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Forecasting Recessions in the U.S.A.

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ABSTRACT

Many economists have raised concerns about the next recession in the U.S., especially after the Great Recession in 2008. Many believe that the next recession will strike either this year (2019) or the next year (2020). This paper first analyzes different macroeconomic indicators such as Buffet Indicators, interest rate, unemployment rate, etc. In terms of modelling the data, a Probit model is applied to determine what variables can affect the probability of a recession. Then, going beyond whether or not a recession is likely at any time in future, a relevant question will be how long a time might elapse before the next recession will set in. This can be answered by using a Poisson model. Our results from the Probit model suggest that the government should focus on improving unemployment rate rather than interest rates by having more open policies for small businesses. In addition, the Poisson model forecasts that the next recession will likely occur in 2020.

Keywords: recession, forecasting

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CHAPTER ONE

INTRODUCTION

Many have known or experienced the economic downfall arising from the 2008 financial crisis, which is regarded as the worst economic disaster since 1929 despite the preventive efforts of the Federal Reserve and the U.S. Congress (Amadeo, 2018). Amadeo (2018) argued that the crisis was rooted in the Gramm-Rudman Act that allowed banks to trade derivatives and use mortgage-backed securities as collateral. The banks then chopped up the original mortgages and resold mortgage tranches (Amadeo, 2018). This action is a form of monetary debasement even though debasement is usually referred to when issuance of large amounts of money made for the government to access greater resources leads to higher inflation and lower value of money.

One of the main causes of the Great Recession in 2008 was Collagenized Debt Obligations (CDOs), or basically a type of junk bonds that include subprime mortgage-backed securities, triple-B mezzanine tranches, warehoused to launder into new triple-A tranches (McLean & Nocera, 2010). The main problem with CDOs was that a very low rated stock could become a very high rated stock as multiple collaterals of debts were allowed to be transformed based on different collators. Another serious problem preceding the crisis was when the subprime lending provided borrowers with mortgages requiring 10% or less for down payment which was also known to and accepted by the Federal Reserve and the Wall Street (McLean & Nocera, 2010). In addition, this problem was serious to the point that the lenders' agents even reported wrong information, such as income of borrowers, and placed few restrictions on borrowers in order to issue more mortgages which was to create more sales (McLean & Nocera, 2010). At the end, those borrowers couldn't pay their payments when the deadline came. Those lenders even tried to come to those borrowers' houses to collect payments, but nobody lived there (McLean & Nocera, 2010). The borrowers got their houses so easily, but the house prices fell so much that they did not find it worthwhile to keep paying mortgages based on higher valued houses. This system (CDOs) started to provide misinformation for small investors.

However, the original idea of this creation seemed admirable. It was to encourage homeownership in the U.S.A. According to Shiller (2008, p5), this rate went up by 11.5% over the period 1997 - 2005. Owning a house had never been easier because there were few requirements to qualify for a mortgage. The idea was, however, over-promoted and caused a problem. The largest increase in homeownership was from "the West, for those under the age of 35, for those with below-median incomes, and for Hispanic and blacks" (Shiller, 2008). This basically means the younger age, lower income, and minority group were the major group who had their hands-on big money in an easy way for a short period of time. Things started to get out of control when many borrowers had little ability to pay back their easy loans. It would be a miracle for a $30,000 income household to pay off a mortgage of a $300,000 house.

Figure 1 (Appendices) compares the GDP which represents the market value based on all final goods and services produced and the U.S. households' net worth which represents household wealth by a ratio of the U.S. households' net worth to the GDP. To understand how Figure 1 is created, it's important to know what the U.S. household net worth is. This net worth is the resale (current) value of assets minus the outstanding loans and interests where the assets include real estate as well as financial assets such as mutual funds, bonds, and stocks. This shows that the value of household net worth, and particularly financial assets, can fluctuate widely in a short period of time. When the household wealth is significantly higher than the market wealth, bubbles will be created which is shown in Figure 1. Each recession tends to happen at the end of each inverted U shape of the ratio. The most obvious bubbles are the Real estate bubble in 2008, the dot-com bubble in 2001, and the savings & loan (S&L) in 1990 even though the inverted U shape of the ratio is less obvious in the previous recessions. Figure 1 shows it is very possible that the last bubble (2011-2017) is about half way till it bursts and there is a very high possibility that it will burst anytime soon then create the next recession.

Indeed, many economists warned a recession in the next 10 years (since 2008) would throw us off due to the growing U.S. budget deficit (Turak, 2018). Maloney (Gold & Silver: Why I'm Buying The Safe-Haven Assets, Right Now, 2019) believed that the next recession is going to burst in a near future as the U.S. household net worth will skyrocket. The future bubble, as he suspected, will be a lot bigger than both the Dot-com and the real estate bubbles that he called it the “everything bubble” (Figure 1). Even Bill Gates, the billionaire Founder of Microsoft, firmly agreed that there would be another financial crisis as hard as the one in 2008 (Turak, 2018). However, the real question is when the next recession will be expected to actually happen and that is what this paper is mainly focusing on.

To elaborate the suspicion about the near future recession, this paper will use Buffet Indicator (BI) that is shown in Figure 2 (Appendices). The BI was invented by Warren Edward Buffett, who is considered the most successful investor in the world. The BI is a very quick and simple way to observe how the current market is valued.

Warren Buffet also claimed the BI is "the best single measure of where valuations stand at any given moment" (Langlois, 2018). Langlois (2018) explained that "the indicator is the total market cap of all U.S. stocks relative to the country's GDP" (Langlois, 2018). According to the Buffet Indicators (Figure 2), the value of BI is divided into five major groups of range that is represented in Figure 2. To simplify the concept, according to investors' point of view, when the BI is under 90%, it is safe to invest (prefer buying to selling) and when the BI is greater than 90%, it is better to sell your market shares. Based on the BI concept, when the ratio of market capitalization to GDP is greater than 90%, the economy is in a bubble as the market is significantly overvalued. Figure 2 shows that the market capitalization is significantly overvalued (132.6%). This indicates the current economy is already in a bubble. However, the market has been overvalued since 1995 while recessions had happened within any of the five indicators (from significantly undervalued to significant overvalued). Therefore, it's very challenging to use BI to predict the market even though it provides a great short-term signal. Meanwhile, an interesting thing from Figure 2 is that every time a recession occurred, the market was normalized to be closer to its fair value (75% - 90%). When the market was undervalued, it would increase during a recession; when the market was overvalued, it would decrease during a recession. However, this whole analogy doesn't provide much predictive power for a recession, but it does raise a concern that the next recession is coming soon.

Figure 3 (Appendices) compares the money base (St. Louis Adjusted Monetary Base) and the money that the public is using (Currency in Circulation). Currency in circulation includes paper currency and coin held both by the public and in the vaults of depository institutions while the Adjusted Monetary Base is the sum of currency (including coins) in circulation outside Federal Reserve Banks and the U.S. Treasury, plus deposits held by depository institutions at Federal Reserve Banks. Since 1990, there has been a very small gap between the two measurements then a sudden big gap after 2008. Till 2009, there was a huge gap between the two measurements. This gap means that the money that public is using is less than the available money. The gap also represents the money in the reserves, that refers to an excess reserve that is deposited in institutions such as Goldman Sachs, Merrill Lynch, etc. which also bought Treasury bonds, mortgage-backed securities. The problem with these reserves is that those securities or bonds can be very risky and low graded. The Fed has been attempting to close the gap between the two measurements (money base and money used) since 2017 as shown in Figure 3 because the economy has started to stabilize.

However, the problem is how the Fed is doing it. The Fed attempted to use quantitative easing (QE) three times by purchasing securities in order to lower interest rates and increase money supply: QE3 in 2012, QE2 in 2010, and QE1 in 2008 (Chronology of Fed's Quantitative Easing & Tightening). According to Figure 3, the reserves (gap between money base and currency in circulation) went down or stabilized during QE2 an QE3 while the reserves went up during QE1. This raises a concern that the deposit might have been much greater without the QE1. When the Fed terminated Q3 in 2014 and Q2 in 2012, the reserves went up simultaneously (Figure 3). However, when the Fed terminated Q1 in 2010, the reserves decreased (stabilized) but then increased significantly (Figure 3). In 2017, the Fed decided to normalize the balance sheets in order to close up the gap by basically selling off its assets (Treasury securities and bonds) to get cash then destroying the cash (Federal Reserve press release, 2017). This eventually will decrease the price of bonds as the supply of bonds is increasing and the demand for bonds is decreasing because of less cash to pay for those supplied bonds. This will water down the liquidity of the government's assets.

On the other hand, according to the Federal Reserve data, the deficit of the government budget in the last quarter of 2018 was about $0.8 trillion even though the deficit reached its climax of $1.4 trillion after the Great recession in 2008. That means the government has spent $0.8 trillion more than it takes in from taxes. The deficit has never been this high before the 2008 financial crisis. Our concern about this issue is whether the government can soften the next recession by increasing the deficit even more. The fact is that Federal budget decreased (deficit increased) during most recessions and the deficit has started to increase (the budget decreased) since 2015, according to the Federal Reserve data. However, there is no certain pattern of the government budget before a recession that can signal a recession.

Something, which is very interesting from the data collected, is the effective federal funds rate (EFFR) as shown in Figure 6 (Appendices). The EFFR was kept to almost zero after the 2008 Great Recession till 2017, which is about 35 quarters or 105 months (almost 10 years). This is the longest zero bound interest rate in the financial market history of the U.S.A. since 1950. This could be an after-effect of the Great Recession in 2008. This recession lasted for 6 quarters or 18 months which was the longest recession in the post-war history of the U.S.A. The main cause of the Great Recession in 2008 was the housing (real estate) bubble. The Federal Reserve has kept the interest rate low with a belief that it will prevent the next economic downturn. This study will discuss more on whether the lower bound interest rate can either increase or decrease the probability of a recession.

Another important economic measurement is unemployment rate as shown in Figure 4 (Appendices). According to Figure 4, at the end of 2018, the unemployment rate was under 4%, which was the lowest rate since 1969. During every recession (the grey area of Figure 4), the unemployment rate has always increased. Before every recession, the unemployment rate tends to stay very low then increase a bit. Figure 4 shows that an inverted curve of unemployment (low unemployment rate then a bit of an increase) occurs before each recession. Many economists believe that the low unemployment rate will only last beyond 2019 because of the recent Tax Cuts and Jobs Act, which slashed corporate taxes, and an enlarged federal spending package (Turak, 2018). Therefore, this could be considered as a sign of a near future recession as the unemploment rate is a bit curved up at the end of 2018 (Figure 4).

