TALLINN UNIVERSITY OF TECHNOLOGY
School of Business and Governance
Department of Economics and Finance

Tõnno Tint

PREDICTING U.S. RECESSIONS: A LEADING INDICATOR APPROACH

Bachelor's thesis

Program Applied Economics, specialisation Economic Analysis

Supervisor: Nicolas Andreas Reigl, MA
Co-supervisor: Ako Sauga, PhD

Tallinn 2019

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Tõnno Tint ……………………………
(signature, date)

Student code: 164534TAAB
Student e-mail address: tonno97@hotmail.com

Supervisor: Nicolas Andreas Reigl, MA
The thesis conforms to requirements in force

……………………………………………
(signature, date)

Co-supervisor: Ako Sauga, PhD:
The thesis conforms to requirements in force

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ABSTRACT

The aim of this thesis is to compare how the most popular leading indicators have performed as predictors of United States recessions. The first part gives a theoretical overview of measuring business cycles and describes the most common leading indicators. Statistical methods which have been used to forecast business cycles and results obtained through their application are also presented. The second part focuses on the empirical analysis where probit models are used to now- and forecast United States recessions during the period of 1966-2018. The results indicate that the yield spread between long- and short-term government bonds and returns of the S&P 500 stock index have historically had a considerable ability to predict recessions six months ahead, but strong recession signals cannot be always expected from those variables. Adding the federal funds rate into the financial variables model reduced its ability to forecast the most recent recessions, which is probably due to significant changes in the interest rate environment. On the other hand, The Conference Board Leading Economic Index (LEI) was found to be a remarkably useful indicator for measuring the current state of the economy, as it could timely nowcast the beginnings of all observed recessions. However, revised estimates of the LEI were used, hence it is likely that the results obtained are positively biased to some extent.

Key words: business cycle, recession, forecasting, leading indicators, financial variables, probit regression.

INTRODUCTION

The discussion about business cycles is probably one of the most important topics in economics. History has shown that economy tends to switch continuously between different phases and this affects greatly all economic agents through events like bankruptcies, lay-offs and deflation of asset prices. While policymakers and officials of monetary institutions have some tools at their disposal to mitigate the impacts caused by fluctuations in the economy, it is also important to know when such policies should be implemented. Therefore, they need to measure current economic conditions and use statistical methods to forecast possible changes in future economic activity.

Although it is probably true that economists and statisticians will never be able to predict future business conditions to the extent where cyclical changes can be eliminated with timely decision-making, the research done so far has greatly enhanced the reliability of short-term predictions about upcoming recessions. In addition to providing conceptual knowledge, this research has also singled out a few key economic indicators such as initial unemployment insurance claims, building permits for new housing, interest rate spreads between government bonds and returns of stock market indices, which have historically tended to lead business cycles. Therefore, these indicators have gained popularity among economists and business people alike, because they are easily understandable and can be readily obtained from various economic-related websites.

Considering that these leading indicators have primarily emerged from empirical research, they have been criticised of lacking any theoretical foundations (Koopmans 1947). It probably would be even impossible to create a definitive theoretical framework which would link certain leading variables to business cycles, as it is widely believed that economic fluctuations are caused by various factors and therefore relationships between different indicators can change (Zarnowitz & Boschan 1975). From the forecasting perspective, this problem has been tried to solve by constructing complex composite indices, which are supposedly designed to capture as much information about evolving economic conditions as possible (*Ibid*).

In contrast, other research has interestingly found that simple models with a small number of financial variables have historically tended to outperform the aforementioned indices. In those models, mainly the yield spread between long- and short-term government bonds and stock market returns have been subject to rigorous analysis. (Estrella & Mishkin 1998) The reason for this lies in the fact that both indicators have led numerous recessions in the United States (Moore, 1983; Wright 2006). The usual explanation for this phenomenon is that the expectations of market participants are reflected in the asset prices. (Harvey 1989).

However, despite the absence of clear theoretical foundations, there are still probably thousands of investors, analysts, strategists and business executives who continuously track leading indicators, separately or as components of some index, and use them to make intuitive guesses about the forthcoming business conditions. Therefore, it is definitely important and also interesting to measure empirically how powerful these indicators actually have been as predictors of future economic activity.

The aim of this thesis is to measure the historical ability of the most widely used leading indicators to forecast recessions in the United States. For this purpose, the following questions are addressed:

- Have the observed leading indicators historically had the ability to predict recessions six months ahead?
- Can a parsimonious model with a small number of financial variables capture a change in economic conditions as well as a composite leading index?

This paper is divided into three chapters. The first chapter includes an overview about determining business cycle turning points and describes the variables and methods used to predict the peaks and troughs in aggregate economic activity. The results of previous research are also summarized in this section. In the second chapter, the data along with the models used for empirical research are described. The results of the empirical analysis are reported and discussed in the third chapter. The empirical analysis was conducted using the Gretl econometrics package.

The author wants to thank his supervisors Nicolas Reigl and Ako Sauga for their help and his family for moral support.

1. LITERATURE REVIEW

In this section, the author describes the theoretical and methodological aspects of measuring and forecasting business cycles and explains how the most commonly used leading indicators have been found. The reasons why they lead business cycles are also discussed. The last part of this section summarizes the findings of previous empirical research.

1.1. How the turning points of business cycle are determined

First thorough empirical research on business cycle measurement was done by Artur F. Burns and Wesley C. Mitchell (Moore 1983). They described business cycles as a phenomenon with three important features (Burns & Mitchell 1946):

1) Business cycle is defined as a simultaneous comovement of many economic variables;
2) Changes in business cycle phases are recurrent, but not periodic;
3) A cycle lasts longer than one year, but not longer than ten or twelve years.

Using this definition, Burns and Mitchell analysed the turning points of various economic time series and compared them with reference dates. Approximate reference dates were initially obtained from Williard H. Thorpe's „Business Annals", where the economic conditions in the United States during the period from 1790 to 1920 are chronologically described. (Burns & Mitchell 1946; Thorpe 1926). In order to measure the peaks and troughs of business cycles, they mainly used data related to prices, production, employment, finance, income and trade. Even though they initially argued that business cycles can't be measured with the movement of one time series, they later mentioned that gross national product is a good indicator for measuring cycles in aggregate economic activity. (Burns & Mitchell 1946).

Currently the official start and end dates of recessions in the United States are determined by the National Bureau of Economic Research (NBER) Business Cycle Dating Commitee. It can be assumed that they do not significantly deviate from Burns and Mitchell's seminal work, since they define recession as „significant decline in economic activity, lasting more than a few months, normally visible in GDP, real income, employment, industrial production and wholesale-retail sales“. Although the committee has singled out GDP as the best measure for economic activity, it considers other economic data as well for additional assurance. The exact beginning and ending dates of a recession are determined by consensual agreement between committee members who each have done their research independently. (NBER Business Cycle Dating Committee 2008).

Considering that NBER-defined turning points are regarded as the official peaks and troughs in the United States economic activity, there is certainly some appeal in using them for business cycle forecasting research. However, in addition to subjectivity, one of the main drawbacks of this method is that the Committee decision comes with considerable delay (Chin *et al.* 2000), because the Business Cycle Dating Commitee is looking the data which is released many months before and after the possible turning points in order to clearly distinguish peaks or troughs and thereby avoid false calls. (Boldin 1994)

While some alternative methods exist for identifying cyclical turning points, such as defining a recession as a decline in GDP for two consecutive quarters (Rudebusch & Williams 2009), which are more objective, they are also far from being perfect. It is noteworthy that while the two consecutive quarter decline rule is widely accepted by many economists, such filter could capture only three out of six NBER recessions during the period of 1960-1994, mainly because the decline in one quarter was often followed by mild growth. For example, in the recession of 1960-61, a 0.4% growth and in the recession of 1980, a 0.1% growth followed the decline in previous quarter. (Boldin 1994)

Another widely applied practice, which allows to objectively, but also very timely to detect business cycle turning points is the use of different statistical models to identify peaks and troughs in the raw data of industrial production, GDP or the Composite Coincident Indicator (CCI), which includes industrial production, real disposable income, employees on non-agricultural payrolls and manufacturing and trade sales. In this case, it is considered best to use CCI data, as it is released monthly, while GDP data is published quarterly, and it also covers a larger share of economic activity than industrial production. (Marcellino 2006)

1.2. Leading indicators as predictors of business cycle turning points

The existence of leading indicators was first mentioned in Burns and Mitchell's 1938 paper, where they analysed the statistical indicators of cyclical revival. They compared the peaks and troughs of different time series with reference dates and found that the Dow Jones stock index, production of various goods including passenger cars, trucks, paper and steel tubes, residential building contracts, average weekly hours worked and some other variables have historically tended to lead the revival phase of business cycles. (Burns & Mitchell 1938)

Using Burns and Mitchell's work as base, more thorough research on leading indicators was done by Geoffrey H. Moore (1961). He pointed out that new orders for different types of goods, construction contracts, weekly hours worked in manufacturing sector, business failures and stock market activity have historically had the ability to lead both phases of the business cycle (*Ibid*). According to Moore, many of these results are fairly obvious and could be logically expected. New orders and construction contracts should lead the output of products which they give rise to. In the case of change in workload, average work hours will be normally reduced before lay-offs (*Ibid*). Later, initial claims for unemployment insurance data also emerged as an important leading indicator, mainly because it is more sensitive to labor market changes than other employment data (The Conference Board 2001).

In addition to the previously described real variables, certain financial indicators have also become important leading indicators. The leading properties of stock market returns were already noticed in the earliest research of business cycles, but the spread between long- and short-term government bonds interest rates, which is currently considered to be one of the most important leading indicators, rose to prominence much later. As documented by Estrella and Hardouvelis (1991), term structure did not receive broader attention as a predictor of real activity until the end on the 1980s, when Robert D. Laurent and Campbell R. Harvey used different variations of interest rate spreads to analyse how term structure is related to monetary policy and consumption growth, respectively.

While common sense can help to reasonably explain the connections between real economic indicators, it is rather hard to reach conclusions intuitively for financial variables. Fortunately, over the years several theories about the relationship between capital market and real economy have developed, and considerable amount of explanations have emerged which link the current changes in stock and bond markets to the future changes in real economic activity.

According to the modern asset pricing theory, the prices of stocks and bonds are connected to the real economic activity through the expectations of market participants. On the bond market, recession fears are expressed by the narrowing spread between long- and short-term bonds. During good times, people are buying assets that will provide insurance against a possible downturn. If uncertainty regarding economic conditions increases, it drives up the marginal rate of substitution, because people are ready to give up some of today's consumption in order to be able to consume more during the recession. Such behavior causes the prices of long-term bonds to increase and thus lowers their yields compared to the yields of short-term bonds. Empirically, the yield spread is usually measured by the difference between the rates of 10-year Treasury bonds and 3-month Treasury bills. (Harvey 1989)

The previously described changes in bond prices and hence the expectations of recessions are in part believed to be connected with monetary policy. If inflationary pressures rise in the economy, the central bank will raise interest rates, which in turn will raise the yield of short-term bonds. The yield of long-term bonds is not going to rise, because it reflects longer-term expectations, which assume that inflationary pressures will eventually subside and the central bank can then lower the short-term interest rate again. In the meanwhile, higher interest rates cause a slowdown in the economy. (Estrella & Trubin 2006)

Stock prices in efficient markets are believed to represent the present value of all future dividend payments the businesses are expected to make. According to the theory, anticipated changes in economic conditions will cause investors to revise their forecasts about companies' future earnings and thus share prices should fall ahead of possible recession. (Harvey 1989) Estrella and Mishkin (1998) noticed empirically that forecasting the performance of yield spread model can be enhanced by including stock market returns and concluded that stock prices may provide additional important information that the yield spread does not contain, but which helps to predict economic downturns.

