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Master's Thesis

The Federal Reserve's Monetary Policy, Inflation, the Inverting Yield Curve, and the Next Recession: A Machine Learning Framework for Evaluating Recession Indicators

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Management Summary

After years and years of easy money, interest rates in the US are moving up again the yield curve is inverting. While Quantitative Easing is signalled to end in Europe, too, global debt levels are very high, and inflation is rapidly picking up around the globe. How will the US economy respond to rising rates and the end of easy money?

The goal of the thesis is to understand the mechanism behind interest rate levels, the form of the yield curve, inflation, and the economy as well as the stock market. The policy of the FED needs to be understood and analysed given the background of its historical actions. Furthermore, a machine learning framework is built for trying to evaluate recession indicators.

This thesis revealed that the monetary policy in the Fed aims to achieve its statutory mandate objectives: maximum employment, stable prices, and moderate long-term interest rates.

As the Fed was recently criticized for not achieving its goals of stability and low inflation. This resulted several advocated changes, including alterations to the policy and unconventional monetary policy, that became during the last decade very important. According to the literature, expansionary (contractionary) monetary policy impacts the stock market positively (negatively).

Based on the literature examined in this thesis, it can be concluded that as inflation increased, the Fed hat to increase interest rates as a reaction of high inflation by affecting the money supply and its real impact on the FFR. Longer-term interest rates and asset classes show a responsiveness to changes in the existing and targeted FFR. In this regard, consumer expectations regarding the future development of the key interest rate impact both medium- and longer-term interest rates. If borrowers and lenders currently assume that the FOMC will lower the policy rate substantially in the coming years, medium- and long-term interest rates will reflect these expectations. As a result, interest rates will be lower than they otherwise would have been. Moreover, households and businesses make purchasing decisions based on long-term interest rates, which affect economic performance, employment, and inflation.

Yield curves and their respective spreads can be good indicators for recession prediction. This thesis showed that with less data, using only the 10y and 3m Treasury yield, the corresponding spread, as well as the NBER recession dataset. ML frameworks are ideally suited for this purpose. In conclusion it can be said that the yield curve alone is not structural but is dependent upon monetary policy. For that reason, other macroeconomic variables have predictive power and can help improve recession forecasting accuracy.

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List of Abbreviations

CPI	Consumer Price Index
Fed	Federal Reserve (System)
FFR	Federal Fund Rate
FOMC	Federal Open Market Committee
GDP	Gross Domestic Product
IOR	Interest on Reserves
LSAPs	Large-scale Asset Purchase Programs
ML	Machine Learning
NAIRU	Non-accelerating Inflation Rate of Unemployment
NBER	National Bureau of Economic Research
ON-RRP	Overnight Reverse Repurchase Agreement
PCE	Personal Consumption Expenditures
QE	Quantitative Easing
ROC	Receiver Operating Characteristics
TAF	Term Auction Facility
TRAPS	Trading Room Automated Processing System
US	United States
ZLB	Zero Lower Bound

1 Introduction

Inflation is increasing rapidly across the globe. The U.S. central bank's recent interest rate made this quite clear, with the price of consumer goods continuing to rise. The U.S. central bank, or the Federal Reserve (Fed), has therefore rapidly tightened its monetary policy course to fight inflation. The institution has no choice but to do so because the inflation rate rose to 9.1 percent in June, the highest level in at least 40 years. Not only are interest rates in the U.S. increasing again and quantitative easing signalled to end, but the yield curve is inverting, and global debt levels are very high. It is therefore highly valuable to examine these events more closely to help determine the outlook for the economy, stock markets, and the possible recessionary road ahead. Historically, the inversion of the yield curve in particular has quite reliably signalled a recession in the U.S., including a correction in the stock market. Previously discussed methods that research has employed to predict recessions (probit regression, Markov switching, Bayesian methods, etc.) are well established in econometrics. More recent papers have developed new approaches that address intra-correlation issues when applying probit models or the application of Machine Learning (ML) models presented in academic literature. One overarching question remains unanswered: can the economy expect to see a recession this time, and is the yield curve alone sufficient to forecast U.S. recessions?

1.1 Problem Definition and Relevance

Over the course of its history, free-market economies have repeatedly experienced boom and bust cycles. However, while great economic times are enjoyed by all, economic downturns are often hurtful. The Federal Reserve is designed to administer the nation's money supply, prevent economic harm to the people of the United States, and supervise and regulate financial institutions. What the Fed has at its fingertips are powerful tools for influencing the money supply. The Fed's policymaking body exerts an impact upon the economy, interest rates, inflation, and other indicators important for investment decisions. These policies can in turn affect the relative attractiveness of certain assets, the economic outlook, and discount rates. That is why the link between the interest rate structure, the (looming) inversion of the yield curve, inflation, the economy, and the U.S. stock market is even more important. It is especially crucial to understand the inversion of the yield curve, which has historically predicted recessions with considerable reliability. This thesis further seeks to understand the predictive power yield curve and other indicators that have a predictive power. In so doing, it can help improve recession forecasting accuracy within a machine learning framework.