Much previous literature indicates that yield curve, which is the difference between long-term and short-term interest rate, has a significant impact on the probability of a recession. Figure 5 (Appendices) shows in terms of quarterly data how yield curve responded before, during, and after each recession (NBER) from 1953 to 2018. According to Figure 5, the yield curve tends to invert in an U shape before each recession. Figure 5 shows half of an inverted U shape in the end of 2018. This could be another sign of a near future recession. Indeed, many forecasters worry about the flattening of the yield curve because it suggests a soon-to-occur recession (Turak, 2018). However, investment professional like Saker Nusseibeh, the chief executive at Hermes

Investment Management, is expecting the curve to steepen so that the inflation and interest rates will be higher, signaling a stronger economy (Turak, 2018).

This paper focuses on data analysis to explore objective causes of a recession, rather than more anecdotal investor stories leading to a recession. Chapter 2 reviews the literature on how recession occurs and how researchers estimate models to predict a recession. Chapter 3 sets up models, describes data used in model estimation, and discusses results. Chapter 4 attempts the forecasting of the next recession based on the estimated models. Finally, Chapter 5 concludes by summarizing the main themes coming out of this research including policy implications and indicates directions for future research.

CHAPTER TWO

LITERATURE REVIEW

Models Used

There is a fairly long history behind macroeconomic theories of economic fluctuations. In recent times, New Keynesian, and Real Business Cycle theories have become prominent. Because of the assumption of short-run stickiness in nominal wages and prices which prevent their quick adjustment in the face of slowing demand, the new Keynesian models have become popular among central bankers and other macro forecasters.

This thesis is, however, about empirical modelling of recessions, and forecasting recessions. To this end, Filardo (1999) compared five different models: simple rules of thumb using the Conference Board's composite index of leading indicators (CLI), Neftçi model, Probit model, GDP forecasting model, and Stock-Watson model. Filardo (1999) didn't specify which model could forecast the best as each model has its own pros and cons. However, in terms of their ability to forecast an imminent recession, he favored three models – Probit model, GDP Forecasting model, and Stock-Watson model (Filardo, 1999). Plakandaras et al. (2017) compared Probit model with Support Vector Machines (SVM) and concluded that the probit models can foresee the U.S. recession periods more closely than SVM models for up to 6 months ahead while the SVM models are more accurate at longer horizons. However, Plakandaras et al. (2017) found that SVM models can discriminate between recessions and tranquil periods better than probit ones. On the other hand, Filardo (1999) emphasized that recession signals are the clearest when all the models are in an agreement.

Literature shows greater popularity of Probit models to forecast recession because of the limited nature of the dependent variable, that is, whether the economy at any point is either in recession or not in recession (King et al., 2007; Chauvet & Potter, 2005; Silvia et al., 2008; and Shoesmith, 2003; among others). In these models the dependent variable takes the value 1 if there is a recession in the current period, and 0 if not. The zero value could indicate all other stages of the economy such as recovery, slow or fast expansion, and the peak. One of the advantages of the Probit model is the superiority of the ordered probit framework to forecast all of the phases of a business cycle up to six months ahead under real-time conditions (Proaño & Tarassow, 2018). The other advantage is that the probit model allows analysts to create new composite indexes of leading indicators and evaluate them one at time or jointly (Filardo, 1999). The model also allows the business cycle analysts to identify the most informative set of recession indicators for a given forecast horizon (short horizon is preferred to long horizon) (Filardo, 1999). However, Filardo (1999) believed the probit model might miss a few recessions that exhibit unusual lead times.

The Stock-Watson model is similar to GDP forecasting model since they both try to predict recessions by forecasting consecutive declines in GDP by using a multi-equation regression model called a vector autoregression (VAR) (Filardo, 1999). A recession signal is when there are two consecutive quarterly declines in GDP (Filardo, 1999). However, the Stock-Watson model included a broader measure of economic activity and compared the forecasts with their elaborate up-and-down pattern, called the Experimental Recession Index (Filardo, 1999). Filardo (1999) found that the model might be consistent only when NBER is equal to 1 (recession). In the Stock-Watson model, Filardo (1999) used seven leading indicators: new private housing building permits, durable goods industries' unfilled orders, trade-weighted exchange rate, part-time employment because of slack work, 10-year constant maturity Treasury bond yield, credit interest rate spread, and term interest rate spread to capture the institutional process of the NBER's Business Cycle Dating Committee. These seven leading indicators should be useful in determining the independent variables for this study as well.

Variables Used

Most of the research uses the National Bureau of Economic Research (NBER) to define recessions such as King et al. (2007); Chauvet & Potter (2005); Anderson & Vahid (2000); Filardo (1999); Silvia et al. (2008); Shoesmith (2003); Plakandaras et al. (2017). According to Meyer (1980), “the National Bureau of Economic Research (NBER) has developed a generally accepted procedure for dating the peaks and troughs of business cycles” (Meyer, 1980). “The NBER procedure takes into account the movements of a large number of aggregate time series and identifies cyclical turning points on the basis of the amplitude, duration, and the degree of diffusion of the movements in the various time series” (Meyer, 1980). In simpler words, the value is 1 when the economy is in recession and the value is 0 when the economy is not in recession. A recession occurs when there is “a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales” (Plakandaras et al., 2017). This definition suggests a good set of variables to use to forecast recessions.

The yield curve has been used to forecast recessions in many papers such as King et al. (2007), Chauvet & Potter (2005), Anderson & Vahid (2000), Filardo (1999), Silvia et al.(2008), Shoesmith (2003), and Plakandaras et al. (2017). The exact variable is the difference between the long term and the short term Treasury bond rate. The financial analysts suggest that the greater the spread, the higher probability that the economy is in a recession because bigger spreads indicate higher risk. However, the economists suggest a flatter curve (smaller spread) indicates a weaker growth while a steeper one (bigger spread) indicates a stronger growth.

Filardo (1999) and Dueker (2005) use composite index of leading indicators (CLI) in their models. CLI includes 10 elements: manufacturing hours worked, consumer expectations, stock price, initial unemployment claims, building permits, money supply, difference of long-term and short-term interest rate in government securities, vendor performance, manufacturing orders for capital goods, and manufacturing orders for consumer goods. Dueker (2005) shows that two or three months of declines in CLI could signal at least 1.3% that the economy is in recession.

A negative real GDP growth is a part of the recession definition and is recommended by King et al. (2007); Chauvet & Potter (2005); Anderson & Vahid (2000); Filardo (1999); Silvia et al. (2008); and Shoesmith (2003); etc. Kilian & Vigfusson (2013) claimed that capital stock along with population and technology are the main drivers of long-run growth (real GDP). Kilian & Vigfusson (2013) found oil prices increases matter to one-quarter-ahead U.S. real GDP to the extent they exceed the maximum oil price in recent years while oil price decreases do not matter at all. Since a consecutive 2-quarter decline in GDP is the definition of recession (Filardo, 1999), the results from the two papers, and Kilian & Vigfusson (2013), are able to suggest more variables. The higher the GDP growth, the less likely the economy is in a recession stage. Anderson & Vahid (2000) included growth in M2 together with interest rate spread (yield spread), GDP growth, and growth in M2 in their model to forecast recessions. However, they find that the marginal contribution of M2 growth in preceding recessions, conditional on the spread, is negligible. On the other hand, Plakandaras et al. (2017) confirmed oil prices (in their natural logarithm form), stock returns and the yield spread as leading indicators that provided the most accurate forecating models for recession.

CHAPTER III

EMPIRICAL STRATEGY

This paper will use two different models to forecast recessions as there will be two different dependent variables: one is to predict recessions and the other is to predict how long it will be before the next recession will occur. In a quarterly model, when there is a recession, the dependent variable for that quarter takes the value 1, otherwise it is 0. Because of the binary dependent variable, a Probit model will be an appropriate model of analysis. For the second model that looks at the length of time before the next recession, the dependent variable (quarters) will count numbers of periods (quarters) till the nearest future recession. Poisson would be an appropriate model to analyze count data of this kind. As far as independent variables are concerned, most of them are selected in this thesis as suggested by the existing literature. Important among them are yield spread, leading indicator index, GDP, inflation, broad money, effective federal funds rate, oil price, and unemployment rate.

Since our U.S. data is time series, before estimating the models, it will be important to perform the test of stationarity in order to obtain sensible results based on stationary variables. This study will apply Augmented Dickey Fuller (ADF) test to check the stationarity of each variable. Before applying the ADF test, it is important to determine the correct number of lags to eliminate any autocorrelation in the data. We determine the numbers of lags for each variable (using the varsoc command in Stata). As long as the coefficient of each incrementing lag is statistically significant consecutively, that should be the ideal number of lags in the ADF regression. The VAR model is as follows:

$$y_t = \rho y_{t-p} + v_t$$

where y is the vector of dependent variables and p indicates the number of common lags in each equation. For variables to be stationary, the test statistics in the ADF need to be statistically significant. The ADF regression will look like the following:

$$\Delta y_t = \alpha + \theta y_{t-1} + \sum_{j=1}^{p} a_j \, \Delta y_{t-j} + v_t, \qquad \theta = \rho - 1$$

When the two series are I(1) but their linear combination is I(0), the regression of one on the other is not spurious but says something about the long-run relationship between the two series. Therefore, in most cases for time series date, the next step is to perform test of cointegration. However, as the nature of the both dependent variables in Probit and Poisson models is limited, this problem might not apply. Moreover, each variable has different unit roots. The test of cointegration will be less likely to be applicable.

Probit Model

We use the Probit model to forecast recessions mainly because the model ensures that the estimated response probabilities are strictly between zero and one. The study also considers two interaction terms: percent change in real Gross Domestic Product (GDPG) & percent change in composite leading indicators (Leading), and percent change in real Gross Domestic Product (GDPG) & consumer price index (Infla). The first interaction term is included because some elements in leading indicator index could control GDP growth at some levels and some elements in GDP growth could control Leading. Camacho (2004) and Graff (2010) showed that the leading indicator index could improve the forecasts of the GDP growth. The second interaction term is included because both consumer price index (Infla) and GDP growth (GDPG) measure price changes in goods and services purchased by consumers, businesses, governments, etc. However, GDP is calculated at a fixed price while consumer price index is calculated at a fixed basket of goods. Moreover, GDP doesn't include imports bought by domestics as consumer price index does. As a result, the effect of leading indicator index and consumer price index on the likelihood of a recession will change as GDP changes. However, these interactions terms will be dropped off the model if the results don't show much improvement through the goodness of fit and the percent correctly predicted (PCP) measures.

In the Probit model, the main reason, that GDP growth (GDPG), unemployment rate (Unemp), and Industrial Production (IndProd) are in a lag form, is because those variables are part of the definition of a recession. It would make more sense to use past values of those variables to forecast recessions. When real GDP growth or Industrial Production decreases, or unemployment rate increases consecutively for two or more quarters, a recession occurs. Hence, the number of lags (h) will be 2.