Estrella and Mishkin (1998) prefer to analyse simple financial variables in particular for three other reasons in addition to their historically proven forecasting power. First, the analysis with well-chosen financial variables may be used to double check econometric and judgemental predictions. Second, using a limited amount of financial variables reduces the probability of model overfitting, which can mainly cause problems in the out-of-sample forecasting. Third, forecasting with financial variables is quick and simple, assuming that they are accurate predictors. One great advantage of financial indicators is also their currency and continuous availability. Stock market prices and bond yield spreads are available practically at real-time.

In practice, all of these aforementioned indicators are usually used together, as components of composite leading indices. Researchers of the leading indicators have recommended to use these indicators in unison rather than separately, because recessions can be initiated by different types of shocks, which means that it is very likely that all variables cannot anticipate every downturn similarly. Therefore, the composite leading index is constructed so that it would give the maximum possible information about evolving business conditions by covering a wide array of economic activities. (Zarnowitz & Boschan 1975)

Probably the most widely used composite leading index is published by The Conference Board. Their current index includes the following components: average weekly hours worked in manufacturing sector, building permits for private housing, new orders for non-defense capital goods and consumer goods, return of the S&P 500 stock index, average initial jobless insurance claims, Institute for Supply Management (ISM) Index of New Orders (an index based on the survey responses given by the supply managers about business conditions (ISM 2019)), Leading Credit Index (an index composed of different quantitative and qualitative indicators of financial conditions (Levanon *et al*. 2011)), interest rate spread between 10-year Treasury bonds and 3-month Treasury bills and average consumer expectations. (The Conference Board 2019)

It should be noted, however, that while the idea of existence of empirically proven leading indicators seems definitely enticing, one of their biggest shortcomings, as pointed out by Tjalling C. Koopmans (1947), is the lack of theoretical foundations. Although economic reasons behind the ability of many leading indicators to lead business cycles have been explained (Moore 1961), initially these indicators were discovered through empirical research (Burns & Mitchell 1938).

In addition, composite leading indices in particular have been criticized, because they are subject to ex-post revisions which improves their performance retrospectively. Small revisions are done frequently, because preliminary estimates of component indicators are revised, but sometimes definitional revisions occur if the components that make up the index are reselected. Thus, the most objective way to test the performance of composite leading index, is to make forecasts using real-time data. (Diebold & Rudebusch 1991)

1.3 Statistical methods used to forecast cyclical turning points

Over the years, many different statistical methods have been used to forecast or detect cyclical turning points. The most common are regime switching (Hamilton 1989) and dynamic factor models (Stock & Watson 1989), Bayesian model averaging (Berge 2015) and limited dependent variable regression (Estrella & Mishkin 1998).

The Markov switching model is an autoregressive model where parameters can change, if there is an abrupt shift in the underlying time series. It was first used in business cycle analysis by James D. Hamilton (1989). Based on the assumption that important macroeconomic time series follow nonlinear stationary processes, he estimated the probability of the structural change in GDP data to detect cyclical turning points.

On the other hand, dynamic factor models rely on the idea that business cycles are best measured by the co-movement of many time series. The aim of using factor models is to find a few unobservable factors which capture the variance in many observable indicators using complex statistical methods. (Stock & Watson 1989) These newly found factors can be included in regression models for forecasting (Chen *et al.* 2011).

In the Bayesian model averaging framework, forecasts obtained from multiple regression models with different sets of variables are weighted by the posterior probability which shows how good the model is relative to others. This probability is obtained by multiplying the marginal likelihood of a model by the prior probability (which is initially equal for each model). Thus, the final forecast will be the weighted combination of forecasts provided by each model, where the weight of better models is larger. (Berge 2015) The advantage of using this method is that it helps to mitigate the problem of model uncertainty, by allowing to order models according to their explanatory power (Hoeting *et al.* 1999).

Probit regression was first used in business cycle analysis by Estrella and Hardouvelis (1991), who analysed the ability of the yield spread to predict recessions. This method can be used to estimate the probability of some event occuring, given the values of independent variables. Probit models have gained popularity in business cycle analysis, because despite of being relatively simple, they have shown very good results, as will be discussed in the next sub-section. Therefore, this estimation technique was also used in this thesis and it is described in more detail in the methodology chapter.

However, it should be mentioned in advance that the explanatory power of probit models is measured by the pseudo-R^2, which shows how well the model fits with the observations by comparing the estimated model's likelihood function value with the likelihood function value of the model which only includes constant. (Maddala 1992) While one of the most popular pseudo-R^2 measures is the Mcfadden R^2, some researchers have personally modified it and thus call their version simply an pseudo-R^2 (Estrella & Mishkin 1998). In this thesis, the adjusted McFadden R^2 was used, because it is the default measure for assessing the probit model's explanatory power in Gretl. The adjusted measure was preferred, because it allows to compare different models by taking into account the amount of parameters in the model (McKenna & Smith 2013). The Equation (1) for this measure can be written as follows (*Ibid*):

$$\text{Adjusted McFadden } R^2 = 1 - \left(\frac{Lu - n}{Lc}\right) \qquad (1)$$

Where:
Lu - likelihood function value for the model with all the parameters
Lc - likelihood function value for the null model only with the constant
N - number of parameters in the model

While the McFadden R^2 is a good metric for measuring the performance of a probit model, in business cycle analysis it is also common practice to forecast recessions for the out-of-sample period. The accuracy of the out-of-sample forecasts is mainly measured by the Root Mean Squared Error (RMSE) (Silvia *et al.* 2008; Chen *et al.* 2011). This metric measures the standard deviation of forecast errors (difference between the forecasted value and actual value). As smaller variation in errors is preferred, lower values of the RMSE are better. The Equation (2) for RMSE can be written as follows (Chen *et al.* 2011):

$$\text{RMSE} = \sqrt{\frac{1}{M}\sum_{t=1}^{M}(p_t - y_t)^2} \qquad (2)$$

Where:

M - number of observations

p_t - model's predicted probability of recession at month t

y_t - value of the recession index at month t

1.4. Previous empirical results

Although various databases contain thousands of economic time series and therefore hundreds of them could be possible candidates for leading indicators, a large amount of previous empirical research has focused on a few key indicators which are perceived to be the most reliable predictors. Considering its popularity, the yield spread between long- and short-term government bonds is undoubtedly an indicator which deserves a thorough attention.

Estrella and Mishkin (1998) used the yield spread between 10-year Treasury bonds and 3-month Treasury bills along with stock indices, monetary aggregates and the Commerce Department composite index of leading indicators (CLI)[1] as independent variables to predict U.S. recessions with a probit model during the period from 1959 to 1995. They found that the yield spread, NYSE stock index and real monetary base exhibited significant (at 5% level) predictive power up to eight, four and seven quarters, respectively. The model which combined the NYSE stock index and yield spread had the best explanatory power if recessions were forecasted at least two quarters ahead, but in one quarter horizon it was outperformed by the Commerce Department CLI. This model's explanatory power was the highest (pseudo-R^2 = 0.321) when recessions were forecasted three quarters ahead. On the other hand, growth in monetary base became insignificant when it was combined with the yield spread.

[1] currently known as The Conference Board Leading Economic Indicator (LEI) (The Conference Board 2001)

In the out-of-sample test, the performance and length of the predictive horizon of single variables somewhat deteriorated, but nevertheless, yield spread, real monetary base, stock prices and CLI remained significant predictors of recessions. Yield spread emerged as the best indicator, as it had strongest predictive power and including this variable improved the explanatory power of all two-variable models with forecast horizons between three to six quarters. Again, the model which included both the yield spread and NYSE stock index showed the best fit, as its out-of-sample pseudo-R^2 was 0.367 if the recessions were predicted three quarters ahead. (Estrella & Mishkin 1998)

The superiority of the yield spread as a leading indicator was also clearly documented by Travis J. Berge (2015), who ranked the most popular leading indicators by their predictive power over different forecast horizons by using Bayesian model averaging. Initially, he estimated multiple probit models which used different indicators as independent variables and then calculated the posterior inclusion probability for these indicators. He found that indicators which best described the current state of the economy (forecast horizon of 1 month) were the rate spread between 3-month Eurodollar futures and 3-month Treasury bills, S&P 500 index, housing permits, initial jobless insurance claims and payroll employment. At the six and twelve months horizons, the posterior inclusion probability of interest rate spread between 10-year Treasury bonds and 3-month Treasury bills was 100%, which means that all the models with significant forecasting performance included this particular variable. S&P 500 was another variable which had a 100% inclusion probability at the six month horizon, but this probability became zero at the twelve-month horizon. Apart from payroll employment, which had close to 90% inclusion rate at the six month horizon, other variables did not exhibit a significant ability to predict recessions.

Wright (2006) proposed that the yield curve might contain more information about evolving economic conditions than yield spread alone. Thus he augmented the yield spread model by adding the federal funds rate variable. His results showed that including the federal funds rate does enhance the explanatory power of the yield spread model, as the McFadden R^2 rose from 0.29 to 0.50 if recessions were forecasted four quarters ahead. While the yield spread model estimated that the probability of a recession in the next four quarters after February 2006 was over 50%, the yield curve model's predicted probability of recession was around 20%. Thus, he concluded that narrowing yield spread is not necessarily a harbinger of recession if monetary policy is not too strict.

In contrast to research which has only focused on the yield spread as a key predictor of recessions, Silvia *et al.* (2008) argued that it might be possible to construct a simple model with other indicators, which can outperform the yield spread model, if suitable candidate variables are chosen from a larger sample of indicators. Thus, they used stepwise regression to look for best probit model specification. At first, they included all 570 indicators into their forecasting model and then only kept those with significant predictive power. They found that the model which used the The Conference Board LEI, Chicago PMI Employment Index and S&P 500 stock index as predictors significantly outperformed Estrella and Mishkin's model (which included the returns of NYSE stock index and yield spread between 10-year Treasury bonds and 3-month Treasury bills as predictors) and Wright's (2006) model during the sample period of 1964-2006, if recessions were forecasted six months ahead. The pseudo-R^2 of their model was 0.76 and the RMSE for out-of-sample forecast was 0.19, while the Estrella and Mishkin model's pseudo-R^2 and RMSE were 0.41 and 0.31, respectively. They also found that the LEI model (where the quarterly change in The Conference Board LEI was the only independent variable) outperformed Estrella and Mishkin's model by having the pseudo-R^2 value of 0.56 and RMSE value of 0.27.

Chen *et al.* (2011) used a Probit-dynamic factor model with eight factors extracted from 141 economic time series which explained 56% of the variation among the variables. Six out of the eight factors, which were statistically significant in the model, were then used to forecast recession probability for the current month and six months ahead. Their model performed exceptionally well, as it could forecast all the recessions from 1978 to 2009. For the Great Recession, the estimated probabilities that a recession would occur in six months from September, October and November 2007 were 0.59, 0.50 and 0.45, respectively. The actual recession began in December 2007.

They also compared their model with five different probit forecasting models: the yield spread model, Estrella and Mishkin's (1998) financial variable model, Wright's (2006) model, LEI model and Silvia, Bullard and Lai's (2008) model. The in-sample fit of the probit-DFM (DFM – Dynamic Factor Model) was only inferior to Silvia, Bullard and Lai's (2008) model, as the pseudo-R^2 of those models were 0.62 and 0.72, respectively. However, in the out-of-sample forecast probit-DFM stood out as best performing model with the RMSE value of 0.24, which was the lowest among all models. (Chen *et al.* 2011)

The research described above has exclusively focused on the United States. Jane Haltmaier (2008) used individual and fixed effects panel probit regressions to identify cyclical turning points in eight countries during the period of 1970-2008. In addition to the yield spread and stock returns, she used oil price, exchange rates, business surveys, composite leading indices, employment and industrial production as predictors. The explanatory power of the constructed models varied considerably across countries, but was generally better for the advanced economies. For Mexico and Taiwan, the Mcfadden R^2 was around 0.4, but it rose to 0.6 for the US and Germany and 0.8 for the United Kingdom.

