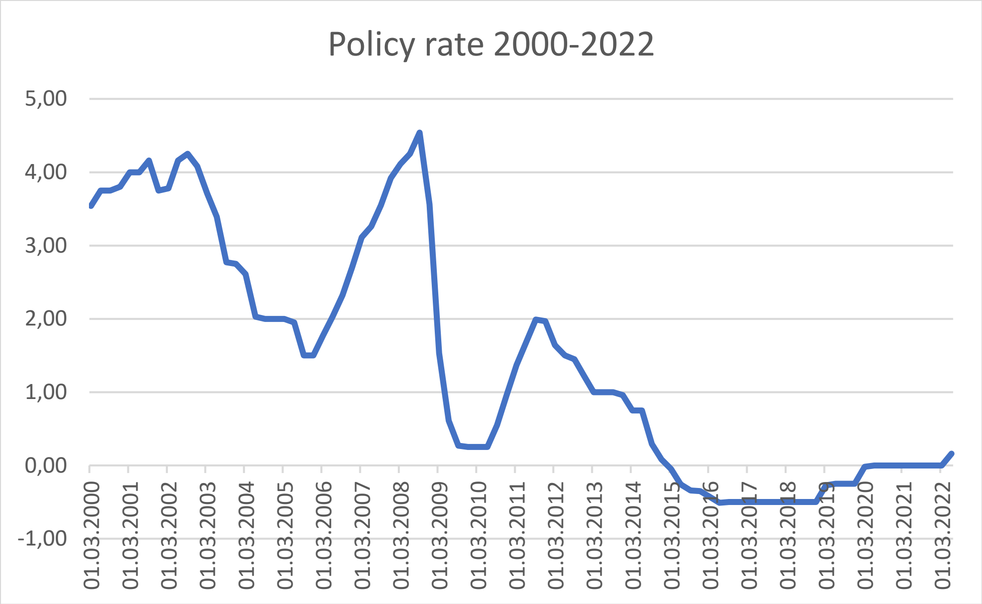

Figure 2.4: Policy rate 2000-2022

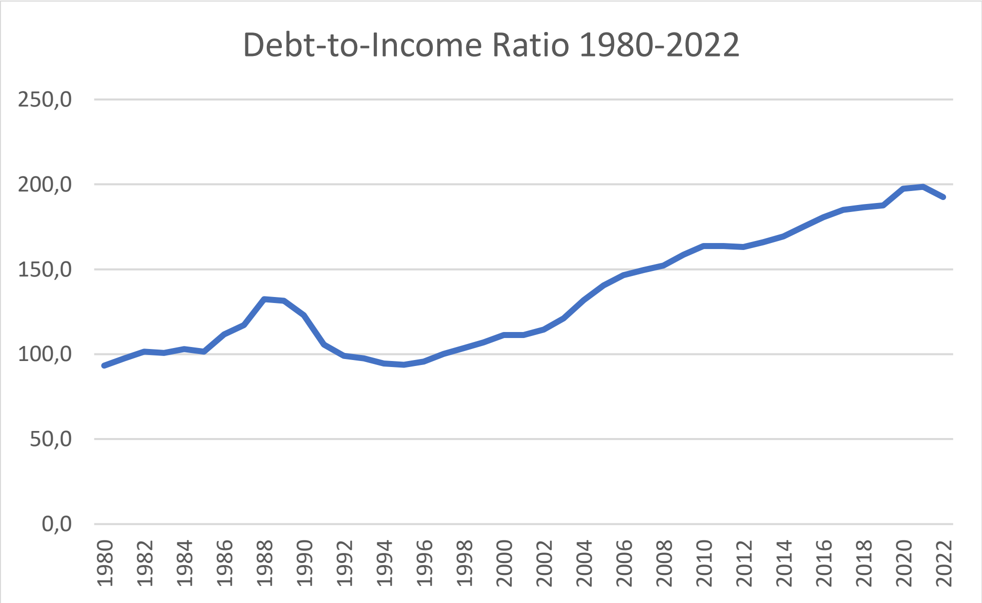

Figure 2.5: Debt-to-Income ratio for Swedish households 1980-2022

The *Lean Against the Wind* perspective on how to conduct monetary policy that would suggest that the policy tools should help financial imbalances to reduce (Smets, 2014; Pál & Lamanda, 2018; Woodford, 2012; Adrian & Liang, 2018).[6] The Riksbank have been criticised to do the opposite by some, as policy rates have been pushed down as far as below zero to push consumer price inflation back up after the GFC only lead to inflation of assets.

[6] Mainly the policy rate but also unconventional tools that have been used to a larger extent, such as quantitative easing.

Furthermore, the indebtedness as well as the increasing prices of asset have been pointed out as vulnerabilities in the Swedish financial system leading to the implication that the policy from the Riksbank have enabled these imbalances to grow. And the benefits that came from negative interest rates does not outweigh the costs (Andersson & Jonung, 2020). However, Riksbank did *Lean Against the Wind* in the 2010-2014 period and was conducting tighter monetary policy to avoid imbalances to foster (Ingves, 2019). This in turn lead to that the Riksbank also got criticised for setting a too high policy rate, only hampering GDP growth and employment level (Svensson, 2014; 2018). Furthermore, Svensson (2017) argues that for policy rate to affect the indebtedness and property prices it would have the rate would have to increase dramatically, causing even further damage to the economy. Moreover, the author also points out that to integrate financial stability and monetary policy would not be beneficial as monetary policy tools are not an effective tool to create financial stability.

To counteract the increasing inflation central banks have globally increased the interest rate, with further increases flagged to come. The combination of high inflation and interest rates have deteriorated the growth prospects and could pose as a challenge for the global financial stability. Moreover, low inflation[7] and low interest rate have contributed to increase asset prices as well as rising indebtedness raising the question of how household and firms can cope with the high inflation and increasing interest rates[8]. In Sweden the financial stability could potentially be threatened by vulnerabilities in the financial system that have been built since before the pandemic. Moreover, with historic high household debt and the high exposure of banks to the commercial real estate sector and with a banking sector that is nearly three times the size of GDP in 2021 the risks are not neglectable (International Monetary Fund, 2023).

2.3 Leading Indicators

A leading indicator, or Early Warning Indicator (EWI) is defined as a measurable variable that may help to forecast the future of economic activity.[9] Ever since the GFC the interest in EWI have been of interest in the literature as well as for policy makers and the literature is extensive (Frankel & Saravelos, 2010). In this section I go over some desirable features of an EWI, and in the next section I will go over how previous literature have approached the challenge of choosing an appropriate EWI and the results.

[7] Below the usual inflation target of 2%.
[8] Even negative interest rates at some points in countries like Sweden.
[9] Leading indicator and EWI will be used interchangeably throughout the paper.

Both Drehman & Juselius (2013) as well as Giordani et al. (2017) emphasises that a high degree of timing, stability and interpretability are key features that an ideal EWI would have. Firstly, timing refers to that the EWI would reach an alarming value (high or low) well in advance of a major financial crisis. The EWI in contrast to a financial stress index is meant to be leading and not a coincident indicator of a crisis, and preferably with long enough lead. Furthermore, the timing ability of different indicators have been investigated in the literature using binary classifications of financial crises.[10] Secondly, stability of the indicator implies that it should not move quickly from high to low or from low to high. Then this would reflect the assumption that financial fragility builds up gradually over the course of time. Lastly, when constructing an indicator, a high degree of interpretability should be a priority. To focus on a handful of variables that possesses the most predictive power gives the most comprehendible indicator. While more variables and complex econometrics would decrease interpretability, without a corresponding increase in performance.

To identify a broad EWI is difficult due to that definitions of a financial crisis and the severity of different crises tend to vary. Furthermore, the type of crises studied varies in the literature, in different time periods and in different countries. Implying that a lesson from a crisis in one country is not relevant for another country, and that one crisis at a point in time is not relevant for another crisis in another point in time. Moreover, empirical work on leading indicators faces the problem of selection bias. As variables examined as indicators are selected with the benefit of hindsight after the crisis have occurred. However, these variables are often based on some underlying economic reasoning to why they are relevant, shedding light on the importance of this when studying leading indicators (Frankel & Saravelos, 2010).

2.4 Literature Review

The literature of leading indicators dates back to the 1970s, when several currency crises generated interest in the subject of explaining such crises (Bilson, 1979; Krugman, 1979). These earlier studies focused on the theoretical aspects of leading indicators. However, two decades later the literature took a shift to focus on the methodological aspect of leading indicators instead. This shift served as a starting point for the stream of literature that was motivated by the GFC. However, there are still a lot of challenges that still prevail that need to

[10] Not unlike what I will conduct in this paper through a probit model.

be tackled (Babecký et al., 2012). A key aspect of leading indicators is that they are expected to move in certain ways before a crisis or recession, either peak or hit bottom for example.

In previous studies crises have been defined differently, whether it be a currency crisis or a banking crisis. However, the ultimate objective for each leading indicator is to warn against these crisis events. There are studies conducted that have focused on dramatic movements of nominal variables, such as currency crisis by Kaminsky & Reinhart (1999), stock market crashes by Grammatikos & Vermeulen (2010), and rapid decreases in asset prices in Alessi and Detken (2011). These studies then assume that such crises are costly in real terms, either by citing stylized facts, or selecting those crises which subsequently affected the real economic activity (Babecký et al., 2012). To represent the crises Frankel & Rose (1996) use one variable in their study, contrast this with the study by (Burkart & Coudert, 2002) that combine several variables into one index using alternative weighting schemes.[11] An alternative approach to specify the costly event (or crisis) is to measure their real cost directly such as loss of GDP and loss of wealth approximated by fiscal deficits that are run to mitigate the costs (Caprio & Klingebiel, 2003; Laeven & Valencia, 2008). Moreover, some studies take both the real costs and the nominal costs into account (Frankel & Saravelos, 2012).

Just as Nissilä (2020) I note that more research is needed for smaller countries, since much focus of previous probit model studies have focused on larger economies. Early work that applied a static probit model was conducted by Estrella & Hardouvelis (1991) to predict a recession in the US focusing on predicting the GDP growth rate in the US. In their study the found that the term spread between the yields on a 10-year and 3-month Treasury securities proved successful in forecasting recessions four quarters ahead. Furthermore, this result also proved to be robust as the result stood when other variables was included. In the subsequent papers on recession probabilities, it became standard to use the 10-year and 3-month bond yields as an estimate of interest rate spread. Moreover, Estrella & Mishkin (1998) considered a variety of horizons from 1 to 8 quarters and included a large set of financial variables as possible predictors. They also found the interest rate spread to be a useful predictor, at horizons larger than two quarters ahead and that stock prices added predictive power when 1 to 3 quarters was considered. Another key finding that was made by Estrella & Mishkin (1998) is that good in-sample results does not necessarily lead to good out-of-sample estimations. In their paper commercial paper spread and a leading indicator of Commerce

[11] Equal weights, weights adjusted for volatility, or principal components are some of the methods used. Slingenberg and de Haan, 2011

department performed well in the in-sample estimation, but these results deteriorated in the out-of-sample setting.

Ahrens (2002) employed a static probit model for several industrialized countries, rather than just focusing on the US. The author could conclude that the spread proved to be a useful predictor for most of the countries in the sample, except for Japan, Netherlands, UK and Italy, a result that implies that the interest spread is not a dominant or even useful indicator for all countries. However, Duarter et al. (2005) investigated the predictive power of the spread in the Euro Area with reaffirming results.

Dynamic extensions to the static probit model have been tested in several studies where Dueker (1997) was the first to employ such a model. Duerker (1997) found that by adding a dynamic component the predictive power of the static model increased. This result has been confirmed by Moneta (2003) and by Duarter et al. (2005) that also found the dynamic component useful. The dynamic probit model was extended with an autoregressive component by Kauppi & Saikkonen (2008) to allow for even more dynamics. However, the results of their study found the dynamic model to be the most accurate. Nyberg (2010) excluded the autoregressive term and allowed an interaction term between a dynamic component and the other explanatory variables. In contrast to Kauppi & Saikkonen (2008) that only considered the interest rate spread, Nyberg (2010) also tested several different financial variables. The author came to the same conclusion as Estrella & Mishkin (1998) that stock prices bring additional predictive power. In these previously mentioned studies, the most common approach has been to apply a single-predictor model or a multi-predictor model with few variables included. Chen et al. (2011) extended their approach to augment the probit model by allowing factors that have ben estimated by principal component analysis to function as explanatory variables.

Financial variables and extending the static probit model have been the focus of forecasting recessions and crises. Christiansen et al. (2014) were the first to investigate the role of sentiment and show that consumer confidence index and Purchasing Managers Index (PMI) are useful predictors, and their prediction power is robust when other financial predictors are included. Their result was supplemented by Karnizova & Li (2014) that also concluded that economic policy uncertainty could be a useful sentiment-based predictor. Other potential recession predictors have also been found, such as credit (Pönkä, 2017), when included in various forms of the probit models. When the quarterly business cycle of Finland was predicted Pönkä & Stenborg (2019) found real house prices to be a useful predictor.