The Probit model will look like following:

$$P(Recession_t = 1|X)$$

$$\begin{aligned}
&= G[\beta_0 + \beta_1 Spread_t + \beta_3 Leading_t + \beta_4 GDP_{t-h} + \beta_5 Infla_t + \beta_6 \mathrm{M2G}_t \\
&+ \beta_6 FFRCh_t + \beta_7 OilPCh_t + \beta_8 UnempCh_{t-2} + \beta_9 IndProd_{t-h} \\
&+ \beta_{10}(GDPG_{t-h} \times Leading_t) + \beta_{11}(GDPG_{t-h} \times Infla_t)] \\
&= G(\beta_0 + \boldsymbol{x\beta}) = G(z)
\end{aligned}$$

where G is the standard normal cumulative distribution (c.d.f.) so that G can only take on values strictly between zero and one for all real number z (Wooldridge, 2012), and h

indicates the number of lags. The *G* function is increasing the most quickly at $z = 0$. The closer to 0 the values of the *G* function are, the larger negative the number *z* is. In addition, the closer to 1 the values of *G* function are, the larger positive the number *z* is. The *G* function looks as follows:

$$G(z) = \Phi(z) = \int_{-\infty}^{z} \phi(v)dv = \int_{-\infty}^{z} \frac{e^{\frac{-z^2}{2}}}{\sqrt{2\pi}} dz$$

The dependent variable in the Probit model is rather not the direct value itself but in a logit form (logarithm of ratio of probability of a recession to probability of a non-recession). Therefore, the coefficients from the Probit model are not the marginal effects of the independent variables on the dependent variable. Since the independent variables are continuous, the marginal effect for each independent variable is as follows:

$$\frac{\partial p(x)}{\partial x_j} = \frac{\partial G(\beta_0 + \boldsymbol{x\beta})}{\partial x_j} = g(\beta_0 + \boldsymbol{x\beta})\beta_j = g(z)\beta_j$$

As the function g(z), called the scale factor, is always positive, the sign of marginal effects of each independent variable is the sign of its coefficient (β_j). However, the magnitude of the effect of each independent variable depends on all independent variables' coefficients as well as the scale factor g(z). Moreover, the scale factor g(z), here is the c.d.f. of the *G* function or standard normal cumulative distribution function. This is important to get the marginal effect of each independent variable. The following equation shows how the marginal effect of a variable is calculated in the Probit model.

$$\frac{\partial p(x)}{\partial x_j} = g(z)\beta_j = \Phi[G(\beta_0 + \boldsymbol{x\beta})]\beta_j = \Phi(G(z))\beta_j = \frac{e^{\frac{-z^2}{2}}}{\sqrt{2\pi}}\beta_j$$

The marginal effect can be calculated by plugging in any values of the independent variables to get the *z* value or the *G* function then use the above function to calculate the marginal effect for each independent variable. The equation shows that different quarters will produce different marginal effects of each independent variable because each quarter has different values of z or the predicted G function. The problem in doing this is that there will be too many possible numbers of marginal effect for each independent variable.

Because of the nonlinear nature of the G function, the marginal effect of a variable, also called partial effect at the average (PEA), is normally evaluated at the mean values of each independent variable. Alternatively, the marginal effect or the average partial effect (APE) of a variable is calculated for each observation in the sample and then the mean of those effects is reported as the APE. The APE, indeed, is preferred to the PEA because it has the scale factor, g(z), that uses all predicted values from the G function. The following equation shows how APE is calculated.

$$\frac{\sum_{i=1}^{n}[g(\hat{\beta}_0 + \boldsymbol{x}\widehat{\boldsymbol{\beta}})\hat{\beta}_j]}{n} = \frac{\sum_{i=1}^{n}[g(\hat{\beta}_0 + \boldsymbol{x}\widehat{\boldsymbol{\beta}})]}{n}\hat{\beta}_j = \frac{\sum_{i=1}^{n}[g(z)]}{n}\hat{\beta}_j$$

Poisson Regression Model

The Probit model predicts whether a recession will or will not occur in a given period. When the next recession will occur can only be inferred indirectly by looking at what it predicts in subsequent periods after creating scenarios for each of the independent variables. There is no direct forecast of the number of quarters in which the next recession is likely to occur. To solve this problem, this paper created another variable called quarters that measures how many more quarters from today will elapse till the onset of the next recession. The quarters variable will count the number of quarters from the end of the previous recession to the start of the next recession. When the economy is in a recession, the dependent variable (quarters) will be zero. Since the dependent variable has a count feature and is nonnegative, we use a Poisson Regression Model that takes as an exponential function to find out how much time on average will elapse from today till the next recession.

$$
\begin{aligned}
E(\text{quarters}) = exp[&\beta_0 + \beta_1 Spread_t + \beta_3 Leading_t + \beta_4 GDPG_{t-h} + \beta_5 Infla_t \\
&+ \beta_6 \mathrm{M2G}_t + \beta_6 FFRCh_t + \beta_7 OilPCh_t + \beta_8 UnempCh_{t-2} \\
&+ \beta_9 IndProd_{t-h}] \\
= e^{X\beta} = \lambda&
\end{aligned}
$$

The Poisson model determines the probability that the dependent variable, quarters, equals a count value, d_i, conditional on all the above listed independent variables as follows:

$$P(\text{quarters}|\text{quarters} = d_i) = \frac{e^{-\lambda_i}\lambda_i^{d_i}}{d_i!} = \frac{e^{-e^{X\beta}}e^{X\beta^{d_i}}}{d_i!}, \qquad d_i = 0, 1, 2, \ldots.$$

Since the dependent variable in the Poisson Model is transformed to the exponential form, the coefficient of each independent variable in the model is not the marginal effect of each independent variable on the dependent variable. Because the Poisson is also nonlinear, there are two ways to get the marginal effects as in the Probit model. However, the Poisson function is different from the Probit function, hence the scale factor to calculate the marginal effect is also different. As all the independent variables are continuous, the marginal effect is calculated as following:

$$\frac{\partial E(y_i|x_{i)}}{\partial x_{ji}} = \lambda_i \widehat{\beta_J} = e^{X\widehat{\beta}}\widehat{\beta_J}$$

To get the partial effect at the average (PEA), as in the Probit model, we take the average of each independent variable to get the predicted values in the Poisson function then take the exponential of it as in the above equation. But the difference from the G function for

Probit also makes Poisson's average partial effect (APE) slightly different as given below:

$$\frac{\sum_{i=1}^{n} e^{X_i\hat{\beta}}}{n}\hat{\beta_J} = \frac{\sum_{i=1}^{n} \hat{\lambda}_i}{n}\hat{\beta_J}$$

In the Poisson model, the coefficients (β's) can be estimated by maximum likelihood (ML). The likelihood function for the dependent variable is the joint probability function of the observed data. The overall significance of the model depends on the estimated log-likelihood as follows:

$$L(\beta) = \sum_{i=1}^{n} l_i(\beta) = \sum_{i=1}^{n} \{y_i x_i \beta - e^{x_i\beta} - \log\,(y_i\}$$

The Probit and Poisson models will be estimated by using data for the variables listed and defined in Table 1:

Table 1

Description of Model Variables

Name	**Unit**	**Description**
Recess	n/a	Average of Base Recession Indicators for the U.S. the Period following the peak through the Trough (NBER)
Recessb	Binary	NBER in binary
Quarters	Quarters	Number of quarters till the next recession
Spread	Percent	10-year Treasury constant maturity interest rate minus 3-month Treasury constant maturity rate
Leading	Percent Change	Leading Indicators OECD: Leading indicators: CLI: Trend restored for the U.S.
GDPG	Percent Change	Percent change from previous quarter of Real Gross Domestic Product
Infla	Rate	Growth rate from previous quarter of Consumer Price Index for the U.S.
M2G	Percent	Percent change of M2 Money stock
FFFRCh	Percent	First differencing of Effective Federal Funds Rate
OilPCh	Dollars per barrel	First differencing of Spot crude oil price: West Texas Intermediate (WTI) in natural logarithm form
IndProd	Percent	Percent change in Industrial Production: mining: crude oil
UnempCh	Percent	First differencing of Civilian unemployment rate

Note: Most independent variables are measured in percentage change form (or growth rate)

CHAPTER IV

DATA AND RESULTS

All data is collected from the Federal Reserve Database (FRED) quarterly from 1950 to 2018. As observed, the number of observations for each variable is different mainly because of its data availability. This means that the actual number of observations for the model will be based on the least number of observations. In this case, there will be 187 observations as the Industrial Production has data for the shortest time span. However, the Industrial Production variable is at the second lag; hence, the sample size in the Probit model will be 185. In the Probit function, the oil price is used in a logarithmic form because of its larger values than the rest of the variables. The use of oil price in logarithms allows the marginal effect to be interpreted in the percent change than the dollar change.

Table 2:

Summary Statistics of all variables (1950-2018 quarterly)

Variable	**Obs**	**Mean**	**Std. De.**	**Min**	**Max**
Recess	278	.133	.323	0	1
Recessb	276	.134	.324	0	1
Spread	262	-.588	7.087	-35.216	27.937
Leading	235	.750	.684	-2.374	2.554
GDPG	276	3.294	3.834	-10	16.7
Infla	236	.918	.816	-2.829	3.951
M2G	239	1.651	.816	-2.829	3.951
FFRCh	258	4.814	3.587	.073	17.78
log(oil)	276	2.616	1.231	.944	4.820
Unemp	276	5.788	1.636	2.567	10.667
IndProd	187	.148	2.454	-11.164	8.872

In Table 2, Recess is measured in terms of the fraction of a quarter. Hence, Recess has four possible values: 0, 0.33, 0.67, and 1. When Recess equals to .33, it means that one third of the quarter is in a recession. A value of 0.67 means two thirds of the quarter is in recession. By looking at whether the previous or the following quarter has a recession, it should be simple enough to tell which month is in a recession. According to the data, the 0 value of Recess appears 233 times; the .33 value of Recess appears 4 times and the .67 value of Recess appears 10 times; and the 1 value of Recess appears 29 times during the period of 1950 - 2018. Statistically speaking, a total of (111 months or) 37 quarters are recession quarters, which translates to 13.40% of the overall sample period of 1950–2018, equal to the average of the Recess variable.

To make the data fit with the nature of the Recess values, it is possible to transform Recess into a binary form shown as Recessb in Table 2. Recessb is one if the average value is greater than 0.5, else it is 0. After the transformation (Recessb), there are total of 39 quarters (14.13%) of recession out of 276 quarters in the sample. However, the Industrial Production (IndProd) series only started from 1972. Hence our sample is restricted to 1972Q2–2018Q4. According to the data, Recess takes the value zero 160 times, 0.33 twice, 0.67 5 times; and 120 times during 1972–2018. This means we have 24 quarters of recessions, or 12.83% of total. Generally speaking, it can be said that the economy is more stable in the period of 1972 - 2018 than in the period of 1950 - 2018. This makes sense because the U.S. economy has gained from policy improvements than in prior periods.