The model for the United States, which included lagged values of oil price, manufacturing PMI composite index, the interest rate spread between 10-year Treasury bonds and the FED funds rate, Nasdaq Composite stock index and industrial production could correctly categorize 92.6% of recession months in-sample, assuming that predicted recession probability over 20% signals recession. However, such a remarkable result was not obtained without problems, as the threshold level was so low, a third of the recession signals were false. When recessions were forecasted out-of-sample, 100% of the recession periods were correctly predicted, but the false signal rate was also 62%. (Haltmaier 2008)

In addition to different leading indicator approaches, Hamilton (1989) demonstrated that regime switching models can also be effectively used to detect cyclical turning points. His approach showed promising results as the recession dates predicted by the structural changes in GDP series (assuming >50% probability signals being in recession) did not deviate more than three months from the NBER dates in most cases. The exceptions were the recessions of 1957-1958 and 1979-1980, where Hamilton's model set the peak date two and three quarters earlier, respectively. In total, seven recessions occurred during the sample period of 1952-1984. Based on these results, he proposed regime switching models as objective independent algorithms for identifying business cycle turning points.

Previous research has found that the most common leading indicators have historically exhibited an ability to forecast recessions. The yield spread along with stock market returns have received a disproportionate amount of attention as they are perceived to be the most reliable predictors. However, the models which use The Conference Board LEI or some different set of variables as predictors have shown similarly good or even better performance. Thus, it can be concluded that it would not be reasonable to solely rely on one type of indicators to forecast recessions.

2. DATA AND METHODOLOGY

The main predictors of interest in this thesis were the yield spread between the United States government long-term and short-term debt securities (SPREAD), measured by subtracting the interest rate of 3-month Treasury bills from the interest rate of 10-year Treasury bonds, and the returns of stock market (STOCK), measured by the monthly change in the S&P 500 stock index. In addition, it was decided to include the federal funds rate (FF) in the financial variables model, as Wright (2006) argues that the slope of the yield curve might provide more information about economic conditions than the yield spread alone. For comparison, The Conference Board Leading Economic Index (LEI) was used to construct a model which is assumed to simultaneously include information from the real and financial sectors. In both cases, these predictors were used to forecast NBER-defined recessions during the period from the beginning of 1966 to the end of 2018. This period includes 636 months, during which the United States economy experienced a recession in 83 months.

Necessary data for these variables were obtained as follows: the recession index (table USREC), 10-year Treasury bonds constant maturity rate (table DGS10), 3-month Treasury bills secondary market rate (table TB3MS) and effective federal fund rate (table FEDFUNDS) were obtained from the St. Louis FED database and monthly series of the S&P 500 index and The Conference Board LEI were obtained from Yahoo Finance (table Historical data…) and Thomson Reuters Eikon (table Economic Indicator…), respectively.

Before this data was used in the regression models, it was transformed in order to remove seasonality and non-stationarity. Seasonal adjustment was done by using the X-13 ARIMA-SEATS program, which is developed by the U.S. Census Bureau and can be added as an extension to the Gretl statistical package. This algorithm uses moving average filters to automatically decompose time series into a trend, seasonal and irregular component and then removes the seasonal component (Stats NZ 2019). While there are no strong seasonal patterns present in the S&P 500 stock index, as can be seen from Figure 1, in order to remove possible unwanted influences from even a small seasonality, smoothing was considered necessary. The time series of government bonds interest rates were also seasonally adjusted, but the LEI source data was already seasonally adjusted.

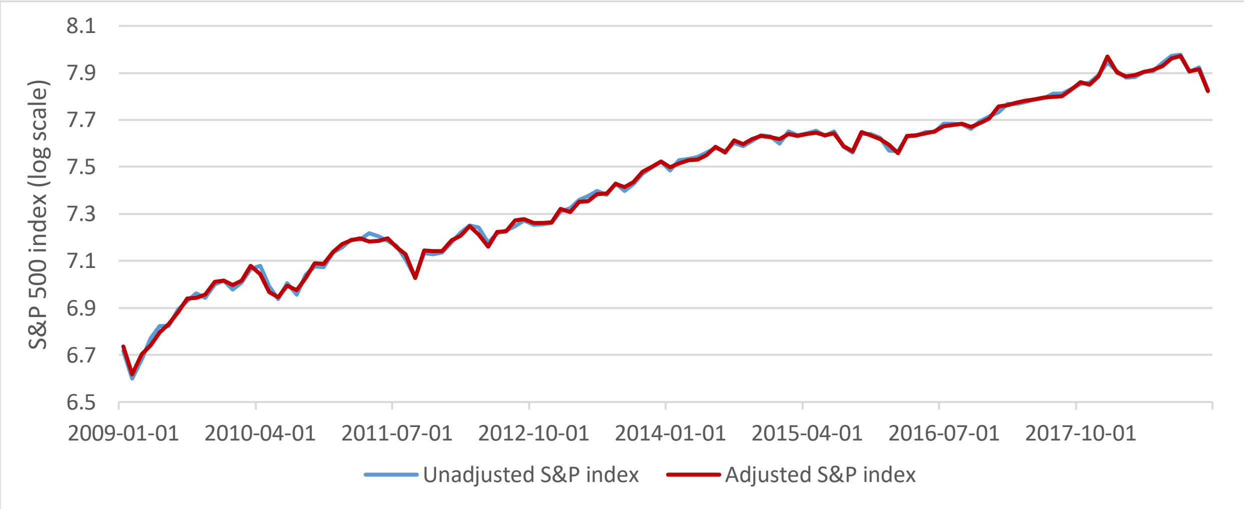

Figure 1. Unadjusted and adjusted time series of the S&P 500 stock index
Source: Yahoo Finance (table Historical data…), compiled by the author
Note: index is on a logarithmic scale.

To achieve stationarity, the Augmented Dickey-Fuller (ADF) test was used to detect the existence of unit root in the explanatory variables. The null hypothesis in this test assumes the presence of unit root, meaning that the time series is non-stationary. Since the LEI and STOCK variables were non-stationary and showed patterns of a stochastic trend, they were transformed by taking logarithmic differences. However, for the LEI variable, the ADF test did not clearly indicate whether the time series is trend or difference stationary and thus for additional assurance the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test was performed which detects if time series is stationary around a deterministic trend. The results of this test showed that the LEI is non-stationary around the trend and therefore this variable should be transformed by taking logarithmic differences. For the FF variable the null hypothesis was not rejected at 5% level, but this variable could not be transformed, because it is necessary to include the level of federal funds rate into the model to evaluate the predictive ability of the yield curve. Therefore the forecasting performance of this model was assessed cautiously. The SPREAD variable was stationary at level and thus it did not require any transformation. The results of the ADF and KPSS tests are summarized in Table 1.

Table 1. ADF test for independent variables

	STOCK	LEI	SPREAD	FF
ADF model used to make the decision	With constant and trend	With constant and trend	With constant	With constant
Number of lags in ADF model	13	3	16	17
ADF test p-value	0.123	0.050	0.001	0.099
KPSS test p-value for LEI		0.001		

Source: Author's calculations in Gretl

Notes: 1. In KPSS test acceptance of the alternative hypothesis means that time series is non-stationary around trend.
2. Data in the first two rows describe the model's specification which was used for inferences about unit root.

The descriptive statistics of the transformed variables are presented in Table 2. The average interest spread of 1.6% between long- and short-term government bonds and its standard deviation of 1.25% indicates that inversion of the yield curve, which signals a recession, is a rather uncommon event. In the case of stock returns, standard deviation, which is more than eight times larger than the average return, refers to substantial volatility and therefore creates a possibility for false signals. Therefore, many researchers have stated that stock market returns do not predict real activity well, because „stock market has correctly forecasted nine of the last four recessions" (Harvey 1989). The standard deviation of the LEI is also quite high relative to its mean, but in absolute terms it does not generally exhibit very large movements, allowing therefore to assume that abrupt shifts, which could create false signals, do not occur very often. The federal funds rate has quite low variation, as can be also seen from Figure 4. This is to be expected, considering that central bank hikes interest rates only when the need for this arises. However, when a recession begins, the federal funds rate declines steeply, as the central bank makes monetary policy more accommodative.

Table 2. Descriptive statistics of independent variables

	SPREAD	LD_STOCK	LD_LEI	FF
Average	1.60%	0.52%	0.12%	5.26%
Min	-2.77%	-24.54%	-3.3%	0.07%
Max	4.57%	15.10%	1.8%	19.1%
Standard deviation	1.25%	4.33%	0.7%	3.81%

Source: St. Louis FED (table DGS10; table TB3MS; table FEDFUNDS), Yahoo Finance (table Historical data…) and Thomson Reuters Eikon (table Economic Indicator…), author's calculations

The relationships between recessions and chosen predictors are visually represented in Figures 2-5 below. The LEI has consistently led cyclical turning points over the observed period as it has stayed flat or started to decline ahead of every recession. The same can be said about the yield spread which has been very low or even negative before each recession. While stock market has been more noisy and provided less clear signals for the upcoming downturns in general, it still has had considerable lead over some of the recessions.

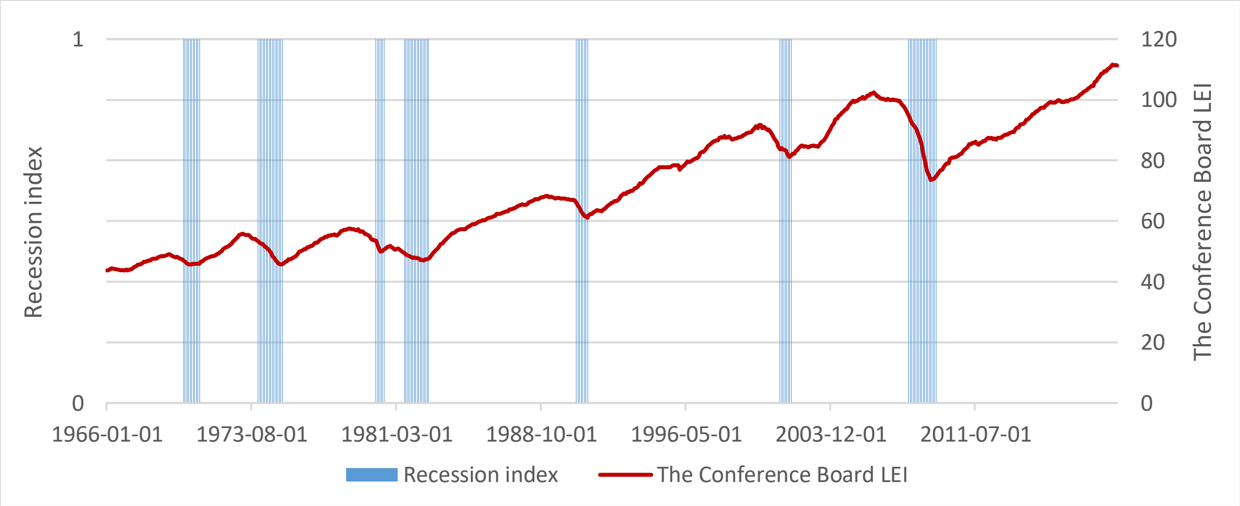

Figure 2. Combination of the recession index (LHS) and The Conference Board LEI (RHS)
Source: St. Louis Fed (table USREC) and Thomson Reuters Eikon (table Economic Indicator…), compiled by the author.