The literature review of the covered studies mainly focuses on the empirical aspect of the predictive ability of different variables and not so much on the theoretical explanations of why these variables might be useful predictors of future recessions and crises. However, some key theoretical aspects are noted. The expectations of the interest rate structure are usually the foundation for most explanations of why the interest spread appears to be useful. This hypothesis states that long-term interest rates are the sum of expected future and current short-term interest rates plus a premium. Furthermore, the premium explains the positive slope of the spread and in general, if consumers expect short-term rates to fall, the spread will approach zero or even turn negative. A negative spread has preceded most of the recession periods in the US (Nissilä, 2020). The predictive ability of the term spread has various possible explanations on whether the decrease is driven by short-term rate rising or that long term-rates are falling. However, empirically it can be observed that long-term rates do not vary in the run-up to a crisis, and instead it is the short-term rates that increases. This implies that the interest margins are declining and that the risk taking by financial intermediaries increase.

The prices of equity can be interpreted as an expected discounted value of future dividends payment, meaning that they incorporate consumers and investors expectation regarding the future profitability of a firm and future interest rates. While sentiment-based variables reflect the expectations of the more general economic situation and tend to move with the business cycle. The studies of Christiansen et al. (2014), Pönkä & Stenborg (2019) and Nissilä (2020) have demonstrated that the role of sentiment cannot be neglected. More specifically, Nissilä (2020) finds that consumer confidence is a useful indicator when predicting the Finnish business cycle. Furthermore, the author finds that the static single-predictor model can be improved by extending it to multiple predictors and allowing dynamic extensions.

Banking crises that are associated with a significant loss of output often occurs in conjunction with the exposure to several risk factors. This is not uncommon in a scenario when the economy is expanding with increasing prices on the housing market and stock market, where the risk is perceived to decline which leads to financing becoming cheaper. This implies that the build-up of financial imbalances should be possible to distinguish from the appreciation of exchange rate, inflow of capital, and the build-up of foreign exchange mismatches. In their article Borio & Lowe (2002) identified three variables that could be perceived to indicate if the asset quality was deteriorating: i) the real effective exchange rate, ii) deflated stock prices, and iii) the ratio of private sector credit to GDP. They computed the deviations of these variables from a trend (calculated with Hodrick-Prescott filter) and if the indicators exceed some critical value, financial imbalances are assumed to be emerging. These variables allow forecasting for various horizons. Furthermore, the authors also found that the credit level combined with asset prices isa superior indicator to the credit level in combination with the exchange rate, with exchange rate not adding any useful information if stock price gap is included. Moreover, studies on credit growth have suggested that a rapid increase in a business cycle upswing leads to a more decisive contraction in the downturn.

3 Methodology

3.1 The Probit Model

I follow the approach conducted by Nissilä (2020) where the latent variable approach to the probit model will be applied to quantify the predictive power of the variables of interest. The dependent variable of a probit model is defined as a binary indicator,

$$y_i = \begin{cases} 1, if\ y_i * > 0\ and \\ 0, otherwise \end{cases} \tag{1}$$

Furthermore, the probit model assumes a linear additive relationship as follows:

$$y_i * = \beta' x_i + \varepsilon_i \tag{2}$$

Where y_i* is the dependent variable that determines if there is a crisis or not for observation *i* also because y_i* is unobserved it is referred to as a *latent variable*, ε_i is a normally distributed error term, and β is the vector of coefficients, including a constant, for the independent variables in vector x_i where . The regression will be tested for different lags of k where once again I will stand on the shoulders of previous research and try different lag horizons. Equation (2) is *static* in the sense that the independent variables have an immediate effect on the probability, as the probability is unaffected unless the values of the explanatory variables change. A limitation of the static probit model is that it does not consider the potential autocorrelation in the dependent variable y_i. Thus, an extension to be made to this is to include the lagged value of the dependent variable in the specification (2). This form of dynamic probit model has been considered by Nyberg (2010), for example,

$$y_i = \beta' x_i + \delta y_{i,t-l} + \varepsilon_i \text{[12]} \tag{3}$$

In general, there is no limit to the number of lags that could be included. However, in this paper the number of lags included will be equal to one as Dueker (1997) argues that three months is probably the minimum recognition lag for a crisis. This is due to that when a crisis is predicted in real time, one must account for the values of the binary indicator are known with a delay.

The probability that y_i assumes the value 1 is as follows:

$$P(y_i = 1) = P(y_i * > 0) = P(\beta' x_i + \varepsilon_i > 0) = P(-\varepsilon_i \leq \beta' x_i) = \Phi(\beta' x_i) \tag{4}$$

[12] Where $l \geq 1$.

where Φ stands for the cumulative normal distribution function of $-\varepsilon_i$.

The model is conceived to generate out-of-sample forecasts of future financial crises, and the prediction will be based on speculative development of the explanatory variables. The period that will be forecasted will be of up to 8 quarters. However, there is a possibility to make predictions even further into the future but following the steps of the previous studies 1 to 8 quarters are commonly chosen. Furthermore, the model will suffer from lower explanatory power when predicting future crises, compared to the in-sample prediction, due to the out-of-sample characteristic. In their paper Killian & Taylor (2003) argued that out-of-sample testing that is based on splitting the sample in parts loses information in the process and has lower power in smaller samples. Thus, a test performed for out-of-sample on half of the sample may fail to detect the predictability that do exists in a population, while the in-sample test of the entire sample may correctly detect it. However, that the power of the prediction is adequate or not cannot be determined when the model is applied to various speculative scenarios.

The parameters of the probit model can then be estimated by the traditional maximum likelihood (ML), with the likelihood function defined as:

$$L(\beta) = \prod_{y_i=1} \Phi(\beta' x_i) \prod_{y_i=0} [1 - \Phi(\beta' x_i)]. \tag{5}$$

Consequently, with the log likelihood defined as follows:

$$l(\beta) = \sum_{i=1}^{N} [y_i ln(\Phi(\beta' x_i)) + (1 - y_i) ln(1 - \Phi(\beta' x_i)] \tag{6}$$

First order conditions of the ML function are nonlinear implying that to obtain estimates for the coefficients an iterative process is required. The marginal effects of each explanatory variable in a probit model can be interpreted through their partial derivatives given the probability that y_i is equal to one, respectively:

$$\frac{\partial P(y_i=1)}{\partial x_{i,k}} = \phi(-\beta' x_i)\beta_{i,k} \tag{7}$$

ϕ stands for the standard normal probability density function and the value of the function depends on all the regressors in *x*.

The partial derivative, defined as above, depends on the slope of the probit function and the size of the β coefficient. Thus, the partial derivative shows the effect on P of an increase in x_i. Since the probability density function is always positive, the marginal effect of an independent variable will assume the sign of the estimated $\hat{\beta}_i$ coefficient. Moreover, the larger the value of the $-\beta' x_i$, the smaller effect it will have on the probability of a crisis since the probability density function has lower values further out in the tails of the distribution. This in turn reflects the low marginal effect the cumulative distribution function has in its tails. Resulting in that a high value of $\Phi(-\beta' x_i)$, that is close to 0,5, has the most impact on the probability of a crisis. Implying that an estimated marginal effect only is valid in a slim sample of observations and a mean of marginal effects contains no relevant effect for any analysis.

The probit model is not the only binary choice model that could be applied to estimate the probability of a crisis. Other approaches could be a linear probability model or a logistic regression (logit) model. Empirical studies have found that the probit and logit model yield similar results. Comelli (2014) compared the performance of the two models when it came to predicting in-sample and out-of-sample currency crises in emerging markets. Leading to the conclusion that the choice of the model is not crucial to the results or conclusion. For the linear probability model, the probability of a crisis is set to either 1 or 0 if $\beta' x_i$ exceeds an upper or lower threshold. However, this approach is not used to any large extent in the literature and the probit model is the model of choice for this paper. The ML estimators are asymptotically unbiased and consistent but cannot be shown to be unbiased for finite samples. However, if the predictors of the model are satisfactory defined this will not pose as a serious problem.

3.2 Statistical properties of the model

The maximum likelihood estimators have the property of being consistent, under the condition that the likelihood function is correctly specified. More specifically, this implies that for consistency one must be sure about the entire distribution imposed upon the data sample. Furthermore, deviations in binary choice models typically arise when the probability that $y_i = 1$ is misspecified as a function of x_i.[13] This misspecification often renders from non-normality or heteroscedasticity in the error terms (Verbeek, 2017). The error terms of the sample are assumed to be normally and independently distributed,

$$\varepsilon_i \sim NID(0, \sigma^2) \tag{8}$$

[13] That is when (3) is misspecified.

As the dependent variable of the model are correlated to most of the explanatory variables, there is reason to doubt the normality and homoscedasticity conditions. I will test for both normality and heteroscedasticity in the final model used.

To test for normality in the error terms, which corresponds to a test for omitted variables at the same time. The test will check the distribution for skewness and excess kurtosis and is defined as follows:

$$P\{y_i = 1\} = \Phi(\beta' x_i + \gamma_1(\beta' x_i)^2 + \gamma_2(\beta' x_i)^3). \tag{9}$$

If the distribution suffers from skewness $\gamma_1 \neq 0$, whereas if the distribution suffers from kurtosis $\gamma_2 \neq 0$.

If the error terms suffer from heteroscedasticity, it does not necessarily eliminate the forecasting ability of the model. However, if the estimators do not suffer from heteroscedasticity the estimators can be studied and trusted. The test assumes that the variance of the error terms depends on an exogenous variable z_i,

$$V(\varepsilon_i) = h(z_i{}'\theta). \tag{10}$$

Where $V(\varepsilon_i)$ is the variance of the error term and h represents a function of the form $h > 0, h(0) = 1$ and the derivative is separate from zero. The test is constructed to evaluate the significance of θ, if θ should be equal to zero the function h takes the value of 1. This in turn implies that the variance of the error terms is constant fulfilling the requirement of homoscedasticity. If the value of θ is not equal to zero, then the exogenous variable $z_i$will affect $V(\varepsilon_i)$, i.e., heteroscedasticity. However, the test only depends upon the variable z_i that has an impact on the variance and not on the form of the function h.

The hypothesis is then tested through an LM-test where the test statistic is computed as follows. The uncentred R^2 is multiplied by the number of observations N, which is Chi-squared distributed with J degrees of freedom, in this case J is the dimension of z_i. Then, as the LM-test consists of an auxiliary linear regression computed from a series of ones regressed upon $\hat{\varepsilon}_i^G{}' x_i$ and $(\hat{\varepsilon}_i^G \widehat{\beta}' x_i) z_i$. Where $\hat{\varepsilon}_i^G$ stands for the generalized residuals of the estimated probit model, and z_i does not include a constant because of the normalisation (Verbeek, 2017).

3.3 Estimation & Goodness-of-fit

The testing procedure looks as follows. First, I test the potential leading indicators and the probability of a financial crisis is to first use single-predictor probit models, where each of the explanatory variables are tested separately. Then several multi-predictor probit models will be tested where all explanatory variables will be included at first to then be excluded one by one. This is then repeated for the computation with the best goodness-of-fit measure. Furthermore, the lag horizons for the explanatory variables will also differ and the optimal lag interval will also be determined. The goal is to find a final model that satisfies the appropriate conditions which is determined by a goodness-of-fit measure. These models are then tested in an out-of-sample setting. One aspect to keep in mind is that when terms are removed from the model the error degrees of freedom increases. That is the precision of the estimates, and the power of the tests goes up when parameters are removed. As degrees of freedom is a combination of the sample size and how many parameters needs to be estimated a larger sample would have the same effect as fewer variables. Also, a higher degree of freedom means that the power to reject a false hypothesis and find significant results increases.

There are several different goodness-of-fit measures that have been proposed to evaluate both the fitted values and forecasts obtained through probit models (Nissilä, 2020). The measure can be compared with the standard R^2 from a linear regression model and is a summary statistic that indicates the accuracy with which the model approximates the data. However, the standard R^2 is the single measure used for linear regression models, contrary to the binary choice model where there are several measures.[14]

The goodness-of-fit measure that will be used in this paper is the pseudo-R^2 (R^2_{ps}) that was suggested by McFadden (1974),

$$R^2_{ps} = 1 - \frac{logL_u}{logL_c}. \tag{11}$$

Where $logL_u$ denotes the unconstrained maximum value of the log-likelihood function and $logL_c$ denotes the maximum value when all coefficients are but a constant are restricted to zero. The McFadden R^2_{ps} is sometimes referred to as the likelihood ratio index, due to the loglikelihood is the sum of all log probabilities. This implies that $logL_c \leq logL_u < 0$, from which it becomes obvious that the measure takes on values of an interval [0,1]. In the case

[14] For a description of other commonly used goodness-of-fit measures see Nissilä (2020) and Verbeek (2017).

where all estimated coefficients are equal to zero then $logL_c = logL_u$, and R_{ps}^2 is also equal to zero.