1.2 Objective

The goal of this thesis is to first outline the FED's policy, drivers, and motivation. These aspects are analysed given the background of the organisation's historical actions to assess the changes in the Fed's policymaking. Afterwards, the thesis explains the mechanism behind interest rate levels, the form of the yield curve, inflation, and the economy as well as the stock market. It also seeks to determine whether a recession is imminent by considering the evolution of the yield curve inversion with a focus on the U.S. In a next step, the predictive power of the yield curve and other recession indicators are evaluated within a machine learning framework, which are evaluated against each other.

1.3 Research Question

Based on the problem and the objective, this thesis addresses the following two questions:

- What are the linking changes in the interest rate structure—such as the inversion of the yield curve, inflation, the economy, and the stock market—and can the inverted yield curve forecast if a recession is imminent?
- Which recession indicators are best at forecasting U.S. recessions within a machine learning framework, and which machine learning model performs best?

This thesis aims to conduct three machine learning models, which are ultimately evaluated against each other.

1.4 Limitations of the Study

This thesis focuses on the U.S. economy. Its limitations further include the analysis of the FED policy's qualitative rationale and the drivers and motivations embedded into the context of its actions over the past two decades. An insight into earlier decades is only provided in cases of relevance. The same applies for the understanding of the mechanism behind interest rate levels, the form of the yield curve, inflation, the economy, and the stock market. The quantitative analysis specifies the recession data to set a target for the modelling that uses the Ten-Year Minus Three-Month Term Spread, NBER-Dated Recessions data, and further economic indicators.

1.5 Choice of methods

This section briefly overviews the structure of this thesis, which is designed to answer the research question. The structure is divided into four parts.

First, the theoretical background and a literature review is provided. This requires defining central terms and analysing what scientific knowledge is available on the topic and how that understanding has developed. The basic idea of this approach is to outline the Fed policy as well as its drivers and motivations and embed them into the context of its historical actions. In so doing, the thesis can gain insight into the changes in the Fed's policymaking. Furthermore, the mechanisms behind interest rate levels, the form of the yield curve, inflation, the economy, and the stock market are presented. They provide an outlook for the economy, the stock markets, and a possible recessionary road ahead considering the yield curve inversion. In addition, the analysis focuses specifically on the U.S. Lastly, the thesis presents the usage of machine learning and the most common models applied to evaluate recession indicators and recession forecasting.

The next chapter builds on the qualitative rationale identified above. It outlines a quantitative investigation conducted by several analyses performed within a machine learning framework that evaluates recession indicators. The machine learning models' individual performances are then compared. The data for this section are taken from the Federal Reserve database and complemented. Section 3.1 (Data) predefines the chosen data, the studied time horizon, and the selected machine learning models. Following that, the results are presented in relation to a prediction of a possible recession by interlinking the qualitative rationale with the quantitative analysis.

In addition, the thesis critically discusses and synthesises the qualitative rationale and the quantitative analysis.

Finally, the study concludes by answering the research question posed at the beginning and identifying possible implications for practice and research.

2 Theoretical Framework and Literature Review

The current chapter presents the theoretical background and literature review. This involves defining central terms and analysing the development and current state of scientific knowledge on the topic. Initially, the Federal Reserve (Fed) policy and its drivers and motivations are outlined and embedded into the context of its historical actions to outline the changes in the Fed's policymaking. Subsequently, the mechanisms behind interest rate levels, the form of the yield curve, inflation, the economy, and the stock market are presented.

2.1 The Federal Reserve System

The Federal Reserve System, also known as the Fed, is the central bank of the United States. The Federal Reserve was created by Congress in 1913 to provide the nation a safer, more flexible, and stabler monetary and financial system (Feliz, 2021, p. 21). Before examining the U.S. central bank in greater detail, two key terms, "central banking" and "monetary policy", must be clarified.