The effective Federal Funds Rate can measure most of the change in monetary policy (Bernanke & Blinder, 1992). It is often that the government lowers the interest rates (monetary easing) when the economy is not doing well in order to increase aggregate demand (Bernanke & Blinder, 1992). As a result, GDP tends to increase when the effective Federal Funds Rate is lowered. Therefore, the lower the effective Federal

Funds Rate, the higher the chance of a recession, which means the coefficient of the effective Federal Funds Rate should be expected to be negative. However, Laopodis (2006) found that monetary easing or monetary tightening is not necessary to improve stock returns and economic activity. Therefore, the sign of effective Federal Funds Rate might not be statistically significant as well as negative, as expected.

A change in the consumer price index (Infla) measures the average percentage change in CPI or, in simple terms, inflation. Higher inflation generally signals a stronger economy (Turak, 2018), meaning the coefficient of the inflation is expected to be negative. This is true in most cases when the level of aggregate demand in an economy outpaces aggregate supply triggering a demand pull inflation. During such a period, the purchasing power of consumers could be the main driver in the market from an increase in employment levels as an example. This clearly explains Turak's claim that higher inflation signals a stronger economy as the employment levels increase. However, the aggregate supply could decrease due to an increase in cost of production such as raw materials, labor, and other inputs leading to a cost push inflation. Therefore, such an inflationary situation worsens the economy making the coefficient of inflation positive. As a result, the expected sign for the coefficient of CPI will depend on the behavior of aggregate supply and aggregate demand. Hence, it is undetermined.

The higher the leading indicator index (Leading), GDP growth (GDPG), and industrial production (IndProd), the lower will be the probability that a recession will happen because the economy will then be performing better. As a result, the coefficients of those variables are expected to be negative. However, the marginal effects of Leading, and GDPG not only depend on their own coefficients but also the coefficients of the interaction terms. Therefore, the signs of these coefficients are uncertain. Moreover, GDP growth is what determines whether there is a recession. It would be tautological to use current GDP to explain a current recession. Therefore, it should make sense to apply lags of GDP.

According to King et al. (2007), Chauvet & Potter (2005), Anderson & Vahid (2000), Filardo (1999), Silvia et al. (2008), Shoesmith (2003), and Plakandaras et al. (2017), among others, a wider yield spread makes a recession more likely to happen. As steeper yield curve means stronger economy, the sign of the yield spread's coefficient should be expected to be negative as the bigger value of yield spread increases the risk of a recession. Another important element to forecast a recession is the unemployment rate. A higher or rising unemployment will increase the probability of a recession. Therefore, the coefficient of unemployment rate is expected to be positive.

Test of stationarity and cointegration

The null hypothesis in an augmented Dickey-Fuller type test is that the variable is non-stationary. Therefore, the variables whose coefficients are statistically significant would be stationary. Table 3 shows the augmented Dickey-Fuller results. There are two nonstationary variables: the effective federal funds rates (FFR), and oil price per barrel (OilP). Moreover, the p-value for unemployment rate (Unemp) is very close to 0.05. Therefore, it is better to do error correction by first differencing for the three variables: FFRCh, OilPCh, and UnempCh.

Table 3

Augmented Dickey-Fuller tests and conclusions

Variables	**Test statistics**	**p-value**	**Conclusion**
Recess	-7.702	.0000***	Stationary
Spread	-5.175	.0001***	Stationary

Leading	-5.696	.0000***	Stationary
GDPG	-8.707	.0000***	Stationary
Infla	-6.493	.0000***	Stationary
M2G	-6.708	.0000***	Stationary
FFR	-2.809	.1937	Non-stationary
log(oil)	-2.277	.4466	Non-stationary
Unemp	-3.596	.0302**	Stationary
IndProd	-8.858	.0000***	Stationary

Note. (*) Significant at the p<0.1 level, (**) Significant at the p<0.05 level, (***) Significant at the p<0.01 level

Test of collinearity

It's also important to make sure all variables are not highly correlated to each other, especially to the dependent variable (NBER). The problem of multicollinearity is that the results will be overvalued. According to Table 4, the variables are not too highly correlated as the absolute values of all correlations are not higher than 0.8. However, because of the discreate characteristics of the dependent variable, the rule of thumb for a bad collinearity might not be applicable. However, the correlation matrix still brings a good support for the Probit regression results later on.

Table 4

Correlation matrix

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
(1) Recess	1.000								
(2) Spread	0.307	1.000							
(3) Leading	-0.478	-0.229	1.000						
(4) GDPG	-0.464	-0.293	0.588	1.000					
(5) Infla	-0.006	-0.103	-0.016	0.247	1.000				
(6) M2G	0.170	0.240	-0.010	0.042	0.026	1.000			
(7) FFECh	-0.222	-0.362	-0.026	0.278	0.453	-0.156	1.000		
(8) OilPCh	-0.226	-0.149	0.216	0.193	0.517	-0.211	0.233	1.000	
(9) UnempCh	0.628	0.338	-0.422	-0.599	-0.087	0.112	-0.292	-0.195	1.000

(10) IndProd	-0.010	-0.088	-0.051	0.028	-0.215	0.042	-0.012	-0.131	-0.111

Probit Model

According to Table 5, Leading, Infla, FFRCh, and UnempCh variables are statistically significant at the 5% significant level in the model without the two interaction terms. However, the Infla variable is no longer statistically significant in the model with the interaction terms. The negative sign of coefficient of the FFRCh variable is caused by the Fed's reaction to a recession, lowering the interest.

Table 5

Probit Model Results

VARIABLES	**(Without Interaction terms) Recession**	**(With interaction terms) recession**
Spread	-0.0563	-0.0603
	(0.0384)	(0.0379)
Leading	-3.085***	-3.241***
	(0.835)	(0.959)
GDPG	-0.0332	-0.124
	(0.120)	(0.186)
Infla	0.696**	0.495
	(0.312)	(0.466)
M2G	0.159	0.249
	(0.336)	(0.359)
FFRCh	-1.828***	-1.757***
	(0.483)	(0.479)
OilPCh	-1.343	-0.937
	(1.472)	(1.577)
UnempCh	3.834***	4.263**
	(1.381)	(1.771)
UndProd	0.126	0.124
	(0.145)	(0.162)
Grth*Leading		0.0877
		(0.175)
Grth*Infla		0.0580
		(0.0981)
Constant	-1.409*	-1.277
	(0.768)	(0.863)

Observations	185	185

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 shows clearly the signs are as predicted. According to Table 6, most of the signs are as predicted even though the sign for Industrial Production (IndProd) is not as predicted. It makes sense that when the Industrial Production is greater, it means that the industrial sector in mining for crude oil is doing well. The U.S. has been facing the scarcity of crude oil for many years. Many products produced have been accommodated to use less oil such as hybrid cars or electronic cars (Tesla). Because of the scarcity, the oil price went up significantly. As a result, the demand for oil will go down as well. An example is that national consumers have been adapted themselves by using smaller cars and preferring electrical heaters. However, the coefficient of Industrial Production is not statistically significant which means the Industrial Productions has little impact on a recession.

Table 6

Sign of coefficients

Variable	**Hypothesis**	**Results**
Spread	-	-
Leading	-	-***
GDPG	-	-
Infla	- or +	+**
M2G	- or +	+
FFRCh	- or +	-***
OilPCh	- or +	-
UnempCh	+	+***
IndProd	-	+

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 shows and compares the overall significance of the two Probit models. The interaction terms, indeed, improved the model overall (Table 7) but the improvement is not significant. The Pseudo R-square is slightly improved with the interaction terms (from 72.87% to 73.26%); the chi-square is also slightly improved from 112.06 to 112.66. On the other hand, the correctly predicted percent for both models are almost identical (there might be a very small difference that couldn't be shown by the round-up). There is no improvement in correctly classified percent as well. Therefore, it is appropriate to stay with the Probit model without the interaction terms. The model overall predicts very well, 95.68%. Nevertheless, this might be a sign that the correctly predicted percent in both Probit models are over-estimated. The reason is that there are many variables used to determine a recession such as GDP growth (GDPG), Industrial Production (IndProd), Leading Indicator Index (Leading), unemployment rate (Unemp), and Consumer Price Index (Infla).

Table 7

Overall significant of Probit Model

	Without Interaction terms	**With interaction term**
Observations	185	185
Pseudo R2	.7287	.7326
LR chi2	112.06	112.66
Positive prediction value	91.30%	91.30%
Correctly classified	95.68%	95.68%

The results in Table 8 show each variable's partial effect evaluated at the averages for all of the independent variables. These averages are indeed calculated based on observations for which all the variables have non-missing values. The marginal effects retain the signs of the respective coefficients estimated by the Probit model and as shown in Table 6. These effects are, however, statistically not significant. None of the variables seems important enough to affect probability of a recession. Thus, we move to a discussion of another model.

Table 8

Partial effect at the average (PEA)

	dy/dx	Std.Err.	z	P>z	Mean
Spread	-0.001	0.001	-0.840	0.401	-0.632
Leading	-0.042	0.048	-0.880	0.378	0.661
GDPG	-0.000	0.002	-0.240	0.806	2.813
Infla	0.010	0.012	0.770	0.442	0.977
M2G	0.002	0.005	0.430	0.668	1.596
FFRCh	-0.025	0.029	-0.860	0.391	-0.014
OilPCh	-0.018	0.030	-0.610	0.540	0.015
UnempCh	0.053	0.058	0.910	0.363	-0.010
IndProd	0.002	0.003	0.680	0.498	0.088

The other method to get the marginal effects of independent variables on Recess is APE. The scale factor can be calculated by applying the normal distribution, c.d.f., function in Stata (normalden) for all predicted values in the Probit model and then taking the average as follows:

$$\frac{\partial p(x)}{\partial x_j} = \frac{\sum_{i=1}^{n}[g(z)]}{n}\hat{\beta}_j = \frac{\sum_{i=1}^{185}[g(z)]}{185}\hat{\beta}_j = \frac{\sum_{i=1}^{185}\{[normalden[(G(z))]]\}}{185} = .5519\hat{\beta}_j$$

The scale factor for APE method can also be calculated manually by using the following formula.

$$\frac{\partial p(x)}{\partial x_j} = \frac{\sum_{i=1}^{n}[g(z)]}{n}\hat{\beta}_j = \frac{\sum_{i=1}^{185}[g(z)]}{185}\hat{\beta}_j = \frac{\sum_{i=1}^{185}[\frac{e^{\frac{-z^2}{2}}}{\sqrt{2\pi}}]}{185}\hat{\beta}_j = .5519\hat{\beta}_j$$

Both ways will give the same result for the scale factor values which is presented in Table 9 with the coefficients in the Probit model and the PEA for a comparison purpose. In general, the absolute values in APE approach (which is preferred) are greater than those in PEA method. In the APE approach, the effect of leading indicators index

(Leading) and the change in unemployment rate (UnempCh) are more significant as the APE coefficients are greater than one. Again, however, these estimates are insignificant statistically.