I will use one more performance measure for assessing the in-sample fit, the Schwarz's Bayesian information criterion (BIC), defined as follows:

$$BIC = -2lnL + klnN$$

Where lnL is the maximized log likelihood of the estimated model, N the sample size, and k the number of independent parameters estimated. Also, the lower the BIC for a model would imply that the model performs better. Furthermore, the BIC does not only evaluate the accuracy of the model but also the complexity (Schwarz, 1978).

The R_{ps}^2 together with the BIC form the basis for the in-sample evaluations of the models.

I follow the approach of Nissilä (2020) for the out-of-sample estimation will be conducted through expanding window approach in an out-of-sample setting. The models are estimated using data from 1990Q2 to 2015Q2, for example for the two quarters forecast horizon the first forecast calculated is then 2015Q4. Then the model is estimated again using data from 1990Q2 to 2015Q1 and the second forecast for 2016Q1 is calculated. This process then continues to the end of the sample. The models are estimated with robust standard errors for both in-sample and out-of-sample.

For the out-of-sample part of the results the R_{ps}^2 can take on negative values another measure-of-fit would be to prefer. One such measure is the Receiver Operating Characteristic (ROC) curve for binary response models. This is a goodness-of-fit measure that have gained popularity among economic applications. The ROC curve is a mapping of the true positive rate,

$$TRP(\zeta) = P\left(p_i > \zeta \middle| y_i = 1\right)$$

and the false positive rate, that is when a when a true null hypothesis is rejected (Type I Error),

$$FRP(\zeta) = P\left(p_i > \zeta \middle| y_i = 0\right).$$

For all possible thresholds ζ, described as an increasing function in the space between 0 and 1 for both the X and Y-axis, with the TRP on the Y-axis and FRP on the X-axis. A ROC curve that is located above the 45-degree line indicates predictive accuracy superior to random chance. Rather than presenting this graphically the area under the ROC curve (AUC) will be presented. The AUC is defined the integral of the ROC curve between 0 and 1 ensuring that the AUC takes values in the unit interval. Also, the closer to unity the better the result, and when the AUC takes on a value close to 0,5 the measure implies that the model is not particularly useful (Fawcett, 2006).

4 Data

The data sample collected are of observations from 1990Q2-2022Q2. The choice of quarterly data is purely based on data availability. Furthermore, the data is collected from various sources that are deemed to be valid and can thus be trusted.[15] Moreover, the choice of data is motivated by previous studies and what factors that could potentially affect the financial stability of Sweden. Also, when probit regressions are applied it is preferable to have many observations since the ML estimators are asymptotically normally distributed. Normality is one of the key properties and a relatively large sample is thus required.

4.1 Dependent Variable

In this paper I will focus on the real side of the economy and make use of GDP-growth rate as my dependent variable. Data was collected for the Swedish real GDP and the growth rate was calculated according to the following formula:

$$g_t^{real} = \frac{GDP_t^{real} - GDP_{t-1}^{real}}{GDP_{t-1}^{real}}. \tag{11}$$

Where g_t^{real} stands for the growth rate of real GDP in period *t* and GDP_t^{real} stands for the real GDP in monetary value in period *t.*

The dependent variable of the regression, y_t, is set to 1 if Sweden experience a recession and to zero otherwise. To define the dependent variable, we must specify a threshold τ_i that represents a financial crisis. As previously stated, a financial crisis is not as clearly defined as a recession.[16] There are periods which is viewed that a financial crisis occurred (the GFC, Swedish financial crisis, and even the most recent pandemic) but to be able to quantify this we need to make some appropriate assumptions. To approximate a recession, I choose two of the lower thresholds for this used in the literature generating y_1 and y_2 for the different thresholds.

$$y_{t,i} = 1 \; if \; g_t^{real} \leq \tau_i \tag{12}$$

The first value of τ_i is perhaps the most obvious and is set to 0, that is when the GDP growth rate is less than 0% $y_1 = 1$ and 0 if real GDP exhibits a positive growth rate.

[15] Data source references can be found in the section after the literature references.
[16] A classical definition of a recession states that if the economy experiences a loss of output for two consecutive quarters.

When y_1 is generated the total number of observations assuming the value of 1 is 18 out of 128. This might be a sufficient for the initial regression to be meaningful, but to hedge against this I also increase τ_i to 0,0025. The reasoning behind this specific value is that a quarterly growth rate of 0,25% gives an annual growth rate of 1%, which is considered to be low by convention.

The recoding of the continuous variable to a binary variable is not free of problems. When recoding a variable in this manner, information gets lost. It is a common practice in research to alter variables in a similar way to study a particular question. However, there are some disadvantages to this method and there are arguments to avoid this approach (Altman & Royston, 2006). This is due to the statistical power to detect a relation between variables is reduced. However, there are some advantages to the approach, such as the statistical analysis greatly simplifies, and the results are easy to interpret. Moreover, for the paper I conduct the purpose is to observe whether a recession or crisis occurs and not the magnitude of a specific event. Thus, the recoding is justified but the shortcomings should be kept in mind when interpreting the results.

4.2 Explanatory Variables

The choice of the explanatory variables is in line with the previous literature discussed in this paper. For some of the explanatory variables the logarithmic value and the first difference is calculated. The rationale for this transformation is that relative changes is more informative in reference to the dependent variable. Also, one advantage of taking the log-difference is that the values can be interpreted as percentage changes, which makes the data comparable and interpretable. Other data editing includes lagging the dataset to the corresponding forecasting period.

4.2.1 Asset Price

Financial vulnerabilities have been connected to substantial changes in asset prices. More specifically, equity is one of the most owned assets, to represent assets prices the OMX30 index and the NYSE index is included in the data sample. The reason for including OMX30 is since this paper investigates Sweden, but the NYSE index can be just as informative. As financial markets are integrated globally and with both the GFC in mind, and that the US plays a crucial role in these markets the NYSE could hold some predicative power. The series are transformed into logarithmic values and the first difference are then taken. The data series for the NYSE was collected from Yahoo Finance (2023) and the OMX30 was collected from Nasdaq (2023).

4.2.2 House Prices

A boom-bust cycle of the housing market was present in both the GFC and the Swedish financial crisis. This implies that if house prices grows rapidly or to higher levels than fundamentals would suggest, concerns should be raised about the economy as the bust can affect the real side of the economy. House prices were collected from Statistics Sweden (2023) as an index with 1986Q1 as basis year. The series are transformed into logarithmic values and the first difference are then taken.

4.2.3 Credit

One variable that has the propensity to peak before a crisis hits is the level of credit. More specifically, an indicator often used as a measure of financial stability is the credit-to-GDP ratio to the private, non-financial sector. Data was collected from Bank of International Settlements (2023) on a quarterly basis. The data collected was then transformed into logarithmic values and once again the first difference was taken.

4.2.4 Interest Rate Spread

A variable that has proved to be particularly useful when it comes to predicting future crises and recessions is the yield curve. Furthermore, the steepness of the curve has proven to forecast real activity quite well in previous studies. More specifically, when the short rate increases the yield curve is getting flatter and reduces real growth in the short term. The interest rate spread is representing this behaviour and would then indicate a possible crisis. The data collected is expressed in percentages for the 3-month and a 10-year Swedish government bond, respectively. To calculate the spread, the 3-month bond rate is deducted from the 10-year bond rate. Both bond series were collected from FRED St. Louis (2023)

4.2.5 Current Account

Reversals of the Current Account are typically connected to a slowdown in domestic growth and investments. An observation that implies that if the Current Account would go into a deficit the GDP growth would increase and vice versa. The ratio of the Current Account-to-GDP is intended to reflect this and data for first GDP is collected and then the Current Account, in real terms. The ratio is then taken of these two series and is thus denoted in percentage points. The GDP and the Current Account data was collected from Statistics Sweden (2023).

4.2.6 Inflation

Inflation has been a source of economic instability and has been associated with crises throughout economic history. Whether it be deflation or times of turmoil with high levels of inflation this could function as an indicator if a crisis or recession is due in the near future. Deemed to be a good variable to target to fulfil financial stability it would be interesting to see if when the target is not met this could indicate a crisis. To capture this data of inflation is collected from Statistics Sweden (2023) and as the Riksbank have a 2% target. This target value is deducted from the inflation of each quarter which gives us the *inflation gap.*

4.2.7 Unemployment

Unemployment is a common measure to use of real economic activity. When unemployment is at low levels this would indicate high real activity and a high level of unemployment would indicate low real activity. Thus, a high level of unemployment could be a sign of a coming recession. However, as previous analyses of crises and recessions have emphasized how these events were preceded by an overheated economy, a low level of unemployment could also indicate a higher risk for a crisis in the near future. I collected unemployment data from Statistics Sweden (2023).

4.2.8 VIX

Typically, a financial crisis is recognised by an episode of high volatility on financial markets. To account for this data is collected for a common measure used of financial market volatility, the VIX, where a high VIX value indicates high financial risk and indicate a heightened risk of a financial crisis. In applied financial studies the VIX is one of the most used measures of financial market volatility (Whaley, 2009). Data of the VIX was collected from Yahoo Finance (2023). In the table below descriptive statistics of all the variables, including the recoded dependent variable is presented.

Variable	Obs	Mean	Std. Dev.	Min	Max
Inflation	128	.173	2.04	-1.933	9.033
Interestratespread	128	1.059	1.201	-4.573	3.46
NYSE	128	7590.015	3588.981	1842.367	16449.57
VIX	128	19.691	7.13	10.093	46.707
OMX30	128	60814.174	33746.13	9560.05	154888.3
y2	128	.305	.462	0	1
House prices	128	407.397	215.285	156.757	949.55
CA/GDP	128	3.244	2.222	-2.246	7.501
Credit	128	190.923	45.134	128.2	273.2
Unemployment	128	7.382	1.602	1.767	10.3

Tabel 4.1: Descriptive statistics for all variables. Note, they are presented before the log-difference is taken from the indices and the other variables are interpreted as percentage.

4.3 Excluded Variables

In this section I will account for some of the variables that have been used in previous literature and why they are excluded in this study.

4.3.1 Exchange Rate

The exchange rate is a variable that do hold valuable information about the current state of an economy, especially for a small open economy like Sweden. To observe the movement of the exchange rate could also imply if a currency crisis is likely to happen. However, as argued by previous literature, a good leading indicator has low volatility. The exchange rate is a variable that is known to be volatile and would not be suited to act as a leading indicator. Moreover, since the focus of the paper is to predict the probability of a future recession and forecasting the exchange rate is proved to be a difficult task this becomes problematic for the purpose.[17] Furthermore, as Borio & Lowe (2002) found that the exchange rate does not add any more information if credit level and stock prices are accounted for, I choose to exclude the Exchange rate from the regressions.

[17] A random walk is the superior forecast for exchange rates.

4.3.2 Loan-to-Deposit Ratio & Deposit-to-GDP ratio

Two variables that was excluded due to data availability was the loan-to-deposit ratio and the deposit-to-GDP ratio. Both variables have been considered for papers that investigate banking crises. With the former suggested in a paper by Giordani et al. (2017) for a new early warning indicator for Sweden and the latter found significant for Finland as an early leading indicator (Laina et al. 2015). However, as the interest of this paper is the probability of financial crises the requirement of the data was that it should be available from 1990 on a quarterly basis.

4.3.3 Sentiment Variables

Another variable that was excluded due to data availability was sentiment variables. More specifically, the indices for consumers and producers which otherwise was intended to be included. The data available only reached back to 1996 on an annual basis from Statistics Sweden. Consumer expectation index was the biggest negative contributor to the Conference Board's Leading Indicators in the US and would also be of interest to include when Sweden is in focus. However, the sentiment variables have not been extensively studied in a probit framework and would be interesting to include in future research.

5 Results

5.1 Single-predictor model in-sample

The fist results presented is that of the single-predictor in-sample model at the forecasts horizon of one quarter ahead (h=1), six months ahead (h=2), and one year ahead (h=4). I first account for the case of the initial threshold value equal to zero the result is presented in Appendix A. Both the measures of fit R_{ps}^2 and the BIC-score are presented. Furthermore, after the computations are completed, the residuals are computed and Jarque-Bera test is performed.

Both the BIC and the R_{ps}^2 suggests that the interest rate spread holds the most information when it comes to forecasting the probability of a crisis to occur. Furthermore, it is the only variable that appears to have a significant effect throughout the different horizons. However, when the Jarqe-Bera test is performed, the null-hypothesis of a normal distribution of the residuals is rejected at the 1% level. This implies that the ML estimators cannot be trusted or used for any inference. Moreover, this is something that was suspected as the initial threshold generated to few observations for a regression to be meaningful.