2.1.1 Central Banking and Monetary Policy

Mankiw and Taylor (2017, p. 559) explained that if a country relies on a computational money system, as most nations do, it must install an institution responsible for supervising and controlling that system. Such institutions are typically referred to as central banks. They are tasked with supervising the banking system and controlling the supply of money in the economy. Mishkin (2019, p. 370) noted that central banks, the government agencies responsible for monetary policy, are among the most important market participants in the world. Central banks' actions, according to Mishkin, impact interest rates, the volume of credit, and the money supply. Such actions directly affect not only financial markets but overall performance and inflation as well. Mankiw and Taylor (2017, p. 559) elaborated on this discussion, observing that an economy's central bank has the power to increase or decrease the money supply therein. Corresponding measures taken by the central bank to control the money supply are, as previously mentioned, referred to as monetary policy. One of the instruments used to change the money supply, Mankiw and Taylor introduced, is the open market operation. It involves the purchase of securities from the banking sector and the sale of securities to the banking sector by the central bank. The authors further explained that the monetary policy's main objective is to maintain price stability, full employment, and economic growth. More specifically, "monetary policy is the set of actions taken by the central bank in order to affect the money supply" (Mankiw & Taylor 2017, p. 559).

2.1.2 Overview of the Federal Reserve System

The following section uses the aforementioned concepts of central banking and monetary policy to more closely examine the Fed and the U.S. central bank. As discussed previously, the central banking system of the United States, the Fed, was established in 1913 based on the Federal Reserve Act. According to Feliz (2021, p. 2), the Fed Act framers deliberately avoided the concept of a single central bank. Instead, as Feliz further introduced, the central bank system was established with three key features:

1. a central governing board,
2. decentralized operations with 12 Reserve Banks, and
3. public/private partnerships.

Labonte (2020, p. 1) stated that the Fed has four general responsibilities for serving the American economy and, more generally, the public interest: "monetary policy, provision of emergency liquidity through the lender of last resort function, supervision of certain types of banks and other financial firms for safety and soundness, and provision of payment system services to financial firms and the government". The rest of the thesis focuses specifically on monetary policy. Feliz (2021, p. 12) demonstrated how the Federal Reserve Act outlines the Fed's monetary policy objectives. They are as follows: a high level of employment, modest long-term interest rates, and price-level stability. This means that the Fed's tasks extend beyond ensuring monetary stability (Feliz, 2021, p. 1). In that regard, Feliz showed that the Federal Reserve System has both private and public law elements and consists of the Board of Governors, the 12 regional Federal Reserve Banks, and the Federal Open Market Committee (FOMC), which are presented in the following chapters.

2.1.2.1 The Federal Reserve Board

Feliz (2021, p. 7) stated that the Board of Governors directs the Fed; it is also the central and supreme supervisory body and consists of seven members appointed by the U.S. president. According to Feliz, each of the seven members serves a 14-year term to ensure independence from short-term political influence when determining monetary policy. The chairman and vice chairman of the Board of Governors, however, both serve four-year terms (Feliz, 2021, p. 8). As Feliz outlined, the essential responsibilities of this institution are determining the statutory minimum reserve and bank discount policy and regulating credit interest rate restrictions and the minimum capital shares for securities purchases. The board is also tasked with enacting consumer protection regulations. In addition, Feliz highlighted that the Board of Governors supervises the 12 Federal Reserve Banks and their member banks, as well as bank holding companies. In addition, given that the Board of Governors provides seven of the twelve members of the FOMC, it is also indirectly responsible for determining the open market policy. Feliz demonstrated how, in effect, these powers make the board the exclusive decision-making body on the Fed's money creation and credit policy.

2.1.2.2 Federal Reserve Banks

“The 12 Reserve Banks and their 24 Branches are the operating arms of the Federal Reserve System” (Feliz, 2021, p. 8). Feliz showed that a variety of data and other information are collected about businesses and communities in every Reserve Bank region. The FOMC and the Board of Governors then use that information to make monetary policy decisions. The core functions performed by the FOMC include the supervision and examination of state member banks, depository institution lending, finance-related services, and the review of certain financial institutions (Feliz, 2021, pp. 10–11). Feliz concluded that the Reserve Banks serve as a financial institution for banks, thrifts, and credit unions in their districts. Therefore, they are the “banks for banks” (2021, p. 11).

2.1.2.3 Federal Open Market Committee (FOMC)

The Federal Open Market Committee (FOMC) is responsible for monetary policy within the Federal Reserve System (Feliz, 2021, p. 12). According to Feliz, the committee meets eight times each year in Washington to assess the current economic situation. Where appropriate, it also considers monetary policy changes, which include alterations in the most important interest rate: the U.S. federal funds rate (FFR). Indeed, depository institutions lend to each other at the FFR. Feliz explained that the FOMC has used forward guidance regarding its policy rate as an additional policy measure to influence expectations about future monetary policy. Additionally, the committee may use balance sheet policy to enhance market functioning and foster accommodative financial conditions by adjusting the size and composition of the Federal Reserve's asset holdings. Feliz further described the FOMC’s composition. It consists of seven members from the Board of Governors and the regional Reserve Banks’ 12 chairs, of whom only five have the right to vote.