Table 9

Marginal effects to Recess from Probit

	$\hat{\beta}_j$	**APE**	**PEA**
Spread	-0.056	-0.021	-0.001
Leading	-3.085	-1.705	-0.042
GDPG	-0.033	-0.013	-0.000
Infla	0.696	0.265	0.010
M2G	0.159	0.060	0.002
FFRCh	-1.828	-0.696	-0.025
OilPCh	-1.343	-0.512	-0.018
UnempCh	3.834	1.460	0.053
IndProd	0.126	0.048	0.002

Poisson Regression Model

Our second model is a Poisson model which gives us a count of the number of quarters it will take for the next recession to arrive conditional on the included variables. Here, the estimated results are as follows:

$$quarters = \underset{(S.E.:)\ (0.073)}{2.610} + \underset{(0.006^{***})}{0.020}Spread + \underset{(0.047^{***})}{0.822}Leading + \underset{(0.011)}{0.011}GDPG - \underset{(0.044^{***})}{0.345}Infla$$

$$-\underset{(0.029^{***})}{0.314}M2G + \underset{(0.037^{*})}{0.071}D.FFRCh - \underset{(0.203)}{0.280}OilPCh - \underset{(0.112^{***})}{0.382}UnempCh + \underset{(0.012^{**})}{0.028}IndProd$$

$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

The results in the last equation show that most of the coefficients are statistically significant except for the GDP growth (GDPG) and the oil price (OilPCh). The coefficient for leading indicator index (Leading), for instance, indicates that on average, as the leading indicator index increases by 1 unit, the number of quarters till the next recession will increase by 141.57%, [exp(.882)-1]*100, all else equal. As an example, a

1 unit increase equals 0.4 standard deviation of the change in industrial production. This means an improvement in leading indicator index will push the next recession further out in the future. Another example is that, on average, a 1 unit increase in inflation rate (Infla) means a 41.20% [exp(.345)-1]*100 decrease in numbers of quarters till the next recession, all else qual. A 1 unit increase equals 1.23 standard deviation of the change in inflation rate. This means an increase in inflation rate will pull the next recession closer in the future.

The null hypothesis for the fit of the overall model is that the data are well represented by the Poisson model. This is not true because of the large chi-square (679.15) and low p-value. Yet our goal here is to see whether our variables have significant effects on the mean number of quarters before the next recession. Figure 7 (Appendices) shows the actual period of time (quarters) before each recession.

Just as the Probit Model, in the Poisson Model, the coefficients are not the marginal effect of each independent variable on the dependent variable. Table 10 shows the partial effect at the average of each independent variable. According to Table 10, there are four independent variables that are statistically significant: leading indicator index (Leading), Consumer Price Index (Infla), broad money (M2G), and unemployment rate (UnempCh). When the leading indicator index (Leading) increases by 1 unit, the next recession is expected to occur in about 8 quarters. When the inflation rate increases by 1 unit, the next recession is expected to occur 3.4 quarters further out in the future. Among all those statistically significant variables, the leading indicator index (Leading) has the highest absolute value of coefficient while the GDP growth has the lowest absolute value of coefficient.

Table 10

Partial effect at the average (PEA)

Variables	Mean	dy/dx	Std.Err.	Z	P>z
Spread	.0765443	0.192	0.061	3.130	0.002
Leading	.6759613	8.008***	0.412	19.420	0.000
GDPG	3.017687	0.108	0.104	1.030	0.301
Infla	1.118649	-3.360***	0.412	-8.160	0.000
M2G	1.643794	-3.060***	0.273	-11.200	0.000
FFRCh	-.0310204	0.693	0.361	1.920	0.055
OilPCh	.0191629	-2.732	1.975	-1.380	0.167
UnempCh	.007483	-3.719**	1.082	-3.440	0.001
IndProd	-.4123588	0.273	0.118	2.300	0.021

**** p<0.01, ** p<0.05, * p<0.1*

However, the average partial effect of each independent variable (APE) is usually preferred to the partial effect at the average (PEA). The following shows how to get the common scale factor for the APE.

$$\frac{\partial p(x)}{\partial x_j} = e^{x_i\hat{\beta}}\hat{\beta}_j = \frac{\sum_{i=1}^{n}[e^{x_i\hat{\beta}}]}{n}\hat{\beta}_j = \frac{\sum_{i=1}^{185}[e^{x_i\hat{\beta}}]}{185}\hat{\beta}_j = 12.660\hat{\beta}_j$$

Meanwhile, Table 11 compares coefficients from the Poisson regression and the marginal effects in both APE and PEA methods. The overall result shows that APE produces higher marginal effect values than does PEA.

Table 11

Poisson coefficients, APE, PEA

	$\hat{\boldsymbol{\beta}}_{\mathbf{j}}$	APE	PEA
Spread	0.020	0.250	0.192
Leading	0.822	10.409	8.008
GDPG	0.011	0.140	0.108
Infla	-0.345	-4.367	-3.360
M2G	-0.314	-3.978	-3.060
FFRCh	0.071	0.901	0.693
OilPCh	-0.280	-3.551	-2.732
UnempCh	-0.382	-4.834	-3.719
IndProd	0.028	0.354	0.273

***p<0.01, ** p<0.05, * p<0.1

To summarize, our first model (the Probit) is unable to discriminate between recession or a lack of it for most of the time periods since neither the coefficients estimated, nor the overall fit of the model turned out to be significant. On the other hand, the Poisson model tracked the path of the economy toward actual recessions better. The next chapter attempts forecasting based on these models even though greater reliance can be placed on the Poisson.

FORECASTING

Probit Forecasting

Figure 8 (Appendices) shows in-sample forecasting by the Probit model based on the actual values of the independent variables and the estimated coefficients. When the predicted probability of a recession is over 50% (0.5), we take the model to have predicted a recession in that period. In addition, if the model-predicted start of a recession is close to the period, albeit not exactly the same period, in which an actual recession started, we can say the model has predicted well. Based on the results, the Probit model predicts that there was a 90% chance of a recession in the first quarter of 2008 while the Great Recession in 2008 occurred between December 2007 and June 2009 (18 months). With a 93% probability, it predicted a recession would have begun in the first quarter of 2001 while the dot-com recession was observed between April 2001 and November 2001 (8 months). The Probit model predicted a 73% probability of a recession in the third quarter of 1990 while the recession occurred between August 1990 and March 1991 (8 months). The model also predicted 98% probability of a recession in the third quarter of 1981 while the real recession began in August 1981 and ended in November 1982 (16 months). The model assigned a 55% probability for a recession in the first quarter of 1980 and 56% in the second quarter of 1979 while the real recession happened between February 1980 and July 1980 (6 months). Finally, for the real recession that occurred between December 1973 and March 1975 (16 months), the Probit gave a 75% chance for the last quarter of 1973.

It is remarkable that the Probit model's overall prediction of recessions comes out so well within sample despite the fact that few of our variables acquired statistical significance. However, this model is not able to forecast out of sample, that is, when the next recession will occur, without a clear set of data for independent variables for the future. In order to estimate a reasonably decent model, it was necessary to save all the observations for estimation. We could create scenarios in terms of projections for the independent variables in order to make forecasts of a recession within the next four or eight quarters. This would probably have been an unrealistic adventure when the fit of the model was not good enough. Hence, we move to the next model.

Poisson Forecasting

Figure 9 (Appendices) shows the trends of predicted and actual numbers of quarters till a next recession from the Poisson Regression. Figure 9 shows that the Poisson model predicted well the trend from the beginning of the period to the third quarter of 1991. The closer the quarters are to zero, the economy is nearer to a recession. However, the model seems to predict recessions a few quarters after the actual data. Meanwhile, there is a certain pattern in Figure 9 that when the predicted numbers of quarters are less than five, it seems that a recession is coming close. When the predicted quarters go lower than ten, it could be a red flag that a recession is coming. However, after the 2008 financial crisis, there was one time that the predicted quarter went below 5, and a few times that the predicted quarter went below 10, a recession hasn’t happened yet since the financial crisis in 2008. This could be a sign that the next recession could happen anytime soon, even though the way the predicted quarters shown in Figure 9 makes it very challenging to predict when the next recession will occur.

Table 12 shows a better detail of when the next recession might occur from the most recent results. The Poisson model forecasts that the next recession will be likely some time between the last quarter of 2019 and the first quarter of 2021. The last quarter of 2020 seems to show up the most for the next recession in Table 12. However, the forecasts of a recession in the first quarter or up to fourth quarter from the last period in the sample does not seem accurate. We can rely on the prediction over the next five quarters or even a longer time frame.

Table 12

Predicting number of quarters till the next recession

Date	**Predicted # quarters**	**Predicted the next recession**
1st quarter of 2017	11.531	~ 3rd quarter of 2019
2nd quarter of 2017	13.932	~ 3rd quarter of 2020
3rd quarter of 2017	16.189	~ 2nd quarter of 2020
4th quarter of 2017	14.360	~ 1st quarter of 2021
1st quarter of 2018	14.663	~ 4th quarter of 2020
2nd quarter of 2018	13.066	~ 4th quarter of 2020
3rd quarter of 2018	12.057	~ 4th quarter of 2020
4th quarter of 2018	14.090	~ 1st quarter of 2022

The predicted numbers of quarters throughout Table 12 would have made more sense if the predicted number of quarters decreases at the later quarters. For example, the model predicted about 12 more quarters till the next recession since the third quarter of 2018 while the model predicted about 14 more quarters till the next recession since the last quarter of 2018. According to the data, the main causes that pushes the next recession further away were the yield spread that increases from -5.14% in the third quarter of 2018 to 0.37% in the last quarter of 2018 and the effective Federal Funds rate that increases from 1.92% in the third quarter of 2018 to 2.22% in the last quarter of 2018.

CHAPTER V

CONCLUSION

The main purpose of this paper is to analyze models that might realistically indicate when the next recession might occur after the Great Recession of December 2007 – June 2009. This paper sets up two models (Probit and Poisson) to forecast the next recession. However, forecasting a recession has been a challenge for decades as it can never produce an accurate result. Therefore, a close forecasting result should be considered a good result. Since forecasting is hazardous and good policies to forestall a recession are, therefore, hard to implement on time, it is impossible to avoid a recession. But once a recession has been observed, it is important to offset or at least reduce its negative impact. The results from this paper not only estimate when the next recession will be but also suggest what can be done to reduce the probability of a recession.

The results from the Probit model, to the extent we can discuss them, show that what may trigger and sustain a recession is Leading (leading indicators), Infla (inflation rate), FFRCh (effective federal funds rate), and UnempCh (unemployment rate). The model suggests increasing the leading indicators, decreasing inflation rate, and decreasing unemployment rate in order to enhance the economy's performance. This means that the government should undertake policies that favor the 10 elements of CLI including hours worked in manufacturing, building permits, interest rate spread, and manufacturing orders for both capital and consumer goods. The positive coefficient for the effective federal funds rate that the model indicates suffers from endogeneity of the rate itself. For the unemployment rate, the government should have more favorable policies and less restrictions toward small businesses as well as entrepreneurs, especially in the manufacturing industry since the manufacturing industry is one of the elements that enter the leading indicator index.