The next results that will be presented in Tables 5.1-5.3 is when the threshold now is increased to 0,25%. However, the results will be presented in the similar manner as for the previous threshold.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Dependent Variable: $P(y_2 = 1)$					
Interest rate spread	-7.660***								
	(1.801)								
Credit		16.57**							
		(7.945)							
House prices			-21.94***						
			(7.125)						
OMX30				-4.105***					
				(1.206)					
NYSE					-5.462***				
					(2.018)				
VIX						0.290			
						(0.557)			
CA/GDP							1.845		
							(10.99)		
Inflation								-7.829	
								(15.26)	
Unemployment									8.819**
									(3.424)
Constant	0.187	-0.636***	-0.303**	-0.511***	-0.469***	-0.543***	-0.544***	-0.547***	-0.614***
	(0.191)	(0.128)	(0.136)	(0.123)	(0.120)	(0.118)	(0.119)	(0.119)	(0.123)
Observations	127	126	126	126	126	126	126	126	126
Pseudo R2	0.230	0.0339	0.0937	0.0849	0.0580	0.00214	0.000201	0.00183	0.0534
BIC	129.059	157.051	147.929	149.283	153.382	161.904	162.199	161.952	154.082

*Tabel 5.1: Forecast horizon one quarter ahead, threshold=0,25%. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Dependent Variable: $P(y_2 = 1)$				
Interest rate spread	-7.352***								
	(1.708)								
Credit		13.85*							
		(7.801)							
House prices			-12.66*						
			(6.537)						
OMX30				-5.737***					
				(1.293)					
NYSE					-7.429***				
					(2.151)				
VIX						0.387			
						(0.557)			
CA/GDP							-4.944		
							(11.41)		
Inflation								-23.63	
								(15.20)	
Unemployment									56.33*
									(32.38)
Constant	0.116	-0.636***	-0.414***	-0.537***	-0.479***	-0.560***	-0.557***	-0.580***	-0.600***
	(0.215)	(0.128)	(0.138)	(0.128)	(0.127)	(0.119)	(0.119)	(0.121)	(0.123)
Observations	126	125	125	125	125	125	125	125	125
Pseudo R2	0.222	0.0241	0.0357	0.147	0.0951	0.00376	0.00148	0.0153	0.0220
BIC	128.385	156.126	154.389	137.749	145.476	159.180	159.522	157.452	156.447

*Tabel 5.2: Forecast horizon two quarters ahead, threshold=0.25%. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent Variable: $P(y_2 = 1)$								
Interest rate spread	-2.972**								
	(1.185)								
Credit		4.363							
		(7.553)							
House prices			-0.00688						
			(6.096)						
OMX30				-1.557					
				(1.055)					
NYSE					0.212				
					(1.783)				
VIX						0.0939			
						(0.540)			
CA/GDP							-3.429		
							(11.64)		
Inflation								-4.866	
								(16.18)	
Unemployment									-3.110
									(29.77)
Constant	-0.298*	-0.615***	-0.593***	-0.573***	-0.597***	-0.593***	-0.591***	-0.597***	-0.592***
	(0.177)	(0.127)	(0.143)	(0.123)	(0.125)	(0.121)	(0.121)	(0.122)	(0.122)
Observations	124	123	123	123	123	123	123	123	123
Pseudo R2	0.0604	0.00244	1.02e-08	0.0133	8.71e-05	0.000213	0.000723	0.000705	6.08e-05
BIC	148.298	154.297	154.652	152.723	154.639	154.621	154.547	154.549	154.643

*Tabel 5.3: Forecast horizon four quarters ahead, threshold=0.25%. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

Once again both the R^2_{ps} and the BIC suggest that the interest rate spread holds the most information when forecasting crisis probabilities. Furthermore, the null of the Jarqe-Berra cannot be rejected at all conventional levels for all variables at all horizons which leads to consistent estimators that can be trusted. Considering the horizons of h=1 and h=2 the same variables appear significant, interest rate spread, credit, house prices, OMX30, NYSE and unemployment. However, unemployment, credit and house prices drop to only be significant at the 10% level when forecasting two quarters ahead. The interest rate spread is significant at the 5% level for the one year ahead forecast, but with R^2_{ps} that have decreased from 0,229 to 0,060 implying that it holds value as a leading indicator for shorter horizons.

5.2 Multipredictor Model In-Sample

Following the single-predictor models I present the results for the multipredictor models in-sample forecasts at the three different horizons. In the tables the R^2_{ps} and the BIC score will be presented together with the coefficients for each variable. The initial regression will be consisting of all the potential leading indicators, to then be dropped one by one respectively. Furthermore, this will then be repeated for the model that performed the best at each horizon respectively as well. The results for the model with threshold set to zero will be presented in Appendix A as the normality test rejected the null and the results are not of further interest to be analysed. Instead, the results for the threshold set to 0,25% is presented in Tables 5.7-5.9.

5.2.1 Forecast Horizon One Quarter Ahead

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable: $P(y_2 = 1)$									
Interest rate spread	-6.625***	-6.962***	-6.601***	-6.626***	-6.545***	-6.593***	-6.757***	-6.907***	-6.520***	
	(2.264)	(2.195)	(2.290)	(2.264)	(2.232)	(2.169)	(2.122)	(2.164)	(2.262)	
Credit	14.82*	15.00*	15.37*	15.21*	14.87*	15.34*	14.41*	14.89*		13.26
	(8.286)	(8.271)	(8.198)	(8.311)	(8.327)	(8.265)	(8.041)	(8.310)		(8.727)
House prices	-8.323	-9.545	-9.039	-8.181	-8.382	-9.077	-9.064		-8.220	-14.33*
	(7.674)	(7.154)	(7.925)	(7.729)	(7.668)	(7.843)	(7.701)		(7.428)	(8.134)
OMX30	-2.764*	-2.338	-2.750*	-2.667*	-2.853*	-3.399**		-2.878*	-2.675*	-3.526**
	(1.586)	(1.494)	(1.590)	(1.521)	(1.597)	(1.542)		(1.553)	(1.530)	(1.375)
NYSE	-2.238	-2.922	-2.185	-2.192	-1.781		-4.482	-2.625	-2.647	-1.488
	(3.415)	(3.197)	(3.399)	(3.420)	(2.852)		(3.105)	(3.424)	(3.275)	(2.865)
VIX	-0.213	-0.454	-0.206	-0.171		0.0647	-0.407	-0.240	-0.252	0.204
	(0.714)	(0.721)	(0.715)	(0.705)		(0.587)	(0.694)	(0.729)	(0.698)	(0.665)
CA/GDP	4.026	5.277	3.452		3.300	3.617	0.414	3.181	6.740	5.442
	(11.46)	(11.76)	(11.80)		(11.40)	(11.79)	(10.99)	(11.56)	(11.20)	(11.78)
Inflation	11.44	11.61		11.05	11.31	11.03	10.94	13.81	14.15	1.476
	(20.54)	(19.52)		(20.87)	(20.59)	(20.57)	(22.20)	(18.96)	(19.64)	(16.48)
Unemployment	36.70		36.76	37.89	40.77	44.09	21.09	44.13	37.67	75.75*
	(52.49)		(51.65)	(53.08)	(51.71)	(48.17)	(50.71)	(49.33)	(54.17)	(41.08)
Constant	0.132	0.210	0.139	0.127	0.117	0.104	0.163	0.0445	0.205	-0.458***
	(0.296)	(0.261)	(0.306)	(0.298)	(0.293)	(0.277)	(0.280)	(0.255)	(0.291)	(0.155)
Observations	126	126	126	126	126	126	126	126	126	126
Pseudo R2	0.322	0.316	0.320	0.322	0.322	0.319	0.304	0.314	0.305	0.207
BIC	151.761	147.849	147.297	147.021	147.013	147.485	149.682	148.141	149.516	164.514

*Tabel 5.4: Forecast horizon one quarter ahead, threshold=0.25%. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

The results imply that the interest rate spread is robust to the different specifications and the different horizons as it is the variable that appears significant at the 1% level across all. Furthermore, the OMX30 index appears as a useful leading indicator one and two quarters ahead. Moreover, the same result holds for the NYSE index as it appears significant across most specifications, but not all. Both of the indication value disappears for the stock indices at a forecast horizon of one year.

For the horizon of one quarter, observing the R^2_{ps} it appears that model specification (1), (4), and (5) has the same value for the measure of fit of 0,322. To determine which of the specifications that will be accounted for in the next sequence I observe which of the models that has the lowest BIC score. The model (5) with the VIX dropped from the specification has the lowest score of 147,013 and is the model that will be re-estimated with one less explanatory variable in each regression (Table 5.5).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: $P(y_2 = 1)$							
Interest rate spread	-6.837***	-6.524***	-6.560***	-6.623***	-6.610***	-6.823***	-6.414***	
	(2.236)	(2.257)	(2.224)	(2.212)	(2.083)	(2.134)	(2.232)	
Credit	15.09*	15.42*	15.19*	15.36*	14.50*	14.97*		13.28
	(8.276)	(8.237)	(8.300)	(8.216)	(8.083)	(8.368)		(8.684)
House prices	-9.998	-9.082	-8.247	-9.115	-9.179		-8.307	-14.31*
	(7.088)	(7.926)	(7.718)	(7.905)	(7.690)		(7.418)	(8.118)
OMX30	-2.431	-2.835*	-2.754*	-3.415**		-2.975*	-2.779*	-3.445**
	(1.484)	(1.601)	(1.528)	(1.529)		(1.558)	(1.527)	(1.375)
NYSE	-1.992	-1.743	-1.820		-3.760	-2.123	-2.109	-1.932
	(2.929)	(2.824)	(2.811)		(2.606)	(2.848)	(2.755)	(2.445)
CA/GDP	3.752	2.773		3.875	-1.323	2.322	5.837	6.044
	(11.44)	(11.63)		(11.38)	(10.81)	(11.58)	(11.10)	(11.55)
Inflation	11.41		11.01	11.05	10.61	13.65	14.00	1.458
	(19.33)		(20.85)	(20.60)	(22.48)	(18.97)	(19.71)	(16.43)
Unemployment		40.72	41.08	43.04	27.98	48.83	42.32	72.53*
		(51.25)	(51.95)	(49.66)	(49.84)	(48.86)	(52.90)	(40.91)
Constant	0.193	0.125	0.116	0.108	0.136	0.0285	0.188	-0.449***
	(0.262)	(0.302)	(0.293)	(0.282)	(0.278)	(0.249)	(0.286)	(0.155)
Observations	126	126	126	126	126	126	126	126
Pseudo R2	0.313	0.319	0.322	0.318	0.302	0.314	0.304	0.206
BIC	143.477	142.544	142.244	142.660	145.180	143.418	144.807	159.771

*Tabel 5.5: VIX dropped. Forecast horizon one quarter ahead, threshold=0.25%. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

The results reveal that the R^2_{ps} for the third model specification in Table 5.5 has the same measure-of-fit as the previous model. However, the BIC score of 142.244 implies an improvement of the model when the current account-GDP ratio is dropped. Thus, this is the model specification that now will be re-estimated.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable: $P(y_2 = 1)$						
Interest rate spread	-6.854***	-6.539***	-6.646***	-6.602***	-6.829***	-6.426***	
	(2.226)	(2.245)	(2.206)	(2.065)	(2.129)	(2.230)	
Credit	15.42*	15.68*	15.76*	14.36*	15.19*		13.71
	(8.288)	(8.192)	(8.149)	(8.035)	(8.358)		(8.572)
House prices	-9.866	-8.958	-8.979	-9.248		-8.047	-14.13*
	(7.122)	(8.008)	(7.948)	(7.726)		(7.453)	(8.215)
OMX30	-2.317	-2.753*	-3.310**		-2.903*	-2.602*	-3.300**
	(1.426)	(1.532)	(1.503)		(1.496)	(1.452)	(1.337)
NYSE	-2.030	-1.778		-3.774	-2.148	-2.196	-2.056
	(2.885)	(2.782)		(2.630)	(2.815)	(2.696)	(2.436)
Inflation	11.03		10.70	10.71	13.45	13.60	1.176
	(19.62)		(20.87)	(22.49)	(19.23)	(20.01)	(16.65)
Unemployment		40.96	43.41	27.67	48.99	42.64	73.14*
		(51.50)	(49.81)	(50.23)	(49.02)	(53.19)	(41.05)
Constant	0.193	0.124	0.107	0.137	0.0283	0.188	-0.449***
	(0.262)	(0.302)	(0.283)	(0.279)	(0.249)	(0.285)	(0.156)
Observations	126	126	126	126	126	126	126
Pseudo R2	0.313	0.319	0.318	0.302	0.313	0.303	0.205
BIC	138.729	137.755	137.916	140.355	138.616	140.193	155.186

*Tabel 5.6: CA/GDP dropped. Forecast horizon one quarter ahead, threshold=0.25%. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

None of the model specifications reported a higher or equal R^2_{ps} than 0,322, implying that no further elimination of explanatory variables will improve the measure-of-fit. That is model specification (3) in Table 5.5 corroborates that the findings of the interest rate spread holds vital information to the forecasting ability of the model of a one quarter horizon.