The board and the FOMC have access to many tools for implementing monetary policy (Feliz, 2021, p. 13). According to Feliz (Feliz, 2021, p. 13), two such aids for the Federal

Reserve are interest rate management and the open market purchase and sale of securities. Both are discussed in the following chapters. The Fed's main monetary policy tool, the FFR, which influences interest rates, is also examined more closely.

2.1.3 Policy, Drivers, and Motivations

Monetary policy in the Fed aims to achieve its statutory mandate objectives: “maximum employment, stable prices, and moderate long-term interest rates” (Labonte, 2020, p. 1). Eberly et al. (2019, p. 6) highlighted that this statutory mandate objective is directed by the Humphrey-Hawkins Act of 1978. How to achieve the dual mandate, maximum employment, and price stability is, according to Eberly et al. (2019, p. 4), up to the Fed. Over time, as Fuhrer et al. (2018, p. 6) observed, the Fed and economists developed their monetary policy methods as their theoretical and practical knowledge of monetary policy increased. Among the purposes of monetary policy, which Mishkin (2019, p. 413) highlighted, is the control of the money supply and interest rates, for which the Fed uses several tools of monetary policy. Mishkin explained that these policy tools play a significant role in determining interest rates and economic activity. As a result, it is vital to understand their practical application and relative usefulness. Research by Eberly et al. (2019, p. 4), Feliz (2021, p. 23), FOMC (2012, p. 1), Labonte (2020, p. 20), Mishkin (2019, p. 370), and Svensson (2020, p. 3) showed that, in recent decades, the Fed has emphasized the FFR as the key monetary policy instrument. According to Mishkin (2019, p. 413), the Fed has released the FFR target at each FOMC meeting since February 1994. Because it influences interest rates across the economy, market players closely follow this statement. The FFR is more clearly discussed in subsequent chapters. To completely grasp how the Fed employs its instruments in monetary policy, it is necessary to understand several of its functions. These include the organisation’s influence on the money supply, its real impact on the FFR, and its potential to help reach an FFR that is close to the target.

2.1.3.1 Employment and Inflation

As mentioned in the previous chapter, two of the Fed’s statutory mandate objectives are maximum employment and stable prices. These mandates are introduced in greater detail in this section.

Mishkin (2019, p. 370) established that these two types of mandates are quite similar. They therefore defined maximum employment “as the natural rate of employment” because there is no relationship between the objective of long-term price stability and the natural rate of unemployment. Even so, Mishkin contended that, in practice, there can be substantial differences between the two mandates due to public opinion and politicians' perceptions that a hierarchical mandate is more focused on managing inflation than stabilising the economy. Eberly et al. (2019, p. 4), Feliz (2021, p. 23), FOMC (2012, p. 1), Labonte (2020, p. 20) and Svensson (2020, p. 3) noted the importance of the two mandates. Moreover, the FOMC clarified that the maximum level of employment is a broad and comprehensive target that is not directly measurable and changes over time for non-monetary-policy reasons. Feliz and Svensson wrote that the committee does not set a fixed target for employment but bases its decisions on an assessment of deviations at the level of employment from its peak. In doing so, Feliz (2021, p. 21) demonstrated that the committee considers a wide range of indicators. Eberly et al. (2019, p. 10) discussed the unemployment rate and discerned that it can sometimes be referred to as the natural or non-accelerating inflation rate of unemployment (NAIRU). Regarding price stability, Labonte (2020, p. 1) observed that the committee makes a particular judgment about a 2% inflation rate measured by the annual change in the Price Index for Personal Consumption Expenditures (PCE). Specifically, it considers a 2% interest rate most consistent over the longer run with the Federal Reserve's statutory mandate. Labonte (2022, p. 2) continued by remarking that a slightly higher inflation rate of 2% in 2020 was envisioned as a method to offset inflation below 2% in 2019. As emphasised by Feliz (2021, p. 23), the FOMC manages the transition toward the two objectives. When setting monetary policy, it seeks to moderate deviations on two levels: that of employment from the committee's estimated ceiling and that of inflation from its longer-term objective. However, Feliz added that the FOMC may encounter situations where its objective steers policy to contrary outcomes. In such cases, the committee claims that employment deficits, inflation divergences, and the potentially contrasting time horizons for employment and inflation will rebound to target levels.

2.1.4 The Conduct of Monetary Policy

As the previous chapter observed, monetary policy is used to achieve the Fed’s statutory mandate. Considering this fact, many researchers have studied the conduct of monetary policy.