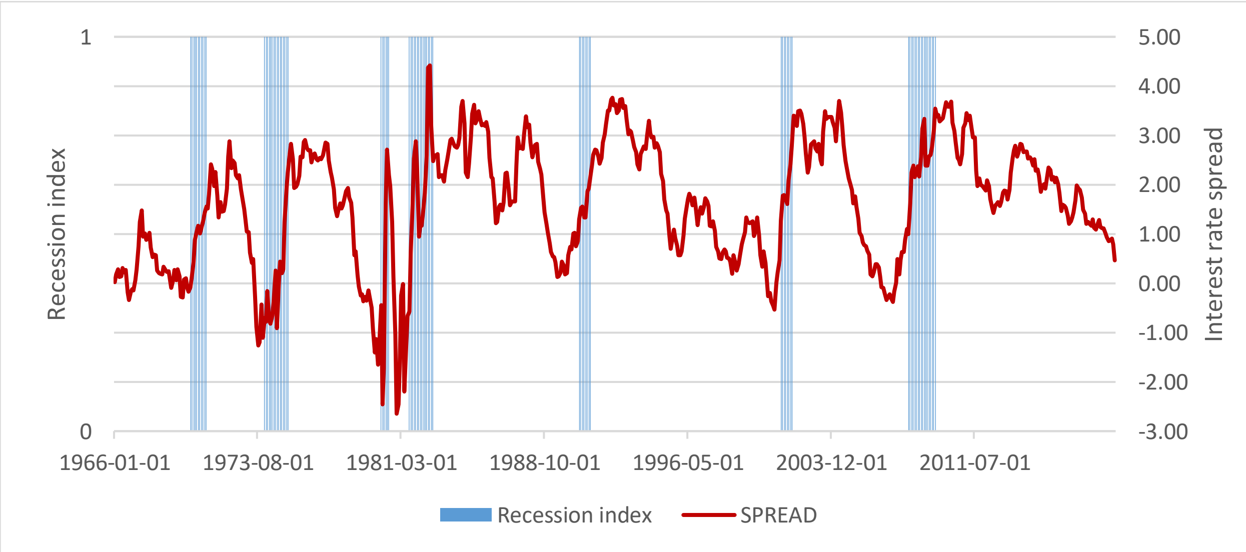

Figure 3. Combination of the recession index (LHS) and the interest rate spread between long- and short-term government bonds (RHS)
Source: St. Louis FED (table USREC; table DGS10; table TB3MS), compiled by the author.

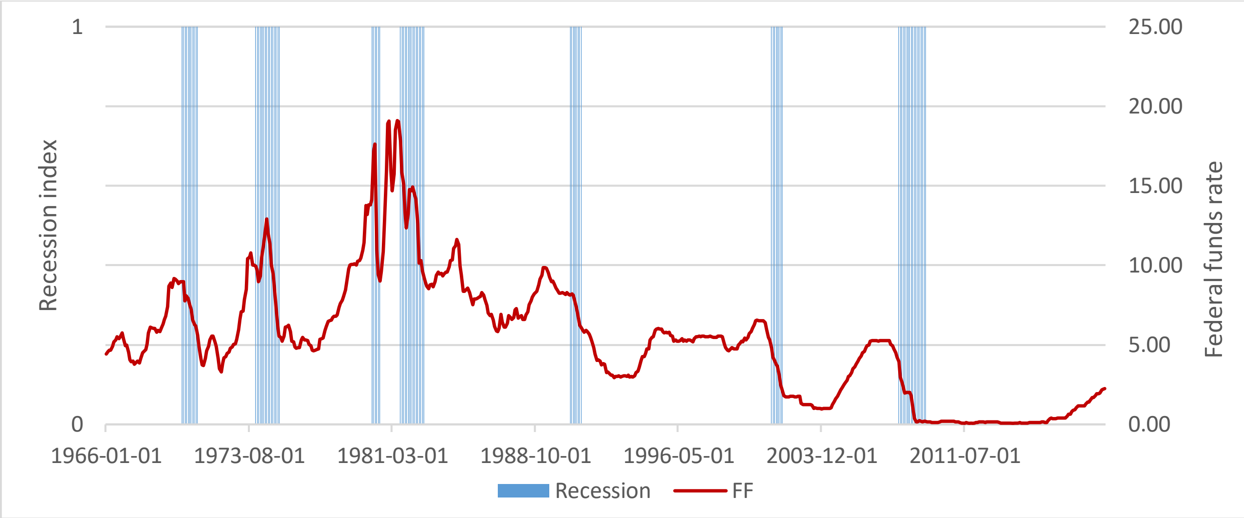

Figure 4. Combination of the recession index (LHS) and the federal fund rate (RHS)
Source: St. Louis FED (table USREC; table FEDFUNDS), compiled by the author

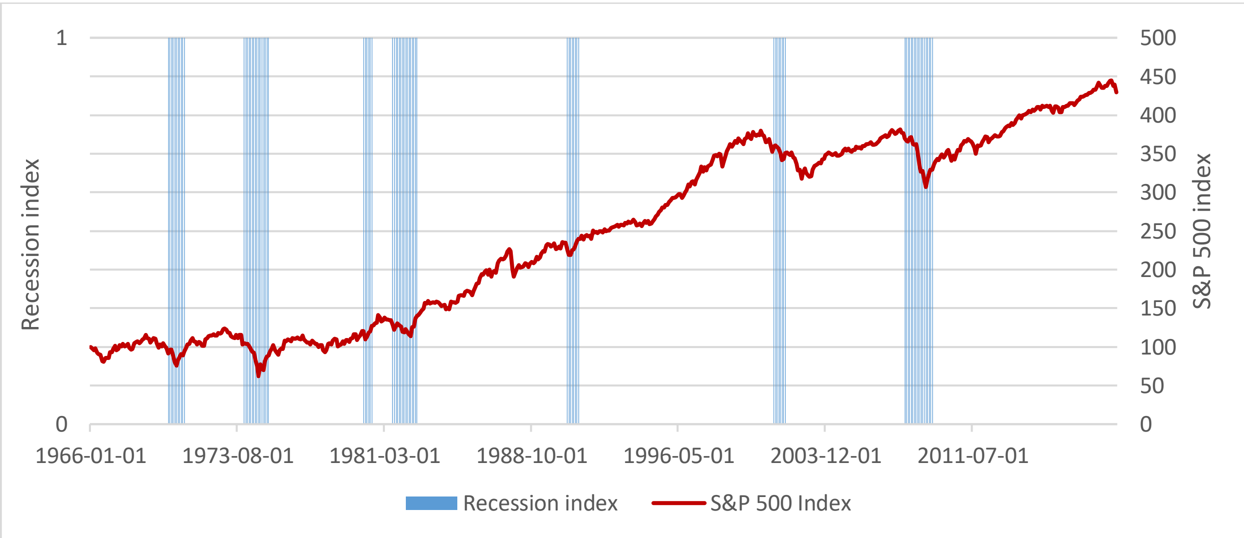

Figure 5. Combination of the recession index (LHS) and returns of the S&P 500 stock index (RHS)
Source: St. Louis FED (table USREC) and Yahoo Finance (table Historical data…), compiled by the author
Note: Stock returns are on an index scale, where 01.01.1966=100

2.1. Specification of probit models

The empirical part of this thesis mainly follows the work of Estrella and Mishkin (1998), where the probit model was used to predict recessions. They assumed that on a certain time period, the economy can be in one of two states – recession or not in recession – and therefore argued that the probit model is well-suited statistical method for predicting changes in the economic state, as it allows to estimate a binary outcome.

In this thesis, three probit models were constructed, which used different sets of indicators as independent variables. The financial variable model, which included the yield spread and returns of the S&P 500 stock index as predictors was used as a base model. It was augmented by adding the federal funds rate variable in order to analyse the predictive power of the yield curve. Finally, both of these models were compared with the LEI model, which only included The Conference Board LEI as the independent variable. The forecasting horizon was six months ahead. This choice was based on the results of previous research, which has found that these indicators have been useful predictors at this particular forecasting horizon. The forecast models were also compared with the nowcast models to see if the leading indicators can predict the future state of the economy more accurately than the current state of the economy.

The NBER recession index was the dependent variable, it describes the state of the economy as follows:

$R_t = 1$, economy is in recession at time t

$R_t = 0$, economy is not in recession at time t

The Equation (3) for the previously described augmented financial variable model can be written as:

$$P_{t+h} (R_{t+h} = 1 \mid X_t) = F (\beta_0 + \beta_1 \text{ SPREAD} + \beta_2 \text{ LD\_STOCK} + \beta_3 \text{ FF}) \quad (3)$$

[2]

Where:
h – forecast horizon in months
P_{t+h} - probability that a recession will occur at time $t+h$
R_{t+h} - value of the binary dependent variable at time $t+h$

[2] The baseline financial variable model does not include the federal funds rate and in the LEI model all financial variables were replaced by The Conference Board LEI.

X_t – row vector of regressor values at time t

F - cumulative normal distribution function

β_0 - model's constant

β_n - independent variable's coefficient

SPREAD - interest rate spread between 10-year Treasury bonds and 3-month Treasury bills.

LD_STOCK - percentage change of the S&P 500 stock index

FF - level of the federal funds rate

Although probit regression is similar to the ordinary least squares regression in that both use a linear function of explanatory variables to estimate the value of the dependent variable, some important differences exist. In linear regression, the impact of continuous or discrete explanatory variables on the continuous dependent variable can be calculated directly by using a linear function, however, this approach cannot be used in probit regression, because a binary dependent variable can only have a value of zero or one. Thus, the estimates obtained from the linear function of explanatory variables need to be transformed so that they would also lie between zero and one. (Gujarati 2004) This can be done by using the cumulative normal distribution function (cdf) (*Ibid*):

$$\int_{-\infty}^{z} \frac{1}{\sqrt{2\pi\sigma^2}} e^{(z-\mu)^2/2\sigma^2} \qquad (4)$$

Where:

z - F ($\beta_0 + \beta_1$ SPREAD + β_2 LD_STOCK + β_3 FF)

π - pi

μ - sample mean

σ - sample's standard deviation

After transforming, the independent variables can be used to estimate the value of the continuous latent variable, which can be interpreted as the probability of observing the occurrence of a recession. In order to categorize the observation as a discrete event (recession or not in recession), certain threshold needs to be set, that determines the probability level from which the observed event is considered to have taken place (Gujarati 2004). Normally, the threshold level is set at 50% and this level is also used as the unchangeable default threshold in Gretl. Although Haltmaier (2008) argued that the 50% threshold might be too strict to capture weaker signals of recession, the results of her work showed that using a lower threshold can substantially increase the amount of false recession predictions. Therefore, it was concluded that the 50% threshold is still adequate for categorizing observations.

The model's ability to correctly categorize observations was used as an another performance measure, since the predicted recession probability of over 50% indicates a strong recession signal. For this, the sensitivity rate was calculated which measures the rate of correctly categorized recession periods. In addition, the specificity rate was used to evaluate the models' ability to correctly categorize periods where recession did not occur and thus not to falsely indicate recessions. Considering that it is very likely that all the evaluated models cannot always clearly detect the beginning of a recession, the predicted recession probabilities were also plotted in the figures to give a better overview about the relative strength of possible recession signals.

In addition to the use of link function and latent variable, another main difference between the linear and probit regression models is the method used to estimate the coefficients of explanatory variables. Instead of the ordinary least squares (OLS) method, which is used for linear regression, the coefficients for probit model are estimated using the maximum likelihood (MLE) method. The idea behind this method is to find the coefficient values of the explanatory variables by maximising the likelihood of observing the values of the dependent variable in the given sample. (Gujarati 2004)

Regarding the assumptions of the regression model, it is relevant to note, that using the MLE method requires that an assumption about the distribution of the error term is made. If the distribution function is misspecified, it can cause the coefficients to be inconsistent, meaning that they do not converge to their true value if sample size increases. In the case of probit model, the residuals are assumed to be normally distributed. (Bera *et al.* 1984) Thus, the normal distribution of residuals was tested along with the possible presence of multicollinearity to confirm the validity of the estimated models. Also, robust standard errors were used by default to avoid making wrong inferences about the statistical significance of the coefficients due to possible heteroskedasticity.

3. RESULTS AND CONCLUSIONS

The aim of this chapter is to present the results of the empirical analysis. First, the ability of the constructed models to now-and forecast recessions is evaluated over the whole sample period. Then the best models are re-estimated using a shorter sample to test their out-of-sample forecasting performance. Finally, after checking the robustness of the models the results are discussed in the last sub-section.

3.1. Main results

In the financial variable model, which was used to assess the present state of the economy, only the stock market variable was statistically significant (at 10% level). The sign of this variable was negative, which means that the probability of observing a recession increases if stock market declines. However, the explanatory power of this model was very low, as the McFadden R^2 was only 0.03 and according to the sensitivity rate, the financial variables could not identify any recession months.