5.2.2 Forecast Horizon Two Quarters Ahead

The next results presented will be that of a horizon of six months ahead with all explanatory variables included. Where once again the R^2_{ps} and the BIC score will be compared between the model specifications in Table 5.7 to determine which will be re-estimated.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable: $P(y_2 = 1)$									
Interest rate spread	-8.307***	-8.032***	-8.396***	-8.190***	-7.973***	-7.445***	-8.642***	-7.967***	-8.390***	
	(2.220)	(2.096)	(2.153)	(2.262)	(2.096)	(2.174)	(1.943)	(2.511)	(2.130)	
Credit	11.29	11.52	10.91	10.76	10.92	12.43	10.51	10.52		12.44
	(9.608)	(9.606)	(9.450)	(9.544)	(9.646)	(8.946)	(9.484)	(9.656)		(8.814)
House prices	5.446	6.021	5.387	5.467	4.787	4.651	3.073		4.679	-1.684
	(9.119)	(8.770)	(9.000)	(9.155)	(8.760)	(8.624)	(8.684)		(8.926)	(8.339)
OMX30	-4.053**	-4.200***	-4.001**	-4.221**	-4.230***	-5.502***		-3.815**	-3.944**	-4.840***
	(1.643)	(1.602)	(1.671)	(1.643)	(1.633)	(1.505)		(1.631)	(1.637)	(1.498)
NYSE	-6.822**	-6.405*	-6.837**	-6.819**	-5.002*		-9.785***	-6.691**	-6.994**	-4.562
	(3.415)	(3.449)	(3.415)	(3.433)	(2.965)		(3.001)	(3.247)	(3.371)	(3.225)
VIX	-0.695	-0.603	-0.679	-0.756		0.215	-0.882	-0.643	-0.661	-0.233
	(0.812)	(0.817)	(0.812)	(0.790)		(0.662)	(0.785)	(0.779)	(0.798)	(0.679)
CA/GDP	-6.030	-6.028	-6.103		-8.171	-6.151	-11.91	-6.106	-4.368	-0.632
	(13.26)	(13.30)	(13.32)		(12.96)	(13.66)	(12.51)	(13.18)	(13.50)	(13.27)
Inflation	-5.533	-5.594		-5.731	-3.716	-5.588	-0.721	-5.141	-1.558	-25.12
	(17.92)	(17.38)		(18.32)	(17.13)	(16.96)	(16.26)	(17.72)	(17.04)	(15.74)
Unemployment	-18.29		-18.41	-18.30	-4.511	11.72	-40.88	-25.33	-21.38	45.30
	(41.46)		(41.21)	(41.53)	(41.43)	(43.81)	(37.46)	(38.80)	(41.12)	(39.63)
Constant	0.123	0.0821	0.134	0.117	0.0815	-0.0124	0.211	0.174	0.200	-0.567***
	(0.314)	(0.291)	(0.305)	(0.317)	(0.301)	(0.304)	(0.284)	(0.298)	(0.301)	(0.168)
Observations	125	125	125	125	125	125	125	125	125	125
Pseudo R2	0.363	0.362	0.363	0.362	0.357	0.334	0.328	0.359	0.355	0.218
BIC	143.857	139.185	139.091	139.242	139.905	143.444	144.380	139.593	140.278	160.763

*Tabel 5.7: Forecast horizon two quarters ahead, threshold=0.25%. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

The interest rate spread, OMX30, and the NYSE are the variables with a significant coefficient. Furthermore, the interest rate spread and the OMX30 variable are significant across the different specifications at the 5% level or even lower. Once again, the normality assumption holds as the null of the Jarque-Bera cannot be rejected for any of the model specifications. When we observe the R^2_{ps} it is noted that the model specification (3) has the same value as the regression with all included variables. However, with a lower BIC score of 139,091 for (3) it is implied that there is room for improvement in re-estimating (3) with removal of the inflation gap.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: $P(y_2 = 1)$							
Interest rate spread	-8.118***	-8.284***	-8.042***	-7.524***	-8.655***	-8.045***	-8.417***	
	(2.038)	(2.187)	(2.036)	(2.123)	(1.905)	(2.455)	(2.080)	
Credit	11.14	10.35	10.66	12.05	10.46	10.18		11.04
	(9.456)	(9.452)	(9.474)	(8.835)	(9.304)	(9.474)		(8.554)
House prices	5.979	5.391	4.768	4.587	3.087		4.674	-3.244
	(8.636)	(9.031)	(8.693)	(8.526)	(8.667)		(8.896)	(8.027)
OMX30	-4.155**	-4.167**	-4.200**	-5.474***		-3.778**	-3.931**	-4.641***
	(1.632)	(1.667)	(1.660)	(1.516)		(1.651)	(1.655)	(1.524)
NYSE	-6.413*	-6.831**	-5.040*		-9.791***	-6.705**	-6.996**	-4.295
	(3.454)	(3.433)	(2.977)		(3.004)	(3.245)	(3.371)	(3.156)
VIX	-0.586	-0.739		0.228	-0.881	-0.630	-0.657	-0.141
	(0.815)	(0.789)		(0.662)	(0.786)	(0.780)	(0.800)	(0.668)
CA/GDP	-6.096		-8.165	-6.164	-11.91	-6.131	-4.398	-1.164
	(13.36)		(12.98)	(13.69)	(12.51)	(13.22)	(13.53)	(13.31)
Unemployment		-18.40	-4.851	11.72	-40.97	-25.53	-21.38	53.23
		(41.29)	(41.18)	(43.73)	(37.24)	(38.43)	(41.09)	(39.08)
Constant	0.0925	0.130	0.0902	-0.00125	0.213	0.184	0.203	-0.535***
	(0.283)	(0.307)	(0.295)	(0.296)	(0.281)	(0.292)	(0.296)	(0.163)
Observations	125	125	125	125	125	125	125	125
Pseudo R2	0.362	0.361	0.357	0.333	0.328	0.359	0.355	0.206
BIC	134.421	134.482	135.107	138.685	139.553	134.820	135.455	157.819

*Tabel 5.8: Inflation dropped. Forecast horizon two quarters ahead, threshold=0.25%. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

It becomes evident from the R^2_{ps} values in Table 5.8 that the model does not improve when eliminating any of the other variables apart from the inflation gap. Implying that regression (3) form Table 5.7 is the preferred specification when forecasting in-sample at a six-month horizon.

5.2.3 Forecast Horizon Four Quarters Ahead

The third and last horizon that is forecasted for the in-sample predictions are a one year ahead forecast. Following the same steps as with the two previous horizons one regression will include all variables to then be dropped one at a time.

The results are presented in Appendix B and concludes that the model with all explanatory variables yields the highest R^2_{ps} and is thus the specification that is most suited for forecasting the probability of a crisis one year ahead. However, as the results shows, the R^2_{ps} have decreased significantly from the shorter horizons to around 0,08 for all specifications. Implying that the model suggested in this paper is more suited for shorter horizons than longer ones. Meaning that the potential leading indicators might not give early warning signals but rather near in time to the crisis. However, the variable that appears significant throughout the specifications are the interest rate spread which still holds valuable information for the crisis probability.

5.2.4 Marginal Effects

The marginal effects must be computed separately to make the coefficient interpretable. That is due to that the marginal effects are smaller when they located at the tails of the PDF. Furthermore, the marginal effects will vary across the time series. To account for this, average marginal effects for the final model of each horizon respectively will be computed for and presented in Table 5.9.

	Forecast horizon:		
	h=1	h=2	h=4
Variable:	Average ME	Average ME	Average ME
Interest rate spread	−1.526***	−1.781***	−1.142***
Credit	3.535*	2.315	1.217
House price	−1.919	1.143	1.961
OMX30	−0.641*	−0.849**	-0.375
NYSE	−0.423	−1.450**	0.591
VIX	-	−.144	0.045
CA/GDP	-	-	-1.373
Inflation	2.562	−1.294	1.642
Unemployment	9.558	−3.905	-11.423

Tabel 5.9: Marginal effects of the final model for each horizon respectively.

The marginal effect of the interest rate spread on the probability of a recession is negative. When the spread between the 10-year government bond and the 3-month government bond increases by one percentage point, the probability of observing a recession decreases by at a 1,526 percentage points at h=1, 1,781 at h=2, and 1,142 at h=4. Conversely, a decrease of the spread would imply an increase of observing a probability would increase across all horizons. A result that confirms what previous theoretical studies have implied that a flattening of the yield curve is likely to reduce real growth in the short term. Thus, the interest rate spread could function as a leading indicator of a crisis.

Neither credit nor house prices appears significant, at an 5% level, for any of the forecasting horizon of the final models. As both credit and house prices have been variables that have empirically been important for the occurrence of boom-bust cycles in Sweden this would be expected to function as leading indicator. However, this could not be confirmed in this paper when modelling the occurrence of a crisis through a probit model. This does not imply that credit and/or house prices does not hold any explanatory power in describing the financial cycle.

The marginal effect of the NYSE index and OMX30 index is a bit ambiguous. For the forecasting horizon of h=1 and h=4 none of the indices are statistically significant. However, for the forecasting horizon of h=2 both are significant and negative. This implies that an increase of stock prices would indicate a lower probability of a crisis. Asset bubbles are usually a predecessor of a stock market crash, which is considered an element of a financial crisis. On the other hand, this could confirm some other conventional theories that stock prices might be interpreted as the expected present values of future outcomes. Furthermore, high dividend streams condition high revenues for the future. Moreover, these revenues are in turn conditioned on higher future consumption which could be the result of real growth in output. For the remaining variables, VIX, CA/GDP, the inflation gap, and the unemployment rate, none was found to be significant, and the regressions did not implicate any of them to be leading indicators of a crisis. The fitted probabilities are presented in Figures 5.1-5.3 for the different horizons. From the figures it becomes evident that the fitted values for the two shorter forecasting horizons outperforms the model for four quarters ahead.

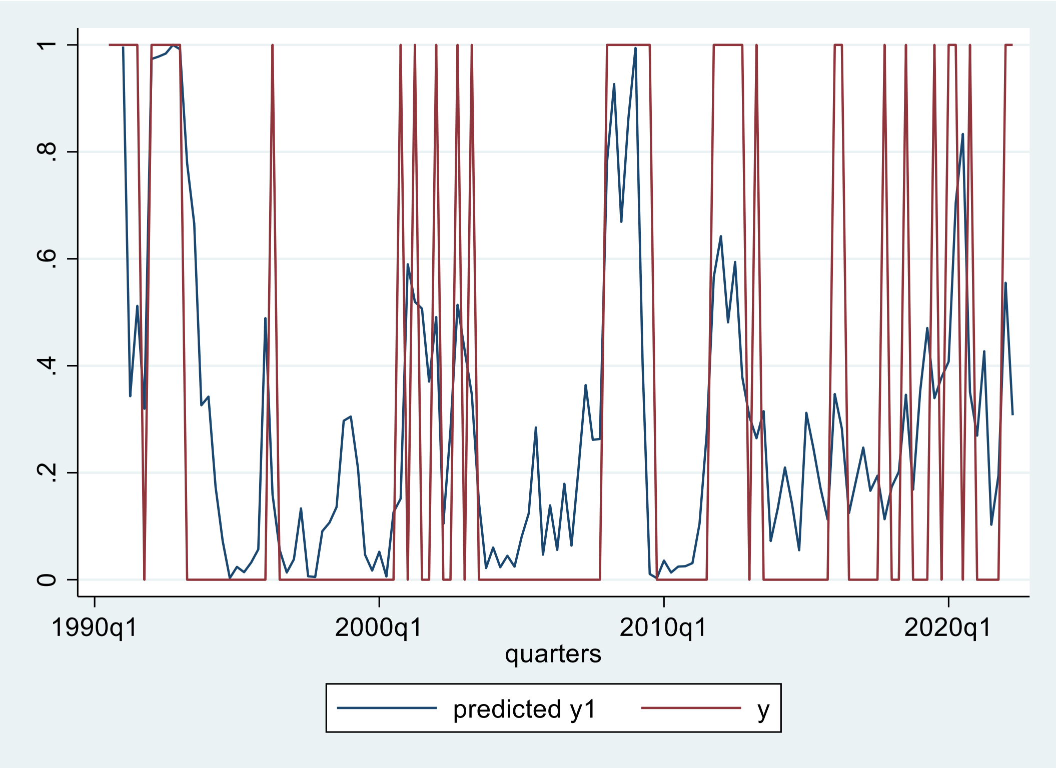

Figure 5.1: In-sample prediction for final model h=1. Predicted y1 stands for the fitted value of the final probit model and y for the dependent variable.