In the Fed’s view, there are three key principles for the conduct of monetary policy.[1] First, a well-understood and systematic approach to monetary policy is required. Second,

[1] (Federal Reserve Board - Monetary Policy: What Are Its Goals? How Does It Work?, n.d.)

monetary policy stimulus may be necessary whenever economic activity and inflation fall below the central bank's stated goals for inflation and full resource utilisation. In contrast, when inflation and the economy are overheated, the central bank should implement a restrictive monetary policy. Third, the central bank should counter a persistent increase in inflation by increasing policy rates by more than one-for-one over time. Similarly, a persistent decrease in inflation should be countered by lowering policy rates. According to Labonte (2020, p. 1), monetary policy neutralises business cycle fluctuations (alternating phases of economic booms and downturns) in the short term. In the long term, it is monetary policy that primarily influences the rate of inflation. The FOMC (2012, p. 1) explained the design of its monetary policy in detail in a statement outlining its longer-term goals and monetary policy strategy. Therein, the FOMC introduced the current framework for monetary policy, which consists of a symmetric 2% inflation target, an undertaking to foster maximum employment. It also consisted of a series of policy measures for the Federal Reserve to take to reach these objectives. More precisely, the FOMC reported that it sets monetary policy as follows: “The Committee’s primary means of adjusting the stance of monetary policy is through changes in the target range for the FFR” (2012, p. 1). The standard definition of these principles in the literature is that decision makers determine policy rates following the equation or by rule linking the policy rate to a set of economic variables. One such rule is the Taylor rule.

2.1.4.1 The Taylor Rule

Taylor (1993, pp. 195–214) described U.S. monetary policy with reasonable accuracy between 1987 and 1992 using a simple equation linking the level of the FFR to three variables; see eq. (1). Regarding the first variable, the Board of Governors of the Federal Reserve System (n.d.) explained that it is the neutral value of the policy rate in the longer run adjusted for inflation. The second variable refers to the divergence of prevailing inflation from the FOMC's objective. The third variable is the deviation of gross domestic product (GDP) relative to its potential value—in other words, the level of output that would be achieved if resources were fully utilised. Taylor's equation assumes the following general form:

$$FFR_t = r_t^{LR} + \pi_t + 0.5(\pi_t - \pi^*) + 0.5(yt - y_t^P) \quad (1)$$

In the above formula, the Board of Governors of the Federal Reserve System (n.d.) stated that FFR_t is the FFR for quarter t, r_t^{LR} is the longer-term neutral inflation-adjusted FFR, π_t is the four-quarter inflation rate. In addition, π^* is the central bank's target for inflation, and $yt - y_t^P$ denotes the difference between GDP and its potential level as a percent. The value of r_t^{LR} was set according to the Board of Governors by Taylor at 2%, implying that the Fed has an inflation target of π^* of 2%. Thus, Taylor's formula dictates the policy rate at 4% for inflation at 2% and for a potential GDP at that level. If inflation exceeds 2%, it increases the Fed Funds Rate by a factor of 1.5, corresponding to the increase in inflation. Above potential, the equation raises the policy rate by 0.5 times the percentage difference between GDP and its potential level. The three basic principles of monetary policy mentioned above can be identified behind the so-called Taylor rule. The policy rate can become predictable through the equation. However, it only does so if the neutral real longer-term policy rate, the actual and target inflation rate, and the level of real GDP and its potential are known. It also mandates an interest rate rise as inflation or resource use rises and a reduction as inflation or resource use falls. This finding is in line and in accordance with the Federal Reserve's dual mandate to create the highest possible level of sustainable employment and price stability. Finally, when inflation rises or falls, the equation stipulates that the policy rate adjusts by more than a one-for-one adjustment; this characteristic is referred to as the Taylor Principle.

Taylor's[2] later work demonstrated that his 1993 equation had, in the context of economic modelling, provided a solid basis for simulating monetary policy using economic models. In the model simulations he considered, the equation further showed that monetary policy complying with his rule did tend to stabilise inflation rates close to 2%. Furthermore, it stabilised unemployment rates near the respective maximum rates acceptable in these models in the longer run. The Taylor formula can be applied in a variety of economic models, but they do not consider the characteristics of the real economy that determine monetary policy.[3] The Taylor rule is among the best-known formulations of a relation between the short-term policy rate and other economic variables. However, a wide range of alternative formulations, including the balanced-approach, the ELB-adjusted, the inertial, and first-difference rule, have been proposed.

The FFR mentioned and described in the previous chapter impacts interest rates across the economy and must therefore be properly specified as well.