After the federal funds rate was added into the model, all the explanatory variables became statistically significant, but the sign of the yield spread coefficient became positive, which was unexpected. According to theory, yield spread should have a negative relationship with the probability of recession, but empirically this relationship has only been tested in models which forecast recessions for a certain period ahead. The sign of the federal funds rate coefficient was positive, indicating that the predicted probability of recession increases if central bank interest rate is higher. Still, the McFadden R^2 value of 0.07 shows that adding the federal funds rate did not improve the explanatory power of the financial variable model considerably.

In contrast, the results of the LEI nowcast model suggested that it would not be reasonable to rely only on a small number of financial indicators to understand the present state of the economy. Compared to the previous models, the LEI nowcast model had a very good explanatory power (the

McFadden R^2 was 0.307) and it also could correctly categorize a significant amount of recession periods (the sensitivity rate was 40.96%). The sign of the LEI coefficient was expectedly negative, as a decrease in the index value means that the predicted recession probability becomes higher. The results of the nowcast regression models are summarized in Table 3.

Table 3. In-sample results of nowcast regression models

	LEI model	Financial variable model	Augmented financial variable model
Constant	-1.260*** (0.081)	-1.019*** (0.098)	-1.971*** (0.180)
LD_LEI	-121.687*** (12.354)		
SPREAD		-0.0624 (0.050)	0.120** (0.050)
LD_STOCK		-3.277* (1.827)	-3.452* (1.855)
FF			0.111*** (0.018)
Adjusted McFadden R^2	0.307	0.003	0.071
N	635	635	635
Sensitivity	40.96%	0%	3.61%
Specificity	98.36%	100%	99.27%

Source: Appendices 2-4, author's calculations
Note: * - variable is significant at 10% level, ** - variable is significant at 5% level, *** - variable is significant at 1% level. Standard errors are in parentheses.

Recession probabilities predicted by the LEI and augmented financial variable nowcast models are plotted in Figure 6. The LEI model could timely detect the beginning of every recession during the observed period, which makes it a very useful indicator for measuring current economic conditions. On the other hand, the augmented financial variable model predicted substantially elevated recession probabilities only during the two consecutive recessions at the beginning of the 1980s. It can be assumed that these probabilities were mainly influenced by the federal funds rate, which was unprecedentedly high during this period. However, it is odd that other financial variables did not exhibit any ability to nowcast recessions.

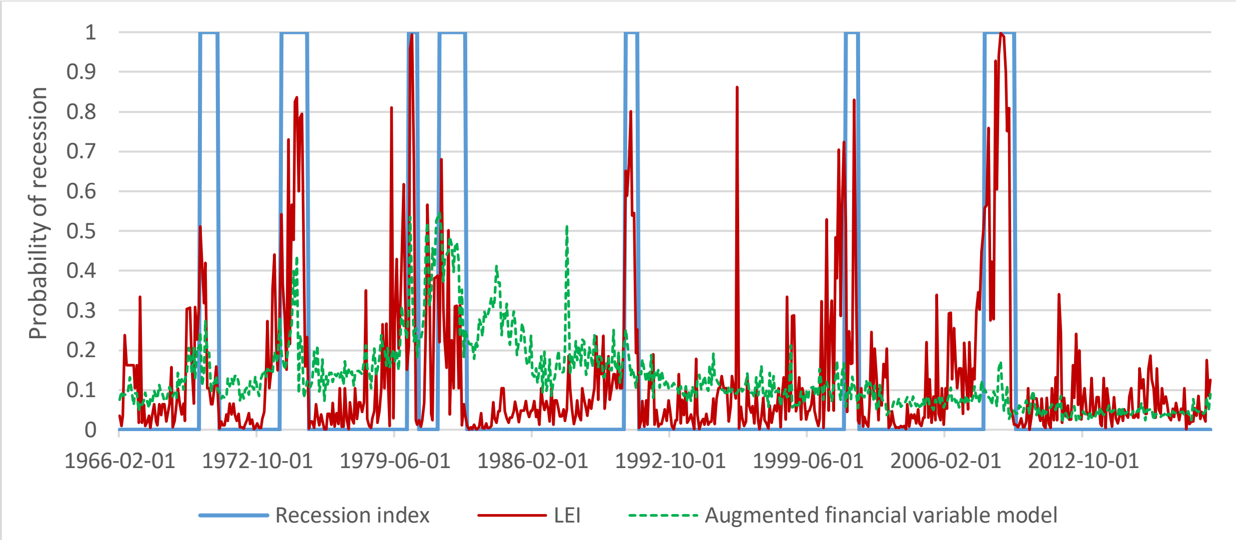

Figure 6. Predicted recession probabilities by the LEI and augmented financial variable models in the nowcast analysis
Source: compiled by the author

Interestingly, the performance of the financial variable models improved considerably when recessions were forecasted six months ahead. The McFadden R^2 for the financial variable model and the augmented financial variable model was 0.22 and 0.26, respectively. In addition, both models could correctly predict more recession periods, as their sensitivity rates were around 25%. All the predictors were also statistically significant and had the expected signs – the probability of observing a recession in six months hence increases if stock market is declining and the yield spread is narrowing. The sign of the federal funds rate variable continued to be positive.

Although the explanatory power of both financial variable models improved with a longer forecast horizon, the LEI still outperformed them in that regard. However, the sensitivity rate of the LEI model fell from 40.9% to 25.3%, when it was used to forecast recessions over a longer time horizon, indicating that despite its name, the Leading Economic Index best describes current economic developments. The in-sample results of forecast regressions are presented in Table 4.

Table 4. In-sample results of forecast regression models

	LEI model	Financial variable model	Augmented financial variable model
Constant	-1.288*** (0.071)	-0.541*** (0.099)	-1.417*** (0.205)
LD_LEI	-116.532*** (14.269)		
SPREAD		-0.497*** (0.067)	-0.311*** (0.065)
LD_STOCK		-8.877*** (1.976)	-8.699*** (2.105)
FF			0.102*** (0.023)
Adjusted McFadden R^2	0.302	0.218	0.260
N	629	629	629
Sensitivity	25.30%	22.89%	27.71%
Specificity	96.88%	99.08%	98.71%

Source: Appendices 5-7, author's calculations

Note: * - variable is significant at 10% level, ** - variable is significant at 5% level, *** - variable is significant at 1% level. Standard errors are in parentheses.

In addition to the reduced ability to correctly categorize the amount of recession months, the LEI forecast model tended to predict highest recession probabilities for the months occuring in the middle or end of a recession as shown in Figure 7, which combines recession probabilities predicted by the LEI and financial variable forecast models with recession index. This result could be expected, as the LEI nowcast model could identify the beginnings of recessions precisely or only with a very short lead.

While models which included only the financial variables were more timely, according to their predicted recession probabilities in Figures 7 and 8, they struggle to give strong signals of upcoming economic downturns. Both financial variable models performed best at predicting the two recessions at the beginning of the 1980s, but neither of them could capture the recession of 2008-2009 at all, if the 50% threshold rate was used. It is important to note that while the inclusion of the federal funds rate improved the financial variable model's ability to predict the recessions of the 1980s, it also reduced its ability to forecast the most recent recessions. Thus, serious thought should be given whether it is appropriate to use a sample, which includes past high values of the federal funds rate to estimate a model, which is meant to forecast recessions in a low interest rate environment. However, the financial variable model without the federal funds rate could not predict downturns significantly better, which confirms the fact that predicting recessions is a very complicated task, even when using the most reliable leading indicators.

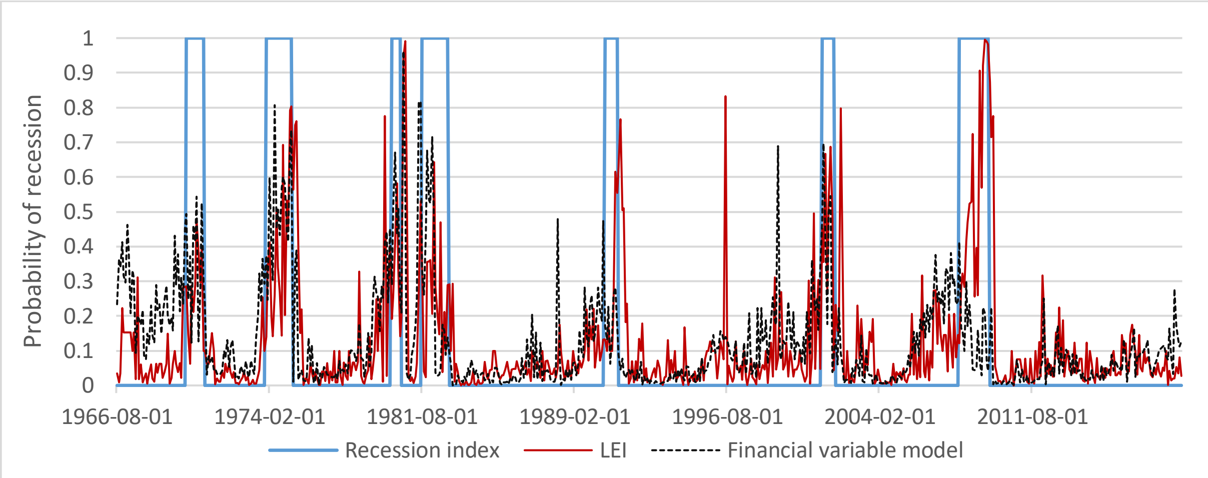

Figure 7. Recession probability forecasted six months ahead by the LEI and financial variable models
Source: compiled by the author

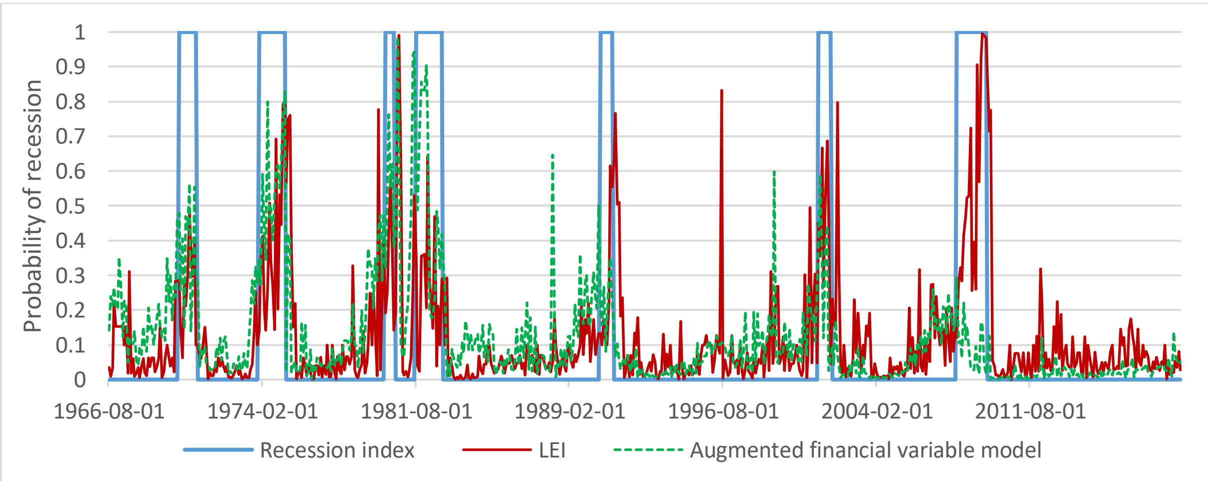

Figure 8. Recession probability forecasted six months ahead by the LEI and augmented financial variable models
Source: compiled by the author

3.1.1 Out-of-sample evaluation

In addition to the in-sample forecast it was decided to test how the best performing models can predict recessions out of the model fitting period. For this, the coefficients for LEI nowcast model and all the forecast models were re-estimated using a sample which still began in 1966, but ended in December 1999. The new models were used to forecast two recessions which occurred during the subsequent ten-year period. The results of the regression models used for the out-of-sample forecasting are presented in Table 5.