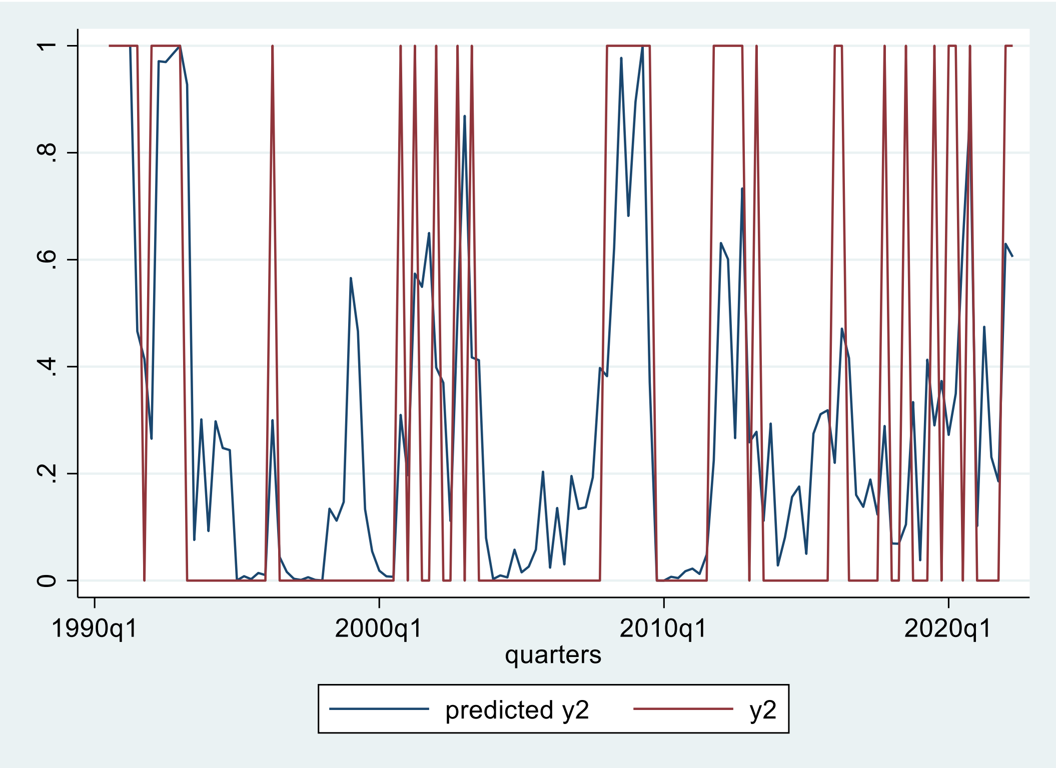

Figure 5.2: In-sample prediction for final model h=2. Predicted y2 stands for the fitted value of the final probit model and y for the dependent variable.

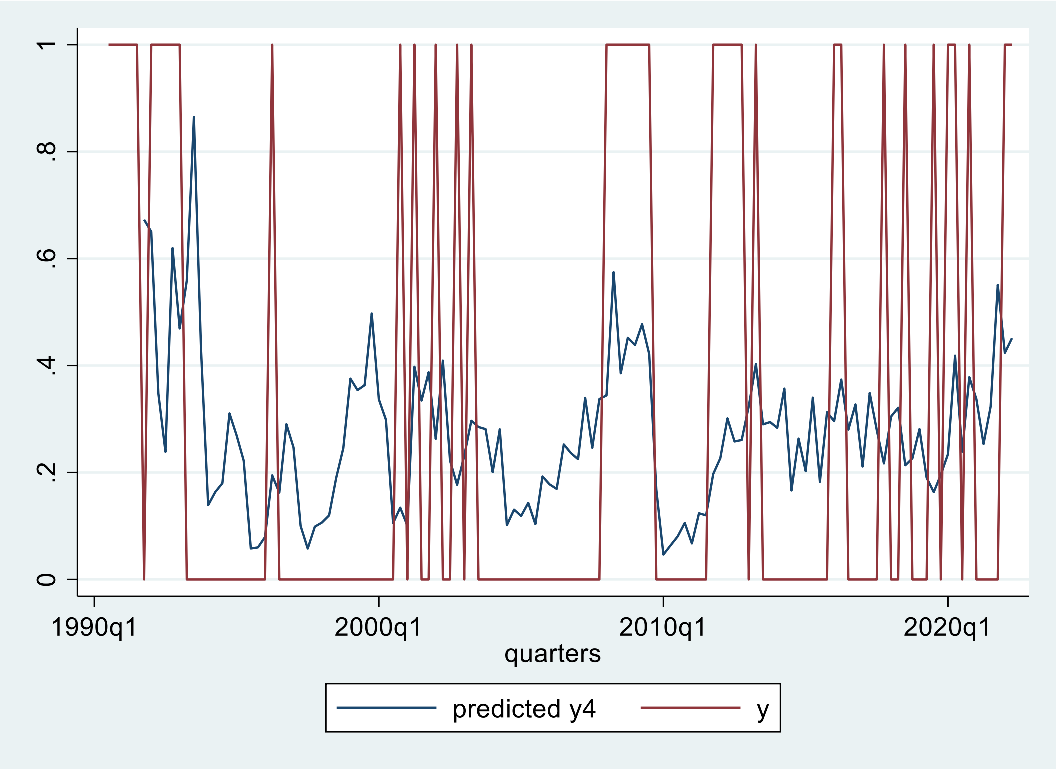

Figure 5.3: In-sample prediction for final model h=2. Predicted y2 stands for the fitted value of the final probit model and y for the dependent variable.

5.2.5 Robustness Check for In-Sample Results

I perform a robustness check for the in-sample results of the final models at each horizon. To perform the test the sample is split into two parts. The first subsample starts at 1990Q2 and reaches 2007Q4 and the second subsample starts at 2008Q1 and ends at 2022Q2, I label the different subsamples in the table as Pre-GFC and Post-GFC. Then the probit models are estimated separately, and the results are presented in Tables 5.10-5.12 below.

	(1)	(2)
Subsample:	Pre-GFC	Post-GFC
Dependent Variable: $P(y_2 = 1)$		
Interest rate spread	-9.873***	-3.455
	(2.698)	(3.048)
Credit	-0.270	29.60**
	(17.41)	(14.17)
House prices	3.928	-35.63***
	(10.30)	(12.62)
OMX30	-3.436*	-0.937
	(1.856)	(2.764)
NYSE	-4.662	-1.654
	(3.947)	(3.530)
Inflatio	6.642	9.028*
	(20.80)	(4.872)
Unemployment	21.74	9.809
	(54.17)	(7.299)
Constant	-0.0542	0.222
	(0.304)	(0.420)
Observations	68	58
Pseudo R2	0.497	0.341

*Tabel 5.10: Robustness results, forecast horizon one quarter ahead, threshold=0.25%. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

First thing to note, not just for the forecasting horizon of one quarter ahead but for all horizons, is that the R^2_{ps} increases for all regressions. This implies that when the sample is split goodness-of-fit measure increases and could confirm the results of a recession or a crisis is not homogenous and that different factors have varying predictive power. Furthermore, as a crisis tend to change fundamentals in both policy and markets. The GFC could just be such an event where these two factors have been altered.[18] For the pre-GFC regression interest rate spread is once again found negative and significant confirming the previous results. However, for the post-GFC regression the spread becomes insignificant, albeit still negative. This does not alter the results two much but could be an implication of the less functional markets following the lower interest rate environment after the GFC where term spreads are less informative compared to prior the crisis.

Another result that from the post-GFC estimation that diverge from the full sample regression is the Credit and House Prices coefficients. Both variables now have significant impact on the probability of recession with an increase of credit implies an increase in probability, and a decrease of house prices implies an increase in probability. These results hold up quite well

[18] Zero interest rate environment and less well-functioning credit markets are two examples.

with theoretical starting points as well as the financial stability reports from the Riksbank and IMF. Credit booms have been observed to proceed financial crises and recessions in the past and crashes of the house markets was observed both in the Swedish financial crisis during the 1990s and the GFC. Furthermore, since the GFC credit and house prices have steadily risen and could explain the predictive power that the variables gain when performing a robustness check. Also, during the last couple of quarters the house prices are starting to fall in Sweden, while stress on households and firms are increasing with higher expenses due to inflation, the war in Ukraine, and still recovering from the Covid-19 pandemic.

	(1)	(2)
Subsample:	Pre-GFC	Post-GFC
Dependent Variable: $P(y_2 = 1)$		
Interest Rate Spread	-8.155***	-12.58***
	(1.847)	(4.192)
Credit	-7.672	19.74
	(15.24)	(16.38)
House Prices	12.11	-9.971
	(10.35)	(14.22)
OMX30	-6.858**	-5.948*
	(2.704)	(3.051)
NYSE	3.481	-12.63***
	(5.453)	(4.402)
VIX	1.394	-2.042
	(1.295)	(1.249)
CA/GDP	-16.36	8.946
	(27.52)	(15.83)
Unemployment	34.31	-9.642
	(52.05)	(9.049)
Constant	-0.589*	1.076*
	(0.331)	(0.557)
Observations	67	58
Pseudo R2	0.478	0.420

*Tabel 5.11: Robustness results, forecast horizon two quarters ahead, threshold=0.25%. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

The results in table 5.15 more or less confirms the results found for the entire sample period. The interest rate spread is significant and negative and the same holds for the OMX30 and the NYSE. However, one interesting observation to note is for the variables VIX, CA/GDP, and unemployment, sign of the coefficient switches between the subsample regressions. This is another result that implies that after a major event on the global financial markets the economic condition changes. Which amplifies the reasoning that a crisis or a recession at one point does not necessarily help us understand or predict a crisis at another point in time.

	(1)	(2)
Subsample:	Pre-GFC	Post-GFC
Dependent Variable: $P(y_2 = 1)$		
Interest Rate Spread	-1.078	-9.279**
	(1.527)	(3.743)
Credit	-6.392	10.73
	(14.48)	(13.81)
House Prices	11.30	-8.664
	(10.91)	(12.75)
OMX30	-2.453	-2.613
	(2.058)	(3.076)
NYSE	3.183	2.815
	(3.960)	(4.618)
VIX	-0.265	-0.269
	(1.307)	(0.881)
CA/GDP	-5.153	4.244
	(19.36)	(16.96)
Inflation	-37.59*	12.59**
	(20.77)	(5.221)
Unemployment	54.04	-14.40*
	(50.84)	(8.542)
Constant	-1.213***	0.632
	(0.316)	(0.474)
Observations	65	58
Pseudo R2	0.163	0.256

*Tabel 5.12: Robustness results, forecast horizon four quarters ahead, threshold=0.25%. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

At a forecasting horizon of four quarters ahead the interest rate spread appears negative for both subsamples. However, the spread is only significant in the post-GFC estimation which implies that the spread still holds predictive power. The results from a one quarter ahead forecast and four quarters ahead forecast diverge in this aspect. For the former case the spread was only significant in the pre-GFC and for the latter only in the post-GFC. The results imply that after the GFC the interest rate spread was an early warning indicator, while prior to the GFC it was only a leading indicator by one quarter.

Inflation is now found significant at the 5%-level, this might be explained by the economic slowdown observed during and after the pandemic and high levels of inflation at the same time. Furthermore, as inflation is a nominal variable it could take time before the result is transmitted to the real side of the economy, such as an increase in policy rate if the inflation is not expected to be transitory might be delayed.

To sum up, the overall results of the robustness check do confirm the predictive power of the interest rate spread. However, the results also point out the fact that a conclusion from one recession does not need hold for another. Also, the fundamental economic conditions alter over time which implies that one factor may have explanatory power for a recession during one time sample, while it does not for another time sample. Moreover, with the somewhat inconclusive results from the robustness check this implies the need of contribution to evaluate leading indicators for recessions in small open economies like Sweden.

5.3 Out-of-Sample Results

The results for the out-of-sample are presented in Table 5.13 for each horizon. Before preforming the out-of-sample estimates a Breusch-Pagan test is performed to detect heteroscedasticity in the models. The p-value exceeds 0,05 and the null of homoscedastic error terms cannot be rejected for any of the models. For the one quarter ahead and the two quarters ahead horizons the final model that was implied to perform the best by the in-sample results are compared to the model with all explanatory variables. This is due to what previous studies have concluded about great in-sample results does not guarantee good out-of-sample results. For the last horizon considered the final model is the initial model and only the AUC score for this one will be presented.

	Forecast horizon:		
	h=1	h=2	h=4
Model:	AUC	AUC	AUC
Final model	0,726	0,689	0,595
Initial model	0,737	0,700	-

Table 5.13: Results for out-of-sample estimations.