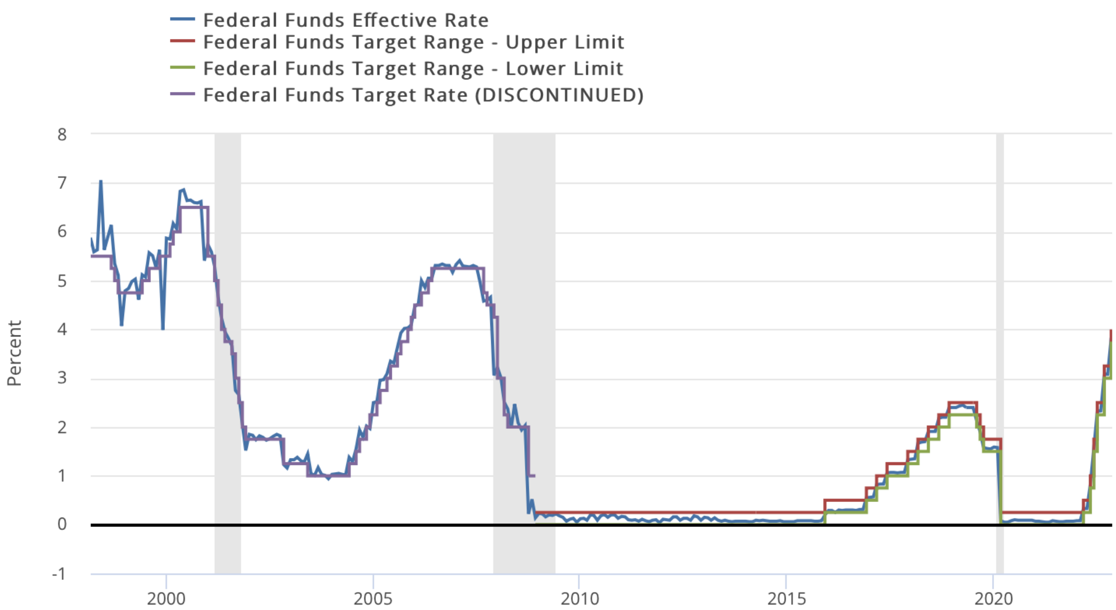
[2] See Taylor (1999, pp. 319–341)

[3] See Board of Governors of the Federal Reserve System (U.S.) et al., 2014

2.1.4.2 Federal Funds Rate

Overnight loans are subject to the FFR (Mishkin, 2019, p. 78). Feliz (2021, p. 25). Labonte (2020, p. 4) indicated that the rate is determined in the federal funds market, a government-funded private market for overnight reserves of depository institutions. Consequently, the FFR acts, as Mishkin suggested, as a sensitive indicator of the monetary policy stance and how much it costs banks to borrow funds from other banks. Labonte emphasised that, when lowering the target, it encourages more lending activity, which increases demand in the economy. In turn, that increase expands money and credit. Conversely, the author described that the Fed will raise the target when it wants to tighten the money supply and credit. Feliz (2021, p. 23) referred to the lowering of the federal FFR as "easing" and the increase of target as a "tightening" of monetary policy. The Federal Open Market Committee (FOMC) sets a target for the federal funds rate every six weeks. At times, it meets on an ad hoc basis if the target requires alteration between regular meetings (Labonte, 2020, p. 4). Labonte noted that a change in the FFR target affects interest rates throughout the economy, although changes tend to be less than one-to-one. In addition, economic activity is affected by changes in interest rates because they alter the demand for interest-sensitive spending (goods and services purchased on credit). Feliz (2021, p. 24), by contrast, distinguished between the effects on short- and long-term interest rates. He concluded that, in principle, a change in the FOMC's target range for the policy rate has a somewhat more pronounced effect on short-term than longer-term interest rates, since the latter typically reflect the likely development of the former over a longer period. Moreover, according to Feliz, longer-term interest rates and asset classes show a responsiveness to changes in the existing and targeted FFR. In this regard, consumer expectations regarding the future development of the key interest rate impact both medium- and longer-term interest rates. If borrowers and lenders currently assume that the FOMC will lower the policy rate substantially in the coming years, medium- and long-term interest rates will reflect these expectations. As a result, interest rates will be lower than they otherwise would have been (Feliz, 2021, p. 24). Moreover, Feliz noted that households and businesses make purchasing decisions based on long-term interest rates, which affect economic performance, employment, and inflation. Labonte (2020, p. 1) elaborated that interest rates also influence the demand for exports and imports by affecting the value of the dollar. In addition, monetary policy, as previously explained, affects interest-rate-sensitive spending, which in turn affects gross domestic product (GDP) in the short term. Monetary policy can thus be used to stimulate or slow aggregate spending in the short term, whereas, in the long-term, monetary policy primarily influences the rate of inflation (Labonte, 2020, p. 1). Over time, the committee has raised and lowered its target range for the policy rate (see Figure 1). Reifschneider and Wilcox (Reifschneider & Wilcox, 2020, p. 2), though, argued that predicting the future path of the FFR and buying large amounts of longer-term financial assets allowed the Fed to prevent the financial crisis from developing into an even greater economic malaise. Moreover, Svensson (2020, p. 5) referred to the aforementioned action as "forecast targeting", which is applied to the dual mandate construed as "flexible inflation targeting". Specifically, Svensson concluded that targeting means adopting both a policy rate and a policy rate path in such a way that the forecasts for inflation and employment appear favourable.