Table 5. Results of regressions estimated for out-of-sample analysis

	LEI nowcast model	LEI forecast model	Financial variable forecast model	Augmented financial variable forecast model
Constant	-1.173*** (0.097)	-1.156*** (0.081)	-0.514*** (0.112)	-2.457*** (0.337)
LD_LEI	-128.342*** (16.410)	-105.247*** (17.166)		
SPREAD			-0.596*** (0.094)	-0.333*** (0.088)
LD_STOCK			-6.572*** (2.305)	-5.588** (2.564)
FF				0.200*** (0.0399)
Adjusted McFadden R^2	0.296	0.232	0.262	0.385
N	407	401	401	401
Sensitivity	36.84%	15.78%	26.31%	42.10%
Specificity	98.57%	96.22%	98.54%	98.25%

Source: Appendices 8-11, author's calculations

Note: * - variable is significant at 10% level, ** - variable is significant at 5% level, *** - variable is significant at 1% level. Standard errors are in parentheses.

The outstanding performance of the LEI continued in the out-of-sample test, as the nowcast model could correctly categorize a majority of recession months. Moreover, this model gave strong recession signals at the beginning of both downturns, as the predicted recession probability for the first recession month was over 50%. The financial variable model also predicted higher recession probabilities for the months preceding recession, but those signals were rather weak, as the predicted probabilities did not exceed 40%. The other two models performed considerably worse – the LEI forecast model again signalled the beginnings of recession too late and the augmented financial variable forecast model predicted only marginally higher recession probabilities before both recessions. The results of the augmented financial variable model again raise the previously mentioned issue whether forecasts made with models, which have been estimated using interest rate levels from a significantly different interest rate environment, are severely distorted. The recession probabilities predicted by the estimated models are plotted in Figure 9.

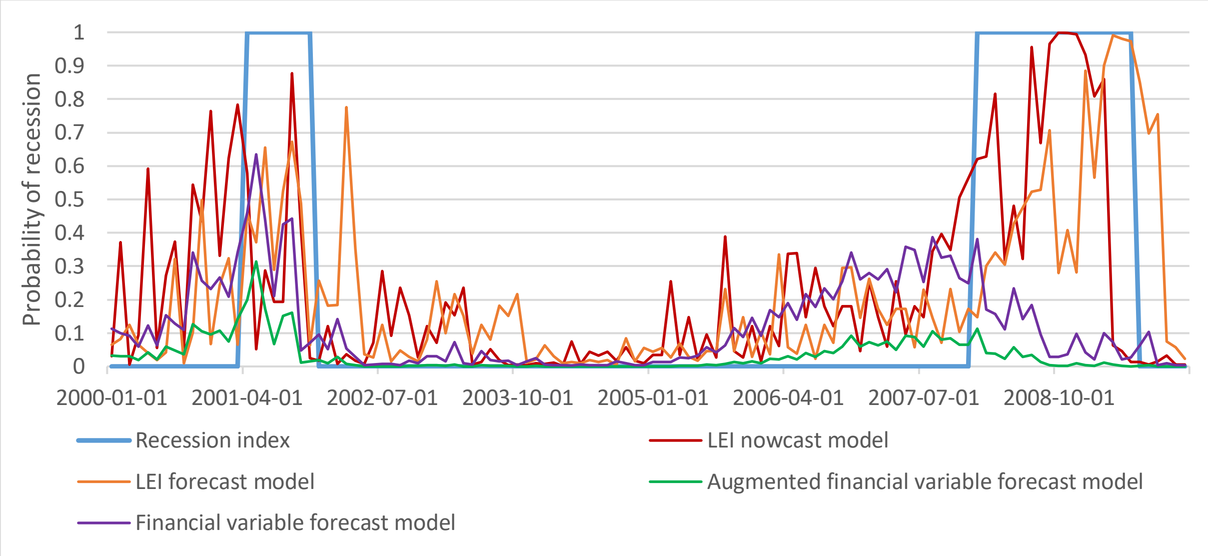

Figure 9. Out-of-sample predicted recession probabilities of the estimated models
Source: compiled by the author

In terms of the RMSE, the best model was the LEI forecast model. However, this measure is a bit misleading, because the predicted recession probability of the LEI nowcast model rose to a very high level some time before a recession and fell to a very low level before the recession was over. While these probabilities indicate that the LEI can lead both business cycle phases in very short term, they can be regarded as errors, because economy was not yet in or out of the recession. The analysis of the out-of-sample forecasts is summarized in Table 6.

Tabel 6. Analysis of out-of-sample forecasts

	Total observations correctly predicted, %	Recession periods correctly predicted, %	RMSE
LEI nowcast model	84.16%	53.84%	0.339
LEI forecast model	85.00%	46.15%	0.316
Financial variable forecast model	79.16%	3.84%	0.413
Augmented financial variable forecast model	78.33%	0%	0.442

Source: author's calculations

3.2. Test of assumptions and robustness checks

The results of the Jarque-Bera-Lee normality test indicated that the residuals of the best performing LEI and augmented financial variable forecast models are not normally distributed. Although this issue raises concerns about the consistency of estimators, from the practical standpoint it was considered more relevant to put the main emphasis on the forecasting ability of the models. Considering that recession probabilities predicted by the LEI now- and forecast models were quite similar, it was assumed that the forecast results were not affected by the non-normal distribution of residuals. Still, for additional certainty, it was decided to re-estimate those models using the logit regression to confirm that the results are practically similar even if a different distribution is assumed. The results of the normality tests for the best performing models are presented in Table 7.

Table 7. Results of Jarque-Bera-Lee normality test

	LEI nowcast model	LEI forecast model	FV forecast model	AFV forecast model
P-value (models for in-sample prediction)	0.327	5.201×10^{-7}	0.320	0.017
P-value (models for out-of-sample prediction)	0.353	1.729×10^{-7}	0.069	1.211×10^{-28}

Source: Author's calculations in Gretl

Notes: 1. FV and AFV are abbreviations for the financial variable model and augmented financial variable models, respectively.
2. Rejection of the null hypothesis in Jarque-Bera-Lee indicates that residuals are not normally distributed.

Considering that logit regression uses a different link function[3], the coefficients of the independent variables are much larger compared to the probit model, but the outcomes of estimated models are very similar in both cases. The same parameters are statistically significant and have the same sign. The performance of all models are also quite similar in terms of the McFadden R^2 and sensitivity, although models estimated by using logit regression could correctly identify more recession months. In addition, it can be seen in Figure 10 that recession probabilities predicted by the augmented financial variable model, which was estimated by using probit and logit regressions, differ only marginally. These results indicate that the forecasting ability of the models is robust to the choice of link function. Results of the logit regressions are summarized in Table 8.

[3] In logistic regression the values obtained from linear function of explanatory variables are transformed by using cumulative logistic distribution function to calculate the values of latent variable. Therefore logit coefficients are approximately 1.81 times larger than probit coefficients (Gujarati 2004).

Table 8. Results of logit regressions

	LEI forecast model	Augmented financial variable forecast model
Constant	-1.955*** (0.152)	-4.606*** (0.758)
LD_LEI	-192.653*** (35.663)	
SPREAD		-0.689*** (0.184)
LD_STOCK		-12.235*** (4.648)
FF		0.409*** (0.091)
Adjusted McFadden R^2	0.223	0.391
N	401	401
Sensitivity	19.29%	50.87%
Specificity	96.22%	97.09%

Source: Appendices 12-13, author's calculations

Note: * - variable is significant at 10% level, ** - variable is significant at 5% level, *** - variable is significant at 1% level. Standard errors are in parentheses.

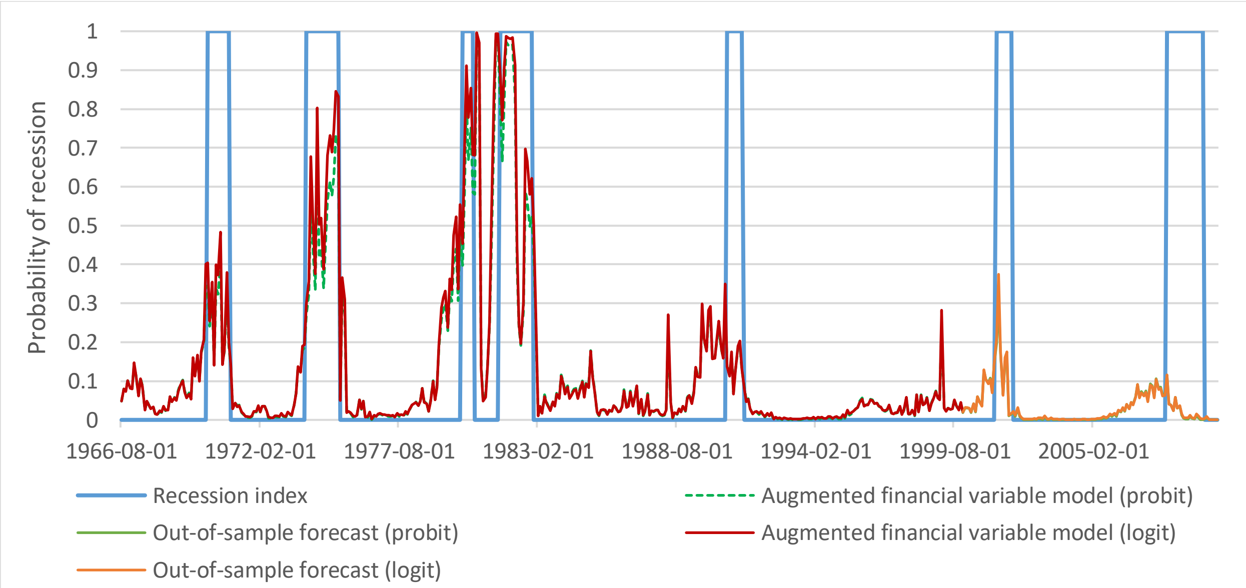

Figure 10. Forecasted recession probabilities by the augmented financial variable models which are estimated by using probit and logit regressions
Source: compiled by the author.

In addition to the residual distribution, possible presence of multicollinearity among the financial variables was also tested. This was done by using the VIF measure. If the value of VIF is over 10, it indicates that multicollinearity might exist. Considering that the values of VIF for the observed financial variables were below two, it is can be assumed that risk of multicollinearity is low. Values of VIF obtained from the augmented financial variable nowcast model are presented in Appendix 1.

3.3. Conclusions and discussion

The statistical significance of coefficients and moderate explanatory power of the financial variable forecast model corroborates the results of previous research (Estrella and Mishkin 1998; Berge 2015), which shows that the yield spread and stock returns have exhibited historical ability to predict recessions six months ahead. Therefore, it is possible that market participants can make accurate forward-looking assumptions about evolving economic conditions to some extent.

However, it is interesting that in terms of the model's explanatory power, financial variables underperformed compared to the LEI, even when the forecast horizon was lengthened. This result contradicts the findings of Estrella and Mishkin (1998), but is consistent with more recent research (Silvia *et al.* 2008). It is therefore possible that the availability of more time series has enabled The Conference Board to construct a better index over the years with the changes made during the last two decades. For example money supply and vendor performance have been replaced by Leading Credit Index and ISM Index of New Orders (The Conference Board 2001; The Conference Board 2019).

On the other hand, the definition of „superior performance“ can be misleading, if it is measured only by the McFadden R^2 or sensitivity rate. Figure 7 showed that the financial variable forecast model predicted considerably higher recession probabilities for the first months of each recession. In contrast, the LEI forecast model usually predicted very high recession probabilities for the months which occurred in the middle or end of the recession. Thus, it can be inferred that certain financial indicators have exhibited longer leads over the business cycle compared to other leading indicators, but considering the abstract relationship between these variables and real economy, it can be expected that they do not always provide very strong recession signals. However, it remains unclear why the predictive power of financial variables disappeared if they were used to nowcast recessions.