The out-of-sample results implies that for h=1 and h=2 the final model does not perform better than the initial model. Confirming the results that good in-sample findings does not necessarily mean that the findings will perform as well out-of-sample. However, the AUC-score is not that too far apart, but the initial model would still be to prefer. Moreover, at both horizons the AUC score is well above 0,5 implying that the models can be used for modelling the probability of a future crisis. The finding for h=4 also implies that the model can have some predictive power when it comes to modelling the probability of a crisis. However, the AUC of 0,595 is not too far from the value of 0,5 and the model have lost some of its predictive power when forecasting further ahead into the future. The results from the two shorter forecasting horizon holds up when compared to the AUC values obtained by Nissilä (2020) with values around 0,7. Furthermore, at a forecasting horizon of 12 months Nissilä

(2020) also got values that varied from 0,42 to 0,66 which also implied that the model specification is not well suited to forecast recession probabilities of one year.

The interpretation of the AUC-values is that they correspond to a chance of predicting the correct outcome. For final model when h=1 there is a 72,6% chance that the model will forecast a recession correctly, when h=2 there is 68,9% chance and for h=4 there is a 59,5% chance. This makes the results intuitive to interpret.

Other papers have also presented point estimates for out-of-sample probabilities of observing a crisis or recession. However, I will not present such a point estimate as the focus and interest of this paper is to see if the model presented can be used for forecasting the crisis probability and if the variables can be used as leading indicators of a crisis.

6 Analysis

The analysis will be conducted in two separate parts. First, the results from the different horizons will be discussed with the previous empirical and theoretical research presented as a foundation. This discussion is focused on how the results could potentially contribute for recession forecasting in Sweden. Second, a partial analysis will be conducted to study how various variables impact the probability of a recession. More specifically, I will try to establish a minimum amount a specific variable needs to change, ceteris paribus, to provoke a recession.

6.1 Discussion of the Results

The first fact that can be concluded from the results is that a multipredictor model improves the predictive power of a probit model trying to forecast crisis probabilities. Which can be confirmed as the goodness-of-fit measure increasing across all the horizons. This is also in line with more recent research that have extended the single-predictor model to include for other variables as well. The second fact that the results imply is that the preferred in-sample model does not necessarily lead to that same model would be preferred when conducting out-of-sample estimations. However, the in-sample model that performed the best for each horizon still had some predictive power out-of-sample.

Most of the research of regression forecasting have focused on the US. However, some of the results appears to be applicable to Sweden as well. The interest rate spread of the Swedish government bonds was found significant for all horizons. A result that confirms what previous theoretical studies have implied, that a flattening of the yield curve is likely to reduce real growth in the short term. Also, that financial distress first appears on the credit market as stated before, when the short rate increases the yield curve is getting flatter and reduces real growth in the short term. Thus, the interest rate spread could function as a leading indicator of a crisis for the Swedish economy. Furthermore, the previous recessions in the US have all been preceded by a negative interest rate. Moreover, when considering longer forecasting horizons the explanatory power of the other variables drops, but the interest rate spread remains significant. Which implies strong predictive power for the term spread when forecasting the probability of a crisis. The last observed interest rate spread for the Swedish bonds in the sample was positive at 1,457% which could indicate that Sweden does not have a crisis in the near term. The results in this paper thus found that the Interest Rate Spread is the leading indicator with most predictive power for the probability of a recession in Sweden.

The marginal effects of the OMX30 and the NYSE indices were found significant at the 5% level when a forecast horizon of two quarters ahead was considered. Both coefficients for the variables were negative which implies that an increase of stock prices would indicate a lower probability of a crisis. Asset bubbles are usually a predecessor of a stock market crash, which is considered an element of a financial crisis. However, the results found in this paper suggests otherwise and the rising of stock prices should not be an element of alarm. Instead, when the stock prices start to drop, an effect on the real economy from the financial markets would be expected. On the other hand, this could confirm some other conventional theories that stock prices might be interpreted as the expected present values of future outcomes. Furthermore, high dividend streams condition high revenues for the future. Moreover, these revenues are in turn conditioned on higher future consumption which could be the result of real growth in output. Also, when observing the volatility measure of the financial markets, the VIX, the results did not imply that this could be used as a leading indicator of a financial crisis. A result that would suggest that turmoil on the financial markets may not have any predictive power, or that this turmoil does not necessarily spill over to the real side of the economy.

As previously mentioned, as the Swedish financial crisis of the 1990s and the GFC was tightly connected to increased credit and increasing house prices, these variables were expected to have a significant predictive power. However, the credit variable was found significant at the 10% level for a horizon of one quarter ahead, but the significance was the reduced for longer horizons. The inflation gap was not found significant either. As the inflation fuelled the Swedish crisis and that more recently the high level of inflation has negatively affected the purchasing power of households and the cost of firms, the inflation gap could be expected to have a positive coefficient and be significant. However, the real effect of inflation is dependent on partly the interest rate and that an increase in inflation can be a result of a recession more than a leading indicator as well. The same argument goes for unemployment. However, as a measure of real activity the unemployment could both have a negative effect and positive effect on the probability of a crisis. Yet the unemployment rates could be a result of lower or higher growth, which calls for a causality problem. The last variable that was not found significant was the current account-to-GDP ratio. This would also be a macroeconomic variable that would capture real activity in the economy. More specifically, as reversals of the Current Account are typically connected to a slowdown in domestic growth and investments a slowdown of the Swedish economy could potentially be captured by the current account.

6.2 Partial Analysis

The partial analysis of each variable will be conducted with the condition that the probability of a recession must be superior to 50% after a period of 8 quarters (to 2024Q2) with respect to the change of one variable, keeping the remaining constant. I will consider the marginal effects for each variable that was found significant, for each forecasting horizon respectively with the starting point of each last predicted probability in 2022Q2. I also note that the last observed probability for the horizon of two quarters ahead the probability already exceeds 0,5 (0,605) and only conduct the partial analysis for the horizon of one quarter and four quarters ahead.

In the case for the model with a horizon of one quarter ahead the last observed probability was 31%. If the interest rate spread were to decrease with 0,125 percentage points per quarter accumulating to a decrease of 1 percentage points, the probability of a recession would surpass the threshold of 50%. A large decrease of the interest rate has been observed in Sweden previously. In the build-up to the Swedish financial crisis the spread started to fall and during first 8 quarters of the sample used 1990Q-1992Q2, the interest rate spread fell with almost 2,5 percentage points. A scenario with a fall of one percentage points does not appear too unlikely to occur, although perhaps not under these assumptions. However, since the second quarter of 2020 the interest rate spread has steadily increased, and the interest rate spread does not imply that the probability of lower future growth will increase.

For the horizon of four quarters ahead the model predicted a recession probability of 45%. As 45% is not too far away from 50% probability this would imply changes to the variables of interest (only interest rate spread in this case) does not need to be too large to imply a possible recession in the near term. If the interest rate decreases with 0,033 percentage points per quarter the 50% would be surpassed after 8 quarters. The decrease would accumulate to a decrease of 0,264 percentage points. This much smaller compared to the interest rate decrease of the 1990s crisis in Sweden and considering this result a recession is much more likely to occur compared to the one quarter ahead model.

However, as we live in a much more dynamic world than suggested by the simple analysis above of only one variable changes between quarters, the results should be interpreted cautiously. Furthermore, it is not until after the change in trajectory has taken place of a variable and continues on that path for some time that the probability of a recession occurs. Other variables may vary considerably and impact the probability of a recession whether it be a negative or positive effect.

7 Conclusion

This paper has investigated what variables that can work as leading indicators for recessions in Sweden and was conducted in a probit framework. There were three predictors that was found significant at some horizon, the interest rate spread, the OMX30 index and the NYSE index with the two latter variables approximate asset prices. The asset price variables were found significant at a forecasting horizon of two quarters ahead. Furthermore, the results implied that with a decrease in asset prices, the probability of a recession in Sweden goes up. This result is in line with conventional theory of the forward-looking aspect of financial markets, and especially for stock prices. However, this result is also the contrary to what could be expected considering the underlying factors of the financial crises observed throughout history and in more recent times. There have been observed large booms of asset prices before the onset of a crisis that goes bust and then affects the real side of the economy. Also, both the IMF and the Riksbank points out the asset price inflation that have been taken place in Sweden during the better part of a decade to be a factor to cautiously observe.

The results regarding the interest rate spread confirms the results of previous empirical studies with financial vulnerabilities first appears in the credit markets. The results from previous studies have been mostly focused on larger economies like the EU or the US but the result from this paper implies that the interest rate spread is the most predictive leading indicator for Sweden as well. If the interest rate spread goes down, the probability of observing a recession goes up. With the 10-year and 3-month spread at positive it does not imply that a recession in Sweden is likely in the near future. However, during the 1990s financial crisis in Sweden the interest rate spread dropped by more than what is implied by the partial analysis to induce a recession in the next two years. Two variables that were not found significant in the models was credit to the non-financial private sector and real house prices. Thus, these two variables are not to implied to be leading indicators, although both the house market and the credit level was at high levels before the 1990s financial crisis and crashed at the onset of the crisis. This empirical finding would imply that the variables could be used as leading indicators but could not be confirmed by the results in this paper.

This paper contributes to the studies that focus on recession forecasting in small open economies, like Sweden, where not many studies have been conducted of this kind. Also, to the best of my knowledge a study on leading indicators in a probit framework have not been applied to the Swedish economy. A major shortcoming of this paper (and similar papers) is that every crisis is unique, and the underlying factors may vary. Furthermore, for a global crisis the effect of each country is not necessarily like another. This leads to the results of this paper needs to be interpreted with caution when it comes to policy implications. Also, this paper investigates real effect on the economy through the real growth of GDP which is only available on a quarterly basis. Moreover, given the new Basel framework, studies that focus on market conditions past 2008 are useful to conduct. If another measure were to be used that is available on a monthly basis for example, other data sets could be used, such as consumer confidence index as an explanatory variable.

For future research, the results from this study can be augmented in many ways. Data richer probit models, such as factor-augmented probit models could be applied to Sweden. Also, as Sweden is a small open economy it would be interesting to study how, and if, the probability of a recession is transmitted from other countries to Sweden. Other sentiment indices are also interesting to extend to the models in this paper, and as previously mentioned other dependent variables can be used. The National Bureau of Economic Research documents data over the recessions in the US, something similar for Sweden could potentially be estimated from official institutions on a monthly basis and could thus be implemented in research.

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Appendix A

Results for single-predictor models with threshold=0

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent Variable: $P(y_1 = 1)$								
Interest rate spread	-6.964*** (1.824)								
Credit		24.10*** (9.173)							
House prices			-20.92*** (7.720)						
OMX30				-4.164*** (1.233)					
NYSE					-4.429** (2.055)				
VIX						0.443 (0.608)			
CA/GDP							12.35 (12.53)		
Inflation								-18.42 (16.24)	
Unemployment									7.597** (3.299)
Constant	-0.253 (0.174)	-0.988*** (0.148)	-0.617*** (0.140)	-0.817*** (0.133)	-0.772*** (0.129)	-0.822*** (0.128)	-0.834*** (0.129)	-0.835*** (0.129)	-0.890*** (0.131)
Observations	127	126	126	126	126	126	126	126	126
Pseudo R2	0.235	0.0738	0.0954	0.0907	0.0449	0.00549	0.00953	0.0108	0.0413
BIC	108.396	128.720	126.014	127.316	132.748	137.699	137.101	136.793	133.090

*Tabel A.1: Forecast horizon one quarter ahead, threshold=0. Standard errors in parentheses, *** p<0.01, **p<0.05, *p<0.1*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent Variable: $P(y_1 = 1)$								
Interest rate spread	-6.518***								
	(1.471)								
Credit		6.709							
		(7.734)							
House prices			-13.61**						
			(6.791)						
OMX30				-3.368***					
				(1.197)					
NYSE					-4.243**				
					(2.045)				
VIX						0.628			
						(0.556)			
CA/GDP							-11.06		
							(12.77)		
Inflation								-21.22	
								(15.51)	
Unemployment									52.67
									(33.64)
Constant	-0.295	-0.877***	-0.701***	-0.832***	-0.806***	-0.849***	-0.840***	-0.863***	-0.885***
	(0.186)	(0.135)	(0.145)	(0.132)	(0.133)	(0.129)	(0.129)	(0.131)	(0.133)
Observations	126	125	125	125	125	125	125	125	125
Pseudo R2	0.212	0.00581	0.0425	0.0618	0.0402	0.0101	0.00773	0.0137	0.0202
BIC	111.488	134.829	130.257	128.533	130.541	134.450	134.895	133.503	132.938

*Tabel A.2: Forecast horizon two quarters ahead, threshold=0. Standard errors in parentheses, *** p<0.01, **p<0.05, *p<0.1*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent Variable: $P(y_1 = 1)$								
Interest rate spread	-3.239***								
	(1.228)								
Credit		3.042							
		(8.326)							
House prices			-2.224						
			(6.644)						
OMX30				-1.589					
				(1.155)					
NYSE					-0.841				
					(1.917)				
VIX						0.612			
						(0.583)			
CA/GDP							9.871		
							(12.14)		
Inflation								-12.86	
								(17.41)	
Unemployment									15.70
									(32.11)
Constant	-0.585***	-0.874***	-0.832***	-0.842***	-0.846***	-0.864***	-0.872***	-0.872***	-0.870***
	(0.178)	(0.137)	(0.152)	(0.131)	(0.134)	(0.131)	(0.132)	(0.133)	(0.132)
Observations	124	123	123	123	123	123	123	123	123
Pseudo R2	0.0778	0.00125	0.00114	0.0147	0.00150	0.00998	0.00595	0.00540	0.00166
BIC	123.860	132.630	132.617	131.243	132.698	131.760	131.843	131.686	132.402

Tabel A.3: Forecast horizon four quarters ahead, threshold=0. Standard errors in parentheses, *** p<0.01, **p<0.05, *p<0.