According to the results, a near future recession is likely to occur when the predicted probability of a recession is greater than 0.5 or 50%, from the Probit model, and when the predicted period is under five quarters from the Poisson model. The Probit model cannot forecast when the next recession will be if we do not have access to projected data for all the independent variables. Most results from the Poisson model, however, agree that the next recession will happen by the last quarter of 2020. This forecast seems to agree with many other economists. Sherman (2019) argues that a majority of economists think the next recession will come by the 2020 election which would be in November 2020. Moreover, a Zillow survey suggests the next recession in the U.S.A is likely to arrive in 2020 (Hinchliffe, 2018) even though many others claim the next recession will hit in 2019.

It has been over 10 years since the last recession. Historically, just this piece of data will suggest that we can expect a recession in the near term. Therefore, I believe the authorities should stay alert and be prepared to take appropriate policies to soften any blow from the next recession. A better model, which might be a better fit to answer how much longer an economy can survive till a recession, is the survival analysis. This model has been used a lot in many medical fields to test a new treatment. However, what is challenging in this model is that there is only one individual (the economy) over multiple periods of time (time series data) while the survival analysis is more about a group of multiple individuals over time (panel data). Once one can figure out how to define the data correctly, the application of the survival analysis could be useful in forecasting when the next recession would be.

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APPENDICES

Figure 1: Ratio of U.S. households net worth to GDP quarterly by index scale value 100 of 1951 (1951 – 2019)

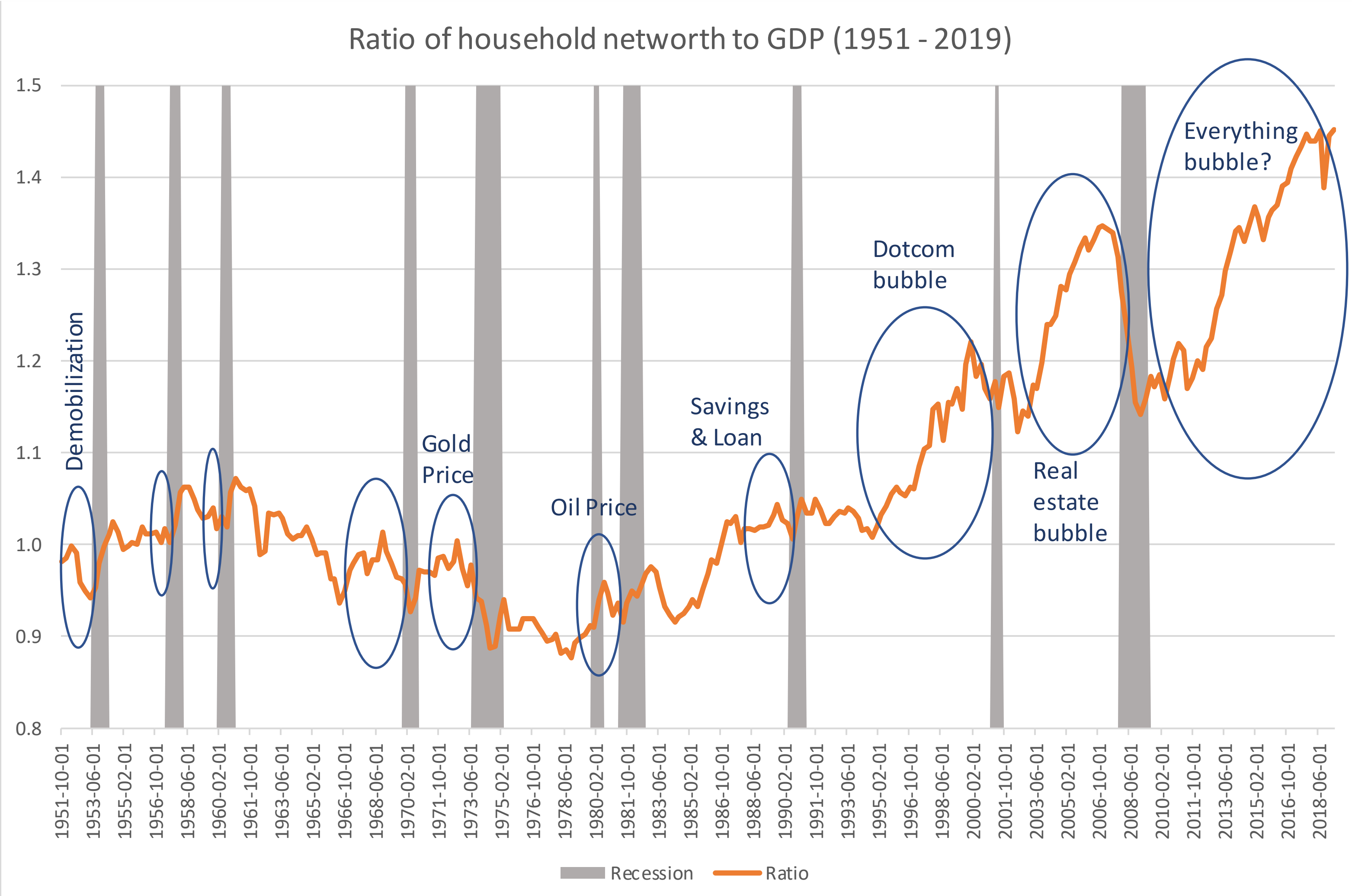

Figure 2: Stock Market Capitalization to GDP for U.S. with Buffet Indicators (1975 – 2017)

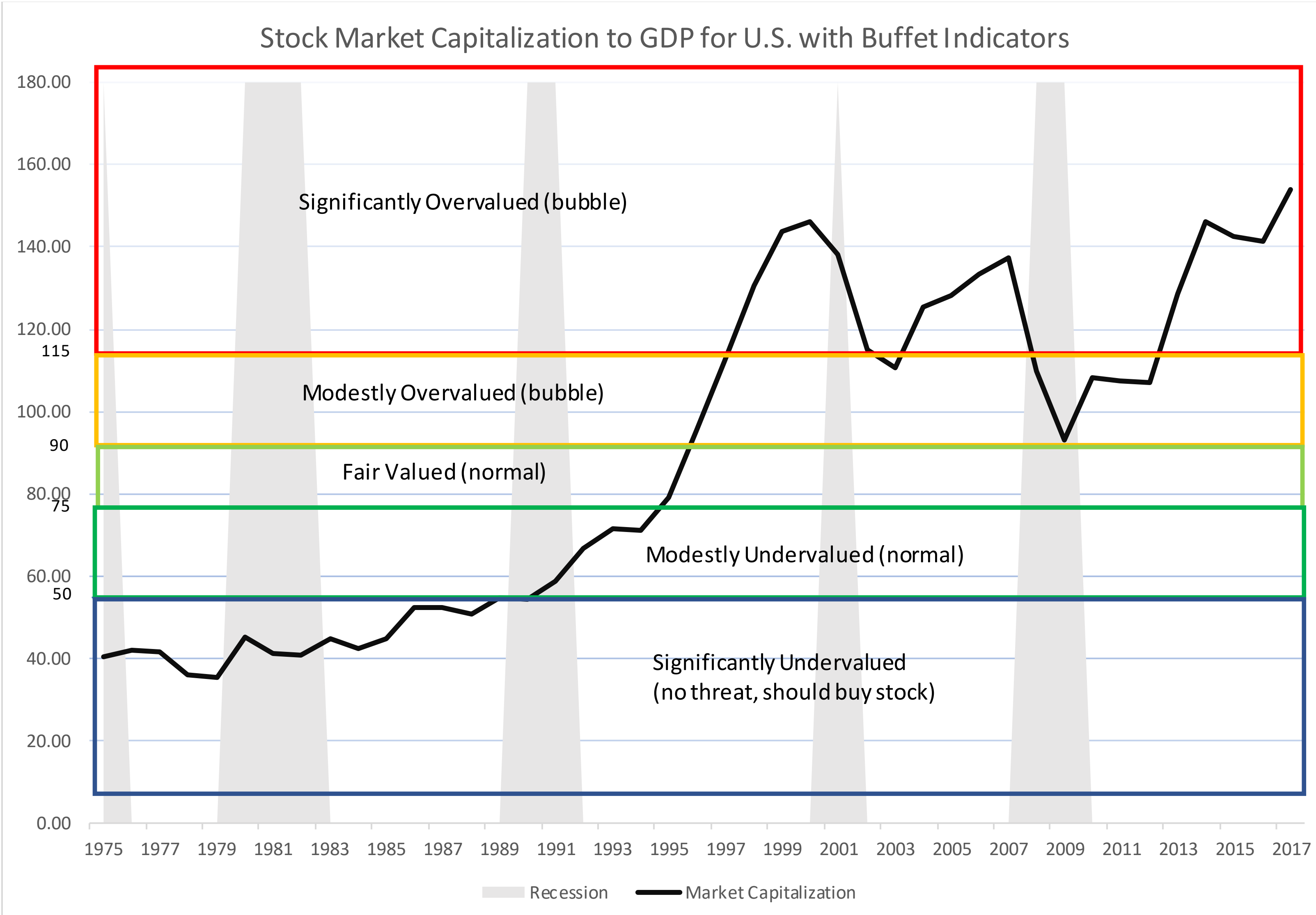

Figure 3: Monetary base vs. Currency in circulation (1941 – 2018)