Although the inclusion of the federal funds rate improved the financial variable model's explanatory power, its ability to actually predict recessions was distorted. In the out-of-sample testing the performance of the augmented financial variable model was significantly worse, as the predicted recession probability did not exceed 20% at the beginning of both forecasted recessions. In contrast to Wright's (2006) conclusions, this indicates that even though the federal funds rate was relatively low compared to the historical standards before the last two recessions, those levels do not necessarily mean that monetary policy was accommodative. Also, these results show that forecasts made with models, which are estimated by using interest rate data from a different economic environment, are not reliable.

In contrast, the LEI nowcast model proved to be very effective at identifying cyclical turning points. This model managed to timely identify all recessions during the whole sample period, as it predicted over 50% recession probability at the beginning of each recession. While it is difficult to certainly conclude which particular indicators contributed to the good performance of the LEI in both cases, it can be assumed that in very short term, real variables outperform financial indicators. For example, Travis J. Berge (2015) has found evidence that changes in initial jobless insurance claims, building permits for new housing and payroll employment can explain the current economic conditions very well.

Reliable recession nowcast can still have a great value, because GDP estimates, which are most commonly used for assessing the state of the aggregate economy, are published with a considerably longer delay than the Leading Economic Index. The results described above hint that it might be beneficial to further test this indicator's ability to identify cyclical turning points. However, Diebold and Rudebusch (1991) have argued that the use of revised estimates to evaluate LEI's ability to forecast recessions can give too optimistic results, so it is necessary to re-estimate the LEI model using real-time data in order to make more objective inferences.

If the overall results of this thesis are compared with the work of Chen *et al.* (2011) who analysed the ability of analogous financial variable and LEI models to predict the same recessions, there is one noticeable disparity. The performance of their models is significantly better in terms of the pseudo-R^2 and RMSE. This difference can be explained by their model specification. They used multiple lags of explanatory variables to capture the predictive content of lag dynamics. While such approach limits the opportunity to predict recessions for a certain period ahead, the results of this thesis show that forecasting future might be a too ambitious goal. Thus it can be suggested that the users and researchers of leading indicators should take into account the dynamics of the analysed variables, which they probably do anyway.

In conclusion, although some financial variables probably do include a substantial amount of information about the economy by incorporating the expectations of market participants into bond and stock prices, it would be more beneficial to look for possible recession signs from a wider range of economic activites. Also, while the predictive power of financial variables is enhanced when the forecasting horizon is longer, some other leading indicators might perform best at nowcasting recessions. Hence, the question of which lags of leading indicators should be used to construct the best performing now- or forecast models requires careful consideration.

SUMMARY

The exact beginning of the next economic downturn offers great interest to all economic agents. However, recession is defined as an abrupt decline in aggregate economic activity and thus predicting recessions is a very complicated task. Over the years, many economic institutions have conducted research to find quantitative statistical measures which describe the business cycles best and have used them as benchmarks to detect indicators which lead the business cycle. Since then, a wide range of leading indicators have emerged from empirical investigations, which have continuously been subject to rigorous testing in order to select variables which are most timely and consistent.

The aim of this thesis was to compare how well the most popular leading indicators have forecasted recessions in the United States during the period of 1966-2018. For this, three probit models were constructed which used different sets of indicators as the explanatory variables. The LEI model included The Conference Board Leading Economic Index as the explanatory variable and in the financial variable model it was replaced by the yield spread between 10-year Treasury bonds and 3-month Treasury bills and returns of the S&P 500 stock index. The third model was the financial variable model which in addition included the federal funds rate, because according to the results of previous research, the yield curve might contain more information about economic conditions than the yield spread alone. These models were used to nowcast recessions and to forecast them six months ahead. In addition, the best-performing models were used for the out-of-sample forecast to test how the leading indicators would have predicted recessions which occurred outside the period used for model fitting.

The results were consistent with previous research in that financial indicators have historically exhibited a moderate ability to forecast recessions six months ahead. The financial variable model which included the yield spread and stock returns forecasted higher recession probabilities for the first months of a recession, but those probabilities only occasionally exceeded the 50% threshold, meaning that the recession signals were timely, but not very strong. Including the federal funds rate improved the explanatory power of the financial variable model, but the augmented financial

variable model could not forecast the most recent two recessions very well. This issue might be related to fact that over the last two decades, central bank interest rates have been relatively low compared to the historical standards. As future recessions will probably also occur in a very low interest rate environment, it is advisable to remain cautious about using the yield curve to predict recessions.

The model that used the Leading Economic Index as the explanatory variable did not have an ability to predict recessions six months ahead, but it could correctly nowcast the beginnings of all seven recessions, indicating that composite leading indices give strongest recession signals when the considerable deterioration of economic conditions has already begun. While reliable nowcast of recessions can still offer value, it is important to note that the LEI's ability to identify recessions should be further tested by using preliminary data in order to assess the predictive power of this indicator more objectively.

Therefore, it was concluded that certain financial variables contain useful information about the expectations of economic agents, which is why they can be effectively used to assess the probability that a recession will occur in the near future. While it was difficult to objectively compare the performance of financial variables with the Leading Economic Index, because their predictive power varied over different forecast horizons and the use of retrospectively adjusted data might have positively biased the results of the LEI model, it can be still assumed that it would be more reasonable to analyse different types of leading indicators together in order to better identify cyclical turning points.

KOKKUVÕTE

USA MAJANDUSSURUTISTE PROGNOOSIMINE JUHTIVINDIKAATORITE ABIL

Tõnno Tint

Järgmise majandussurutise täpne algusaeg pakub kahtlemata huvi kõigile majandusagentidele. Samas majandussurutist defineeritakse kui järsult toimuvat majandusaktiivsuse langust, mistõttu on sellist sündmust väga keeruline usaldusväärselt ette prognoosida. Aastate jooksul on mitmed majandusorganisatsioonid teinud põhjalikku uurimustööd, mille käigus on otsitud statistilisi näitajaid, mis kirjeldavad majandustsüklit kõige paremini ja seetõttu on neid olnud võimalik kasutada ka potentsiaalsete juhtivindikaatorite leidmiseks. Nii on majandustsükli uurimise algusaegadest saati esile kerkinud mitmeid indikaatoreid, mille võimet majandustsüklit prognoosida on põhjalikult analüüsitud.

Antud bakalaureusetöö eesmärk oli võrrelda, kui hästi populaarsed juhtivindikaatorid on suutnud prognoosida majandussurutisi perioodil 1966-2018. Eesmärgi täitmiseks loodi kolm probit regressioonmudelit, milles kasutati seletavate muutujatena erinevaid juhtivindikaatoreid. LEI mudelis oli seletavaks muutujaks The Conference Boardi juhtiv majandusindeks, mis finantsindikaatorite mudelis asendati USA valitsuse 10-aastaste ja 3-kuiste võlakirjade tulumäärade vahega ning S&P 500 aktsiaindeksi tootlusega. Kolmanda mudeli puhul lisati finantsindikaatorite mudelisse keskpanga kehtestatud intressimäär, sest varasemate uurimuste kohaselt võib valitsuse võlakirjade intressikõver sisaldada rohkem informatsiooni majandusolude kohta kui lühi- ja pikajaliste võlakirjade tulumäärade vahe ainuüksi. Nende mudelite abil prognoositi nii käesolevat majandusolukorda kui ka olukorda kuue kuu pärast. Lisaks valimisisesele prognoosimisele testiti parima seletusvõimega mudelite tulemuslikkust ka valimiväliste prognooside tegemisel.

Saadud tulemused olid kooskõlas varasemate uuringutega, mille kohaselt teatud finantsindikaatoritel on ajalooliselt olnud mõõdukas võime prognoosida peatset majandussurutise saabumist kuus kuud ette. Finantsmuutujate mudel, mis sisaldas valitsuse võlakirjade tulumäärade vahet ja aktsiaturu tootlust, prognoosis kõrgemat surutise esinemise tõenäosust nende kuude puhul, mille jooksul surutis tegelikult algas. Keskpanga intressimäära lisamine antud mudelisse parandas mudeli seletusvõimet, kuid uus mudel ei suutnud väga hästi prognoosida kahte viimast majandussurutist. See võib olla põhjustatud asjaolust, et võrreldes ajaloolise tasemega on Föderaalreservi intressimäär olnud viimastel aastakümnetel suhteliselt madal. Arvestades, et tulevased majanduslangused toimuvad tõenäoliselt samuti madalate intressimäärade keskkonnas, on soovitatav olla ettevaatlik intressikõvera kasutamisel surutiste prognoosimiseks.

Mudel, milles juhtiv majandusindeks oli seletav muutuja ei olnud võimeline majandulangusi kuus kuud ette prognoosida, kuid suutis see-eest õigeaegselt tuvastada kõigi seitsme vaatlusperioodil toimunud surutise alguse. See viitab sellele, et juhtivindikaatorid annavad surutisest kõige selgemini märku siis, kui majandusolukord on hakanud juba arvestataval määral halvenema. Kuigi ka käesoleva majandusolukorra usaldusväärne prognoosimine pakub olulist väärtust, siis on oluline märkida, et juhtiva majandusindeksi prognoosimisvõime objektiivsemaks hindamiseks tuleks antud mudelit testida kasutades vastava indikaatori kohta avaldatud esialgseid hinnanguid.

Seega võib järeldada, et teatud finantsnäitajad sisaldavad kasulikku teavet majandusagentide ootuste kohta, mistõttu on neid võimalik tõhusalt kasutada läheneva majandussurutise esinemise tõenäosuse hindamiseks. Kuigi analüüsitud finantsindikaatorite ja juhtiva majandusindeksi tulemuslikkust majandussurutiste prognoosimisel ei olnud võimalik objektiivselt võrrelda, sest nende prognoosivõime varieerus oluliselt erinevate prognoosihorisontide puhul ja lisaks olid juhtiva majandusindeksi mudeli tulemused tõenäoliselt positiivselt kallutatud tagantjärgi korrigeeritud andmete kasutamise tõttu, võib siiski eeldada, et erinevat tüüpi juhtivindikaatorite koos kasutamine võib aidata paremini identifitseerida majandustsükli faasi muutust.

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APPENDICES

Appendix 1. VIF statistics obtained from the augmented financial variable nowcast model

	FF	SPREAD	LD_STOCK
VIF	1.330	1.334	1.005

Source: calculated by the author in Gretl

Appendix 2. Financial variable model for in-sample nowcast

Model 2: Probit, using observations 1966:02-2018:12 (T = 635)
Dependent variable: Recessionindex
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−1.01900	0.0984668	−10.35	<0.0001	***
SPREAD	−0.0624247	0.0501926	−1.244	0.2136	
ld_STOCK_d11	−3.27734	1.82767	−1.793	0.0729	*

Mean dependent var	0.130709	S.D. dependent var	0.337347
McFadden R-squared	0.014968	Adjusted R-squared	0.002784
Log-likelihood	−242.5242	Akaike criterion	491.0484
Schwarz criterion	504.4093	Hannan-Quinn	496.2363

Number of cases 'correctly predicted' = 552 (86.9%)
f(beta'x) at mean of independent vars = 0.337
Likelihood ratio test: Chi-square(2) = 7.37075 [0.0251]

Test for normality of residual -
Null hypothesis: error is normally distributed
Test statistic: Chi-square(2) = 12.7962
with p-value = 0.0016647

Source: Author’s calculations in Gretl based on data obtained from St. Louis FED (table USREC; table DGS10; table TB3MS) and Yahoo Finance (table Historical data…)

Appendix 3. Augmented financial variable model for in-sample nowcast

Model 3: Probit, using observations 1966:02-2018:12 (T = 635)
Dependent variable: Recessionindex
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−1.97159	0.180074	−10.95	<0.0001	***
SPREAD	0.120688	0.0509620	2.368	0.0179	**
ld_STOCK_d11	−3.45224	1.85563	−1.860	0.0628	*
FF	0.111440	0.0188989	5.897	<0.0001	***