Appendix B

Results for multipredictor models with threshold=0

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable: $P(y_1 = 1)$									
Interest rate spread	-6.330***	-6.494***	-6.314***	-6.371***	-6.345***	-6.330***	-6.635***	-6.612***	-5.909**	
	(2.409)	(2.249)	(2.344)	(2.406)	(2.394)	(2.419)	(2.285)	(2.287)	(2.364)	
Credit	25.34***	25.36***	25.39***	26.58***	25.31***	25.19***	24.80***	25.90***		21.45**
	(9.204)	(9.133)	(9.114)	(9.231)	(9.217)	(9.106)	(9.092)	(9.141)		(10.05)
House prices	-5.892	-6.419	-5.943	-5.368	-5.857	-5.720	-6.906		-6.895	-13.32
	(8.047)	(7.658)	(8.085)	(8.134)	(7.990)	(8.290)	(7.992)		(7.240)	(8.565)
OMX30	-3.104**	-2.884**	-3.097*	-2.785*	-3.077**	-2.974**		-3.197**	-2.883*	-4.239***
	(1.572)	(1.414)	(1.582)	(1.443)	(1.545)	(1.444)		(1.523)	(1.504)	(1.458)
NYSE	0.426	0.0965	0.427	0.527	0.303		-2.342	0.0350	-0.827	1.237
	(3.456)	(3.074)	(3.454)	(3.488)	(2.747)		(2.976)	(3.484)	(3.033)	(2.910)
VIX	0.0504	-0.0772	0.0511	0.214		-0.00284	-0.210	0.0125	-0.0730	0.437
	(0.767)	(0.751)	(0.765)	(0.759)		(0.609)	(0.748)	(0.776)	(0.713)	(0.671)
CA/GDP	14.32	15.05	14.24		14.51	14.37	11.17	13.75	17.85	16.09
	(14.50)	(14.76)	(14.55)		(14.37)	(14.46)	(13.79)	(14.49)	(13.62)	(14.62)
Inflation	1.777	1.549		0.688	1.792	1.782	0.369	2.486	5.314	-9.422
	(17.01)	(17.19)		(17.90)	(16.95)	(16.99)	(18.39)	(16.46)	(16.10)	(14.00)
Unemployment	19.91		19.82	25.21	18.90	18.77	3.660	24.06	20.41	59.41
	(51.79)		(51.94)	(52.81)	(50.39)	(47.61)	(49.28)	(49.24)	(55.48)	(38.76)
Constant	-0.433	-0.395	-0.434	-0.436	-0.430	-0.428	-0.368	-0.487*	-0.256	-0.909***
	(0.289)	(0.240)	(0.285)	(0.288)	(0.283)	(0.271)	(0.273)	(0.263)	(0.278)	(0.171)
Observations	126	126	126	126	126	126	126	126	126	126
Pseudo R2	0.353	0.351	0.353	0.345	0.353	0.353	0.332	0.349	0.300	0.240

*Table B.1: Forecast horizon one quarter ahead, threshold=0. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable: $P(y_1 = 1)$									
Interest rate spread	-7.462***	-7.093***	-7.200***	-6.917***	-7.610***	-6.982***	-7.684***	-7.413***	-7.427***	
	(1.751)	(1.532)	(1.662)	(1.835)	(1.749)	(1.921)	(1.713)	(1.749)	(1.731)	
Credit	-1.504	-0.952	-0.743	-2.475	-1.789	1.074	-1.516	-1.611		3.272
	(10.24)	(10.32)	(10.15)	(9.675)	(10.12)	(9.955)	(10.24)	(10.27)		(8.746)
House prices	0.837	1.743	0.908	0.618	1.270	0.245	0.303		0.934	-7.167
	(7.697)	(7.553)	(7.706)	(7.897)	(7.732)	(7.630)	(7.695)		(7.727)	(6.992)
OMX30	-0.913	-1.123	-0.963	-1.303	-0.728	-1.726		-0.886	-0.914	-2.439
	(1.459)	(1.473)	(1.468)	(1.505)	(1.377)	(1.218)		(1.462)	(1.459)	(1.514)
NYSE	-2.812	-2.322	-2.586	-2.925	-3.838		-3.623	-2.781	-2.699	-0.382
	(3.209)	(3.275)	(3.277)	(3.255)	(2.710)		(2.725)	(3.182)	(3.242)	(3.199)
VIX	0.508	0.621	0.512	0.208		0.872	0.442	0.515	0.512	0.845
	(0.772)	(0.777)	(0.770)	(0.735)		(0.651)	(0.747)	(0.766)	(0.775)	(0.699)
CA/GDP	-21.27	-21.18	-20.84		-18.84	-21.51	-22.44	-21.24	-21.40	-13.17
	(14.25)	(14.43)	(14.26)		(13.43)	(14.47)	(14.22)	(14.26)	(14.27)	(14.38)
Inflation	9.154	8.423		7.240	9.483	6.280	9.840	9.190	8.717	-13.13
	(14.32)	(14.11)		(14.91)	(14.45)	(14.36)	(14.48)	(14.35)	(14.17)	(14.28)
Unemployment	-23.56		-22.19	-22.64	-33.45	-8.561	-30.16	-24.92	-22.80	41.41
	(42.25)		(41.65)	(40.80)	(42.97)	(45.47)	(42.21)	(41.80)	(42.36)	(35.80)
Constant	-0.237	-0.295	-0.266	-0.255	-0.208	-0.303	-0.208	-0.230	-0.250	-0.831***
	(0.231)	(0.202)	(0.224)	(0.236)	(0.232)	(0.236)	(0.227)	(0.217)	(0.224)	(0.162)
Observations	125	125	125	125	125	125	125	125	125	125
Pseudo R2	0.271	0.269	0.269	0.251	0.267	0.263	0.268	0.270	0.270	0.119

*Table B.2: Forecast horizon two quarter ahead, threshold=0. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable: $P(y_1 = 1)$									
Interest rate spread	-3.698**	-3.443**	-3.732**	-3.765**	-3.867**	-3.856**	-4.018***	-3.430**	-3.709**	
	(1.521)	(1.469)	(1.462)	(1.523)	(1.511)	(1.513)	(1.483)	(1.500)	(1.532)	
Credit	0.619	0.702	0.495	0.894	0.535	-0.307	0.271	0.371		2.411
	(9.156)	(9.105)	(9.215)	(9.298)	(9.222)	(9.404)	(9.324)	(9.039)		(8.446)
House prices	5.304	5.719	5.212	5.361	6.112	5.831	4.853		5.285	0.564
	(7.510)	(7.199)	(7.523)	(7.413)	(7.621)	(7.514)	(7.428)		(7.513)	(7.275)
OMX30	-1.275	-1.414	-1.257	-1.140	-1.005	-0.805		-1.181	-1.269	-2.439
	(1.630)	(1.558)	(1.635)	(1.550)	(1.554)	(1.313)		(1.623)	(1.640)	(1.555)
NYSE	1.751	2.041	1.727	1.726	0.336		0.453	2.040	1.714	2.906
	(2.759)	(2.677)	(2.766)	(2.716)	(2.292)		(2.236)	(2.764)	(2.810)	(2.638)
VIX	0.598	0.678	0.599	0.670		0.381	0.486	0.666	0.598	0.819
	(0.702)	(0.679)	(0.702)	(0.696)		(0.585)	(0.665)	(0.711)	(0.704)	(0.688)
CA/GDP	7.026	7.021	6.921		8.967	6.948	5.477	7.165	7.072	10.19
	(12.56)	(12.54)	(12.72)		(12.23)	(12.55)	(12.18)	(12.56)	(12.62)	(12.36)
Inflation	-1.694	-1.822		-0.827	-1.788	-0.757	0.0214	-0.0171	-1.510	-13.63
	(17.05)	(16.49)		(17.04)	(17.20)	(17.26)	(16.78)	(16.62)	(17.22)	(17.08)
Unemployment	-19.45		-19.54	-19.51	-29.07	-25.15	-26.57	-24.12	-19.54	23.76
	(40.30)		(40.19)	(40.26)	(38.93)	(39.39)	(39.15)	(39.13)	(40.53)	(37.40)
Constant	-0.625***	-0.666***	-0.618***	-0.613***	-0.594***	-0.585***	-0.576**	-0.584***	-0.620***	-0.946***
	(0.236)	(0.211)	(0.226)	(0.233)	(0.228)	(0.226)	(0.224)	(0.222)	(0.233)	(0.182)
Observations	123	123	123	123	123	123	123	123	123	123
Pseudo R4	0.106	0.104	0.106	0.103	0.0998	0.103	0.100	0.101	0.106	0.0450

*Table B.3: Forecast horizon four quarter ahead, threshold=0. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*

Appendix C

Results for Multipredictor model threshold=0,25% and forecast horizon=4

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Dependent Variable: $P(y_2 = 1)$					
Interest rate spread	-3.777***	-3.323**	-3.677***	-3.742***	-3.816***	-3.938***	-4.085***	-3.467**	-3.839***	
	(1.441)	(1.393)	(1.365)	(1.414)	(1.447)	(1.441)	(1.410)	(1.421)	(1.449)	
Credit	4.022	3.927	4.336	3.810	3.980	3.076	3.738	3.649		5.428
	(7.863)	(7.769)	(7.882)	(7.854)	(7.892)	(8.088)	(7.961)	(7.792)		(7.580)
House prices	6.483	7.474	6.739	6.480	6.648	7.032	6.056		6.342	1.768
	(6.717)	(6.489)	(6.762)	(6.756)	(6.757)	(6.657)	(6.685)		(6.740)	(6.547)
OMX30	-1.241	-1.543	-1.286	-1.335	-1.168	-0.711		-1.133	-1.209	-2.439*
	(1.430)	(1.381)	(1.430)	(1.412)	(1.402)	(1.194)		(1.430)	(1.424)	(1.359)
NYSE	1.954	2.522	2.010	1.976	1.617		0.695	2.276	1.734	3.062
	(2.379)	(2.351)	(2.380)	(2.387)	(2.162)		(2.007)	(2.344)	(2.445)	(2.342)
VIX	0.148	0.300	0.150	0.105		-0.0944	0.0253	0.217	0.141	0.378
	(0.631)	(0.618)	(0.632)	(0.625)		(0.560)	(0.611)	(0.632)	(0.638)	(0.629)
CA/GDP	-4.540	-4.640	-4.341		-4.133	-4.657	-6.078	-4.549	-4.189	-1.999
	(12.15)	(12.10)	(12.18)		(11.97)	(12.13)	(11.81)	(12.11)	(12.23)	(12.10)
Inflation	5.428	5.216		5.045	5.479	6.305	6.740	7.168	6.438	-6.617
	(15.95)	(15.33)		(16.14)	(16.00)	(16.16)	(15.67)	(15.59)	(16.04)	(16.37)
Unemployment	-37.77		-37.65	-37.84	-39.96	-44.23	-45.28	-44.60	-37.86	4.088
	(35.33)		(35.47)	(35.39)	(34.35)	(35.16)	(34.70)	(34.67)	(35.22)	(33.75)
Constant	-0.332	-0.409**	-0.350*	-0.337	-0.325	-0.288	-0.284	-0.282	-0.300	-0.671***
	(0.215)	(0.198)	(0.205)	(0.214)	(0.214)	(0.213)	(0.209)	(0.207)	(0.215)	(0.158)
Observations	123	123	123	123	123	123	123	123	123	123
Pseudo R2	0.0884	0.0825	0.0877	0.0873	0.0881	0.0852	0.0835	0.0820	0.0868	0.0267
BIC	180.324	176.372	175.611	175.672	175.562	175.984	176.231	176.444	175.749	184.460

*Tabel C.1: Forecast horizon four quarters ahead, threshold=0.25%. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1*