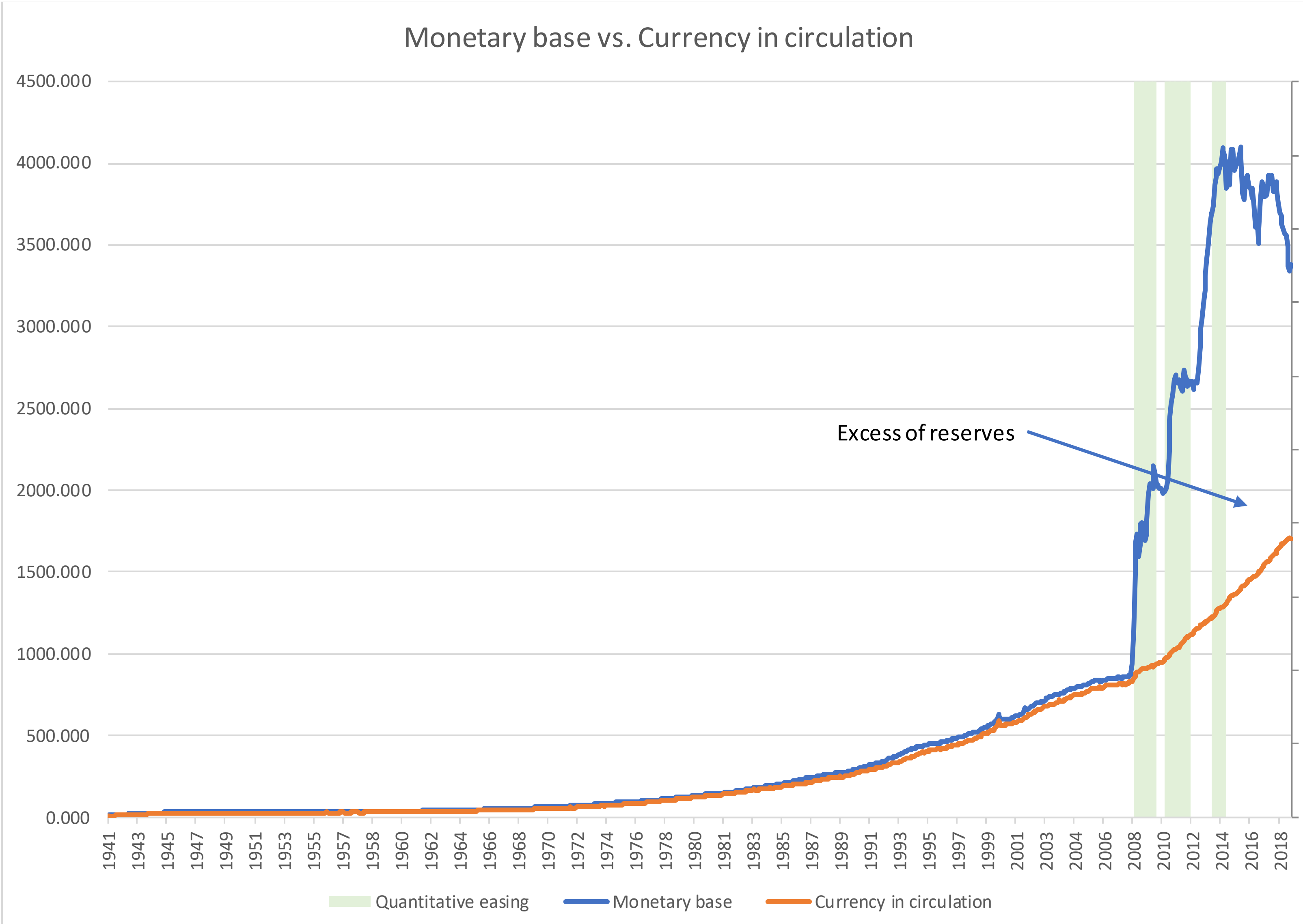

Figure 4: Unemployment rate (1948 – 2018)

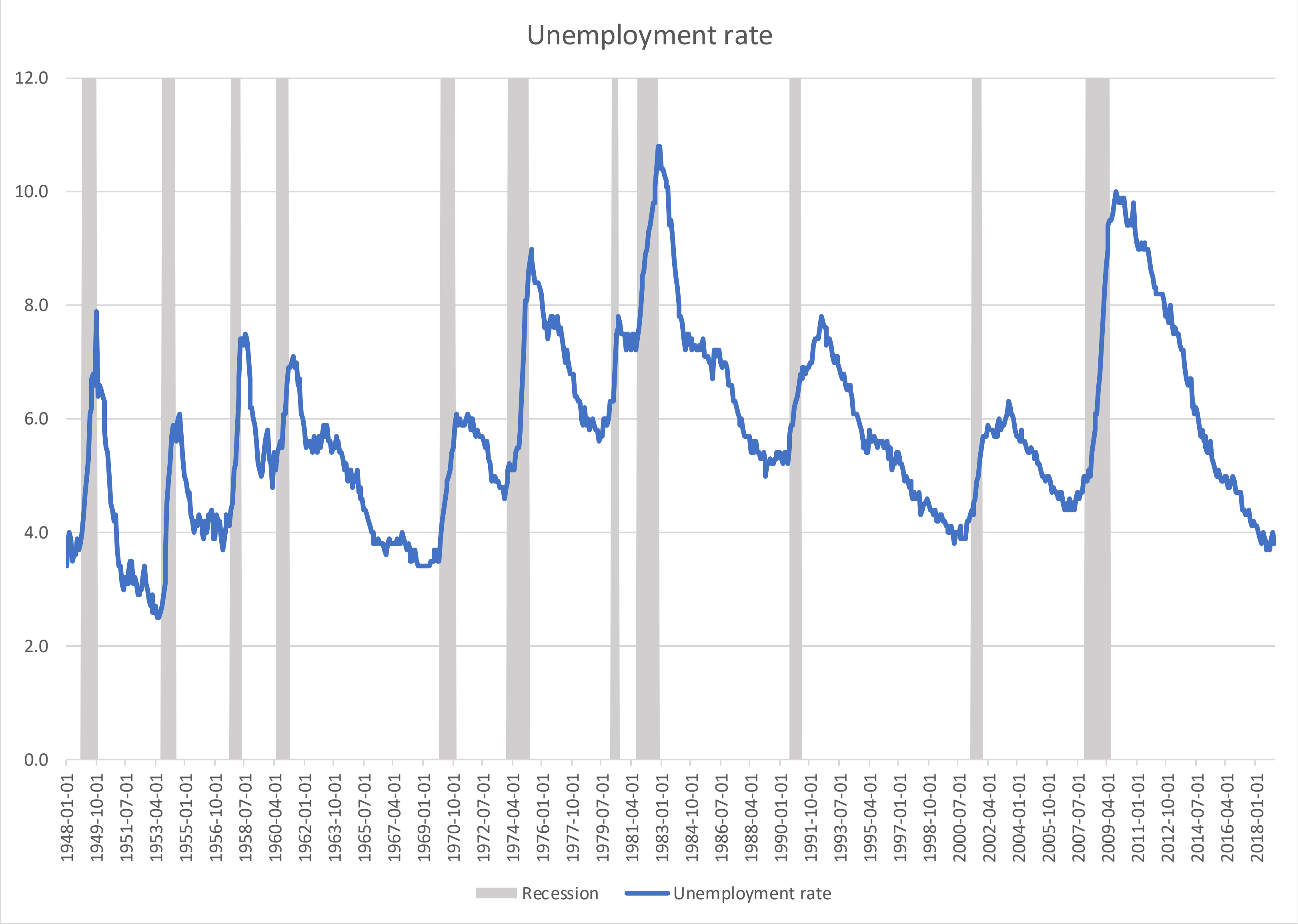

Figure 5: Yield Curve by quarter (1953 – 2018)

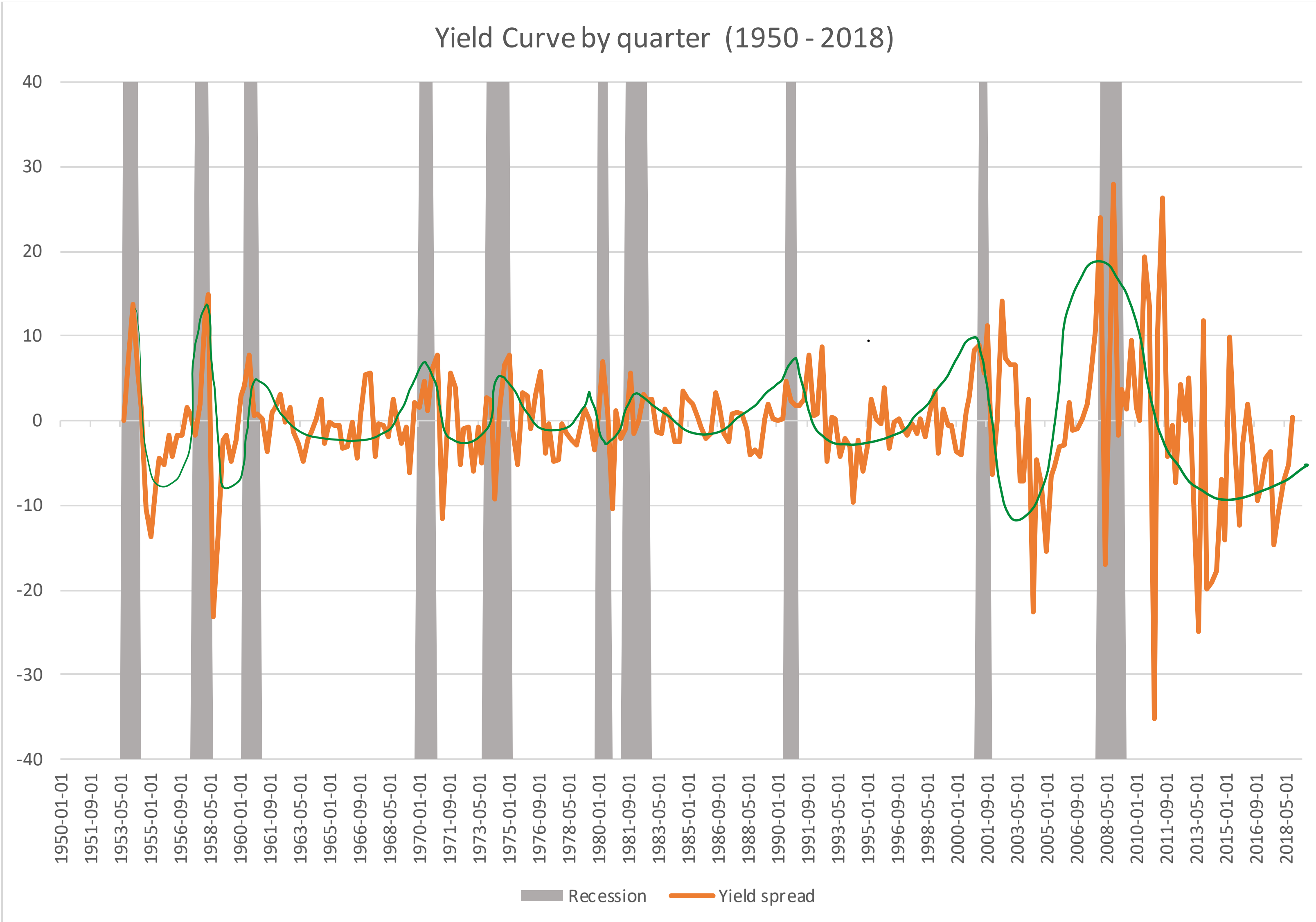

Figure 6: Effective Federal Funds Rate by quarter (1950 – 2018)