Figure 1: Development of Federal Funds Effective and Target Range



Note: Gray bars indicate recessions as determined by the NBER. Source: FRED®, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DFF; https://fred.stlouisfed.org/series/DFEDTARU; https://fred.stlouisfed.org/series/DFEDTARL; https://fred.stlouisfed.org/series/DFEDTARL, accessed September 15, 2022.

2.1.4.3 Determinants of the monetary policy stance

Feliz (2021, p. 26) listed several factors which influence current and future economic development. For instance, the FOMC evaluates their influence on monetary policy, which consists of anticipated factors and demand and supply shocks. Feliz noted that numerous drivers impact expenditure, production, employment, and inflation. As a result, the FOMC can pre-empt and incorporate anticipated factors like tax changes or spending programs in its decision-making process. Feliz further discussed demand shocks, which can occur unexpectedly and affect economic activity in unforeseeable manners. Such demand shocks are shifts in both consumer and business confidence, as well as surprising changes in the credit standards applied by banks and other lenders when granting loans. In the event of an identified demand shock, the committee may seek to offset the economic impact by adjusting the monetary policy stance. Since conventional monetary policy changes have a lagged effect on the economy, Feliz posited that monetary policy measures may require a lagged time of several quarters or more before affecting spending and inflation. Hence, demand shocks might divert the economy from the Federal Reserve's objectives of maximum employment and price stability for a certain period. Conversely, Feliz (2021, p. 26) claimed that factors other than price may affect the production of goods and services by changing associated production costs or the technologies used in the production process. According to Feliz (2021, p. 27), such supply shocks can include harvest shortfalls caused by severe weather conditions and result in lower productivity growth. Such adverse supply shocks typically increase prices and decrease production. To counteract output losses from supply shocks, Feliz recommended that policymakers consider easing monetary policy. Furthermore, they could make financial conditions more conducive to spending or counteracting them through tightening policies. After explaining the federal funds rate and the determinants of the monetary policy, the next chapter examines conventional and non-conventional monetary policy. Changes in the tools of monetary policy, as described by Feliz (2021, pp. 36–37), Mishkin (2019, p. 421), and Labonte (2020, p. 5), impact the market for foreign reserves and the equilibrium of federal reserves.

2.1.4.4 Conventional Monetary Policy

As part of its normal monetary policy, Mishkin (2019, p. 415) explained, the Fed controls the money supply and interest rates through the following tools: open market operations, discount lending, and reserve requirements.

Open market operations serve as the main determinants of interest rate movements and the monetary base, which is the main source of money supply fluctuations. As a result, they constitute the main conventional monetary policy tool (Mishkin, 2019, p. 421). Labonte (2020, p. 5) noted that, over the years, the Fed has primarily relied on open market operations.

Feliz (2021, pp. 36–37), Mishkin (2019, p. 421), and Labonte (2020, p. 5) all explained that changing interest rates and the monetary base are largely determined by market operations. Moreover, U.S. Treasury securities are the source most used by the Fed in open market operations. In the secondary market, Labonte (2020, p. 5) reported, the Fed purchases U.S. Treasury securities previously emitted and sold to private investors. Mishkin (2019, p. 421), however, stated that there are two major types of open-market operations. The first is comprised of the dynamic open market operations, which aim to change the monetary base and reserve levels. The second is comprised of the defensive open market operations. They seek to offset changes in other factors affecting reserve levels and monetary bases, such as treasury deposits at the Fed or changes in the float. Because treasury securities have the largest trading volume and are the most liquid (Mishkin, 2019, p. 421), the Fed conducts most of its open market operations in treasury securities. According to Mishkin, this is because a substantial volume of transactions by the Fed can be absorbed in the treasury security market without causing excessive price fluctuations.