Mean dependent var	0.130709	S.D. dependent var	0.337347
McFadden R-squared	0.087958	Adjusted R-squared	0.071712
Log-likelihood	−224.5534	Akaike criterion	457.1068
Schwarz criterion	474.9213	Hannan-Quinn	464.0239

Number of cases 'correctly predicted' = 551 (86.8%)
f(beta'x) at mean of independent vars = 0.337
Likelihood ratio test: Chi-square(3) = 43.3124 [0.0000]

Test for normality of residual -
Null hypothesis: error is normally distributed
Test statistic: Chi-square(2) = 2.33209
with p-value = 0.311598

Source: Author’s calculations in Gretl based on data obtained from St. Louis FED (table USREC; table DGS10; table TB3MS; table FEDFUNDS) and Yahoo Finance (table Historical data…)

Appendix 4. LEI model for in-sample nowcast

Model 4: Probit, using observations 1966:02-2018:12 (T = 635)
Dependent variable: Recessionindex
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−1.26091	0.0819774	−15.38	<0.0001	***
ld_CONFERENCE	−121.687	12.3542	−9.850	<0.0001	***

Mean dependent var	0.130709	S.D. dependent var	0.337347
McFadden R-squared	0.315790	Adjusted R-squared	0.307666
Log-likelihood	−168.4592	Akaike criterion	340.9184
Schwarz criterion	349.8256	Hannan-Quinn	344.3769

Number of cases 'correctly predicted' = 577 (90.9%)
f(beta'x) at mean of independent vars = 0.337
Likelihood ratio test: Chi-square(1) = 155.501 [0.0000]

Test for normality of residual -
Null hypothesis: error is normally distributed
Test statistic: Chi-square(2) = 2.23441
with p-value = 0.327192

Source: Author's calculations in Gretl based on data obtained from St. Louis FED (table USREC) and Thomson Reuters Eikon (table Economic Indicator…)

Appendix 5. Financial variable model for in-sample forecast

Model 5: Probit, using observations 1966:08-2018:12 (T = 629)
Dependent variable: Recessionindex
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.541376	0.0995930	−5.436	<0.0001	***
SPREAD_6	−0.497921	0.0674030	−7.387	<0.0001	***
ld_STOCK_d11_6	−8.87777	1.97657	−4.492	<0.0001	***

Mean dependent var	0.131955	S.D. dependent var	0.338712
McFadden R-squared	0.230421	Adjusted R-squared	0.218194
Log-likelihood	−188.8276	Akaike criterion	383.6552
Schwarz criterion	396.9876	Hannan-Quinn	388.8342

Number of cases 'correctly predicted' = 560 (89.0%)
f(beta'x) at mean of independent vars = 0.339
Likelihood ratio test: Chi-square(2) = 113.074 [0.0000]

Test for normality of residual -
Null hypothesis: error is normally distributed
Test statistic: Chi-square(2) = 2.27596
with p-value = 0.320466

Source: Author’s calculations in Gretl based on data obtained from St. Louis FED (table USREC; table DGS10; table TB3MS) and Yahoo Finance (table Historical data…)

Appendix 6. Augmented financial variable model for in-sample forecast

Model 6: Probit, using observations 1966:08-2018:12 (T = 629)
Dependent variable: Recessionindex
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−1.41732	0.205447	−6.899	<0.0001	***
SPREAD_6	−0.311232	0.0652508	−4.770	<0.0001	***
ld_STOCK_d11_6	−8.69908	2.10517	−4.132	<0.0001	***
FF_6	0.102659	0.0237475	4.323	<0.0001	***

Mean dependent var	0.131955	S.D. dependent var	0.338712
McFadden R-squared	0.277229	Adjusted R-squared	0.260927
Log-likelihood	−177.3425	Akaike criterion	362.6850
Schwarz criterion	380.4615	Hannan-Quinn	369.5903

Number of cases 'correctly predicted' = 562 (89.3%)
f(beta'x) at mean of independent vars = 0.339
Likelihood ratio test: Chi-square(3) = 136.045 [0.0000]

Test for normality of residual -
Null hypothesis: error is normally distributed
Test statistic: Chi-square(2) = 8.12159
with p-value = 0.0172353

Source: Author’s calculations in Gretl based on data obtained from St. Louis FED (table USREC; table DGS10; table TB3MS; table FEDFUNDS) and Yahoo Finance (table Historical data…)

Appendix 7. LEI model for in-sample forecast

Model 7: Probit, using observations 1966:08-2018:12 (T = 629)
Dependent variable: Recessionindex
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−1.28847	0.0710510	−18.13	<0.0001	***
ld_CONFERENCE_6	−116.532	14.2696	−8.166	<0.0001	***

Mean dependent var	0.131955	S.D. dependent var	0.338712
McFadden R-squared	0.310457	Adjusted R-squared	0.302306
Log-likelihood	−169.1895	Akaike criterion	342.3790
Schwarz criterion	351.2673	Hannan-Quinn	345.8317

Number of cases 'correctly predicted' = 550 (87.4%)
f(beta'x) at mean of independent vars = 0.339
Likelihood ratio test: Chi-square(1) = 152.351 [0.0000]

Test for normality of residual -
Null hypothesis: error is normally distributed
Test statistic: Chi-square(2) = 28.936
with p-value = 5.20755e-007

Source: Author's calculations in Gretl based on data obtained from St. Louis FED (table USREC) and Thomson Reuters Eikon (table Economic Indicator…)

Appendix 8. LEI model for out-of-sample nowcast

Model 9: Probit, using observations 1966:02-1999:12 (T = 407)
Dependent variable: Recessionindex
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−1.17394	0.0970357	−12.10	<0.0001	***
ld_CONFERENCE	−128.342	16.4100	−7.821	<0.0001	***

Mean dependent var	0.140049	S.D. dependent var	0.347465
McFadden R-squared	0.307811	Adjusted R-squared	0.295679
Log-likelihood	−114.1118	Akaike criterion	232.2236
Schwarz criterion	240.2413	Hannan-Quinn	235.3965

Number of cases 'correctly predicted' = 366 (89.9%)
f(beta'x) at mean of independent vars = 0.347
Likelihood ratio test: Chi-square(1) = 101.489 [0.0000]

Test for normality of residual -
Null hypothesis: error is normally distributed
Test statistic: Chi-square(2) = 2.08126
with p-value = 0.353231

Source: Author’s calculations in Gretl based on data obtained from St. Louis FED (table USREC) and Thomson Reuters Eikon (table Economic Indicator…)

Appendix 9. Financial variable model for out-of sample forecast

Model 10: Probit, using observations 1966:08-1999:12 (T = 401)
Dependent variable: Recessionindex
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.514031	0.112397	−4.573	<0.0001	***
SPREAD_6	−0.596535	0.0940123	−6.345	<0.0001	***
ld_STOCK_d11_6	−6.57241	2.30563	−2.851	0.0044	***

Mean dependent var	0.142145	S.D. dependent var	0.349635
McFadden R-squared	0.281098	Adjusted R-squared	0.262799
Log-likelihood	−117.8597	Akaike criterion	241.7193
Schwarz criterion	253.7012	Hannan-Quinn	246.4638

Number of cases 'correctly predicted' = 354 (88.3%)
f(beta'x) at mean of independent vars = 0.350
Likelihood ratio test: Chi-square(2) = 92.1684 [0.0000]

Test for normality of residual -
Null hypothesis: error is normally distributed
Test statistic: Chi-square(2) = 5.32898
with p-value = 0.069635

Source: Author’s calculations in Gretl based on data obtained from St. Louis FED (table USREC; table DGS10; table TB3MS) and Yahoo Finance (table Historical data…)

Appendix 10. Augmented financial variable model for out-of sample forecast

Model 13: Probit, using observations 1966:08-1999:12 (T = 401)
Dependent variable: Recessionindex
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−2.45726	0.337215	−7.287	<0.0001	***
SPREAD_6	−0.333493	0.0880974	−3.786	0.0002	***
ld_STOCK_d11_6	−5.58803	2.56497	−2.179	0.0294	**
FF_6	0.200013	0.0399214	5.010	<0.0001	***

Mean dependent var	0.142145	S.D. dependent var	0.349635
McFadden R-squared	0.409501	Adjusted R-squared	0.385103
Log-likelihood	−96.80867	Akaike criterion	201.6173
Schwarz criterion	217.5932	Hannan-Quinn	207.9434

Number of cases 'correctly predicted' = 362 (90.3%)
f(beta'x) at mean of independent vars = 0.350
Likelihood ratio test: Chi-square(3) = 134.27 [0.0000]

Test for normality of residual -
Null hypothesis: error is normally distributed
Test statistic: Chi-square(2) = 128.561
with p-value = 1.21124e-028

Source: Author’s calculations in Gretl based on data obtained from St. Louis FED (table USREC; table DGS10; table TB3MS; table FEDFUNDS) and Yahoo Finance (table Historical data…)

Appendix 11. LEI model for out-of sample forecast

Model 8: Probit, using observations 1966:08-1999:12 (T = 401)
Dependent variable: Recessionindex
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−1.15698	0.0815302	−14.19	<0.0001	***
ld_CONFERENCE_6	−105.247	17.1668	−6.131	<0.0001	***

Mean dependent var	0.142145	S.D. dependent var	0.349635
McFadden R-squared	0.244535	Adjusted R-squared	0.232336
Log-likelihood	−123.8538	Akaike criterion	251.7077
Schwarz criterion	259.6956	Hannan-Quinn	254.8707

Number of cases 'correctly predicted' = 340 (84.8%)
f(beta'x) at mean of independent vars = 0.350
Likelihood ratio test: Chi-square(1) = 80.1801 [0.0000]

Test for normality of residual -
Null hypothesis: error is normally distributed
Test statistic: Chi-square(2) = 31.1406
with p-value = 1.72945e-007

Source: Author's calculations in Gretl based on data obtained from St. Louis FED (table USREC) and Thomson Reuters Eikon (table Economic Indicator…)

Appendix 12. LEI forecast model estimated with logit regression

Model 15: Logit, using observations 1966:08-1999:12 (T = 401)
Dependent variable: Recessionindex
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−1.95596	0.152358	−12.84	<0.0001	***
ld_CONFERENCE_6	−192.653	35.6639	−5.402	<0.0001	***

Mean dependent var	0.142145	S.D. dependent var	0.349635
McFadden R-squared	0.235969	Adjusted R-squared	0.223769
Log-likelihood	−125.2583	Akaike criterion	254.5165
Schwarz criterion	262.5045	Hannan-Quinn	257.6796

Number of cases 'correctly predicted' = 342 (85.3%)
f(beta'x) at mean of independent vars = 0.350
Likelihood ratio test: Chi-square(1) = 77.3712 [0.0000]

Source: Author’s calculations in Gretl based on data obtained from St. Louis FED (table USREC) and Thomson Reuters Eikon (table Economic Indicator…)

Appendix 13. Augmented financial variable model estimated with logit regression

Model 14: Logit, using observations 1966:08-1999:12 (T = 401)
Dependent variable: Recessionindex
QML standard errors

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−4.60668	0.758055	−6.077	<0.0001	***
SPREAD_6	−0.689207	0.184769	−3.730	0.0002	***
ld_STOCK_d11_6	−12.2353	4.64874	−2.632	0.0085	***
FF_6	0.405468	0.0919854	4.408	<0.0001	***

Mean dependent var	0.142145	S.D. dependent var	0.349635
McFadden R-squared	0.415409	Adjusted R-squared	0.391010
Log-likelihood	−95.84015	Akaike criterion	199.6803
Schwarz criterion	215.6561	Hannan-Quinn	206.0063

Number of cases 'correctly predicted' = 363 (90.5%)
f(beta'x) at mean of independent vars = 0.350
Likelihood ratio test: Chi-square(3) = 136.207 [0.0000]

Source: Author’s calculations in Gretl based on data obtained from St. Louis FED (table USREC; table DGS10; table TB3MS; table FEDFUNDS) and Yahoo Finance (table Historical data…)