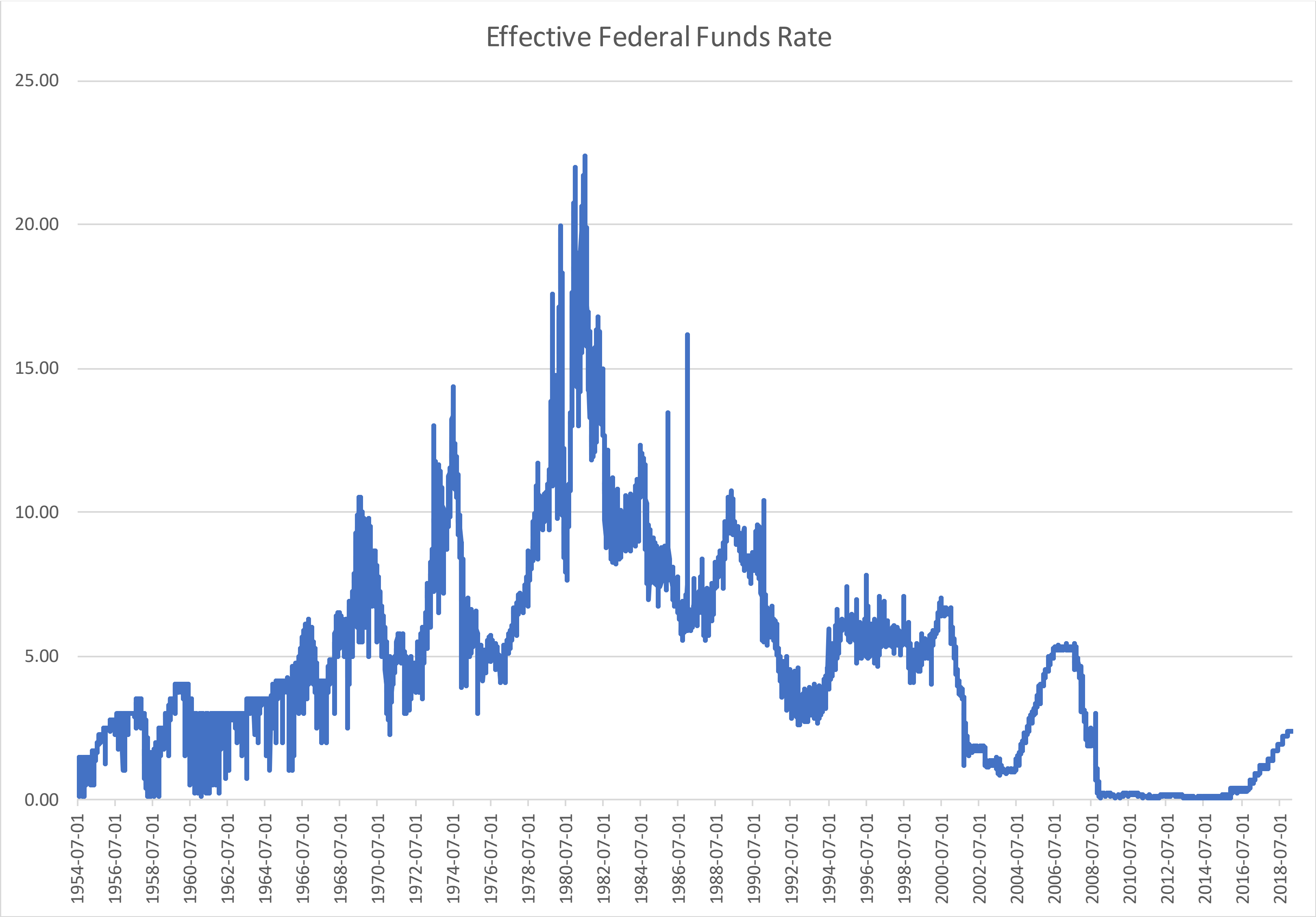

Figure 7: Actual number of Quarters (diffdays) till the next recession quarterly (1950 – 2018)

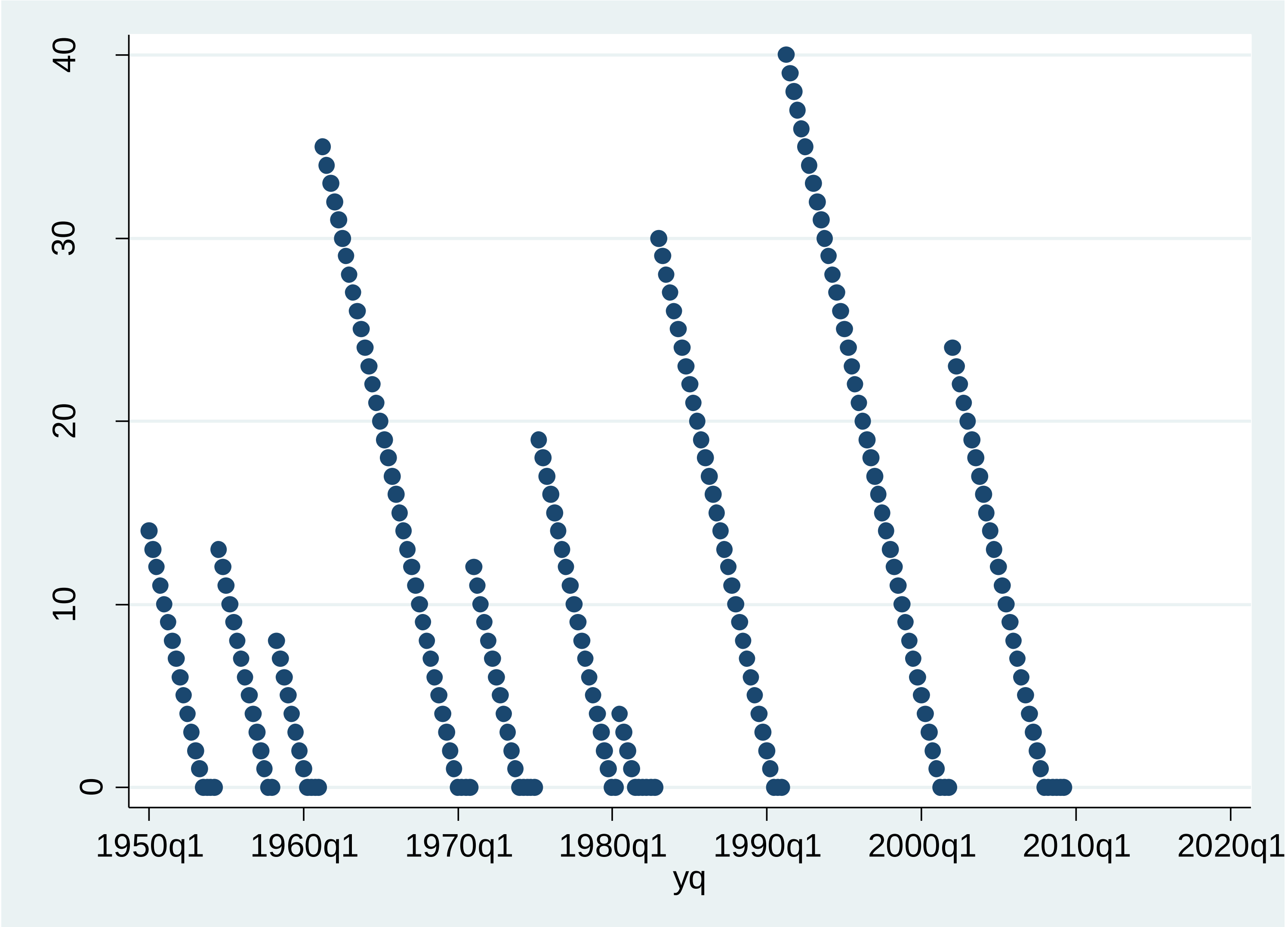

Figure 8: Actual vs. predicted Recession from Probit Regression quarterly

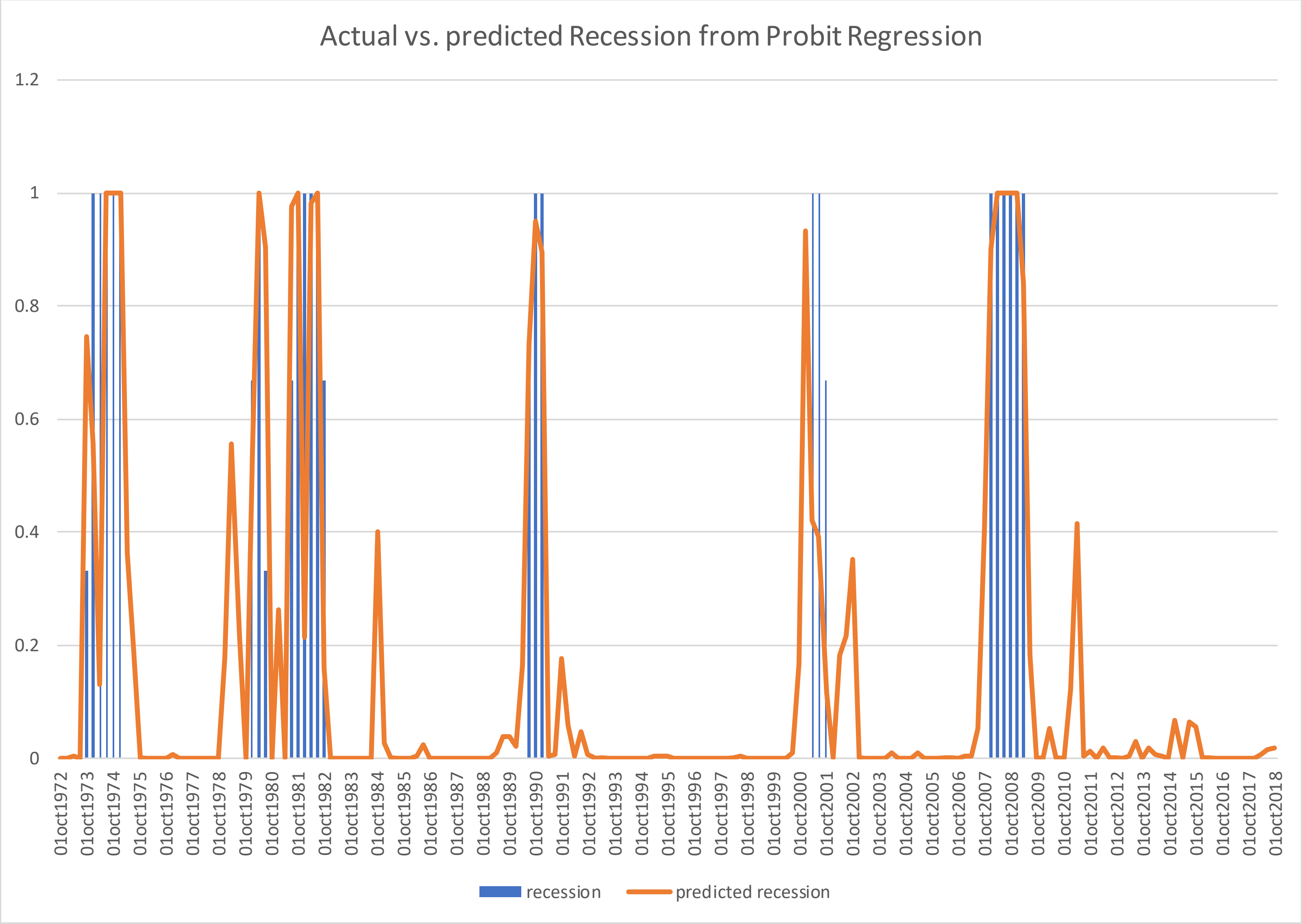

Figure 9: Predicted vs. actual numbers of quarters till the next recession by Poisson Model