As Chapter 2.1.2.3 discusses, the Federal Open Market Committee (FOMC) is the decision-making body for open market operations. In this regard, Feliz (2021, p. 36) discussed how the Open Market Desk at the Federal Reserve Bank of New York, also known as the Desk, conducts an open market operation. Specifically, they do so permanently or temporarily buying or selling securities issued or guaranteed by the U.S. Treasury or U.S. government agencies. Whenever securities are purchased or sold, the financial system's reserves are boosted or diminished (Feliz, 2021, pp. 36–37). Feliz (2021, p. 37) also explained that several private-sector counterparties active in the government securities market have established relationships with the Desk. A competitive auction determines the price at which the Federal Reserve buys securities permanently from primary dealers. To pay for those securities, the Federal Reserve credits the correspondent banks' reserve accounts (Feliz, 2021, p. 37). Mishkin (2019, p. 421) additionally noted that government securities transactions in open market operations are conducted electronically through a computer system known as TRAPS (Trading Room Automated Processing System). Through TRAPS, an electronic message indicating the operation's type and maturity is simultaneously sent to all primary dealers. Through TRAPS, dealers can offer several prices for buying or selling government securities (Mishkin, 2019, p. 421). Relatedly, the Federal Reserve must be on the alert to purchase or sell the number of securities needed to sustain its target federal funds rate level.

However, Feliz (2021, p. 37), Labonte (2020, p. 5), and Mishkin (2019, p. 421) argued that normal open market operations are conducted through repurchase agreements also called repos. Feliz observed that repos form part of the secured, U.S.-dollar-denominated money markets. Within those markets, in more precise terms, these agreements are made between two parties to buy and repurchase securities at a fixed price and a future date. They often take place overnight (2021, p. 37). Feliz further explained that the FOMC instead employs a standing overnight reverse repo facility as a tool to keep the policy rate in the target range. In so doing, it effectively puts a downward cap on the federal funds rate. According to Mishkin, repo agreements are one of two defensive open market operations (2019, p. 421). Since a repo reverses its effect on reserves on maturity, it is a method particularly suited for making a defensive open market purchase that will soon be reversed. As a result, the Fed makes temporary open market sales by entering a matched buy/sell transaction (sometimes referred to as reverse repo). Through that process, it sells securities with the buyer committing to sell them back to the Fed in the near future. Feliz (2021, p. 37) and Labonte (2020, p. 5) demonstrated that, legally, repos are two sales of securities. Economically, though, they correspond to a secured loan. Labonte (2020, p. 5) elaborated on repos, noting that the price difference between the first and the second transactions determines the interest rate on the loan. Furthermore, the repurchase agreement market is one of the most important markets for short-term loans, where banks and other financial institutions are active as borrowers and lenders. The seller of the security who receives the money calls the transaction a repo; for the buyer of the security who lends the cash, it is a reverse repo. Felix (2021, p. 37) added that, as part of reverse repurchase agreements, the Federal Reserve sets "overnight reverse repurchase agreement rates" (ON-RRP rates). These represent the maximum interest rates that the Fed is willing to pay in an ON-RRP operation. For years, the Federal Reserve would purchase and sell a variety of securities, both permanent and temporary and both before and during the financial crisis of 2007–09. The goal of that practice was to influence the supply of reserves and therefore the conditions in the federal funds market so that the FOMC could maintain its target federal funds rate. Market conditions, Felix explained, affected the extent of these operations, but they generally remained modest.

In its current operational framework, Felix (2021, p. 37) demonstrated that the FOMC does not always require active use of open market operations to fine-tune daily reserve levels. The exception is when a sufficient supply of reserves exists in the banking system. In times of turmoil, as well as for monetary policy support of the economy, Felix (2021, p. 38) the Federal Reserve can resort to open market purchases. Felix noted that the policy rate was near zero, and retail investors' yields on long-term securities were low. Consequently, the FOMC implemented several large-scale asset purchase programs during the financial crisis and subsequent recession. Once Federal Reserve purchases of longer-term securities are available in the open market, the number of longer-term securities left available for purchase by the public lowers. In turn, the prices of securities increase and the yields on them are reduced (Felix, 2021, p. 37). In this regard, Felix noted that the FOMC had to react to ramifications of the COVID-19 pandemic. Accordingly, it bought government bonds and mortgage-backed securities to ensure functioning markets.

In addition to open market purchases, Feliz (2021, p. 38), Mishkin (2019, p. 423), and Labonte (2020, p. 6) highlighted the importance of discount window lending and reserve requirements. They explained that discount windows are facilities wherein banks themselves may borrow reserves from the Fed to meet their needs. There are three types of Fed discount credit offered to banks: primary, secondary, and seasonal credit (Mishkin, 2019, p. 423). This means that such institutions can discount part of their proprietary assets to obtain temporary reserves from the Fed (Feliz, 2021, p. 38; Mishkin, 2019, p. 423; Labonte 2020, p. 6). The primary credit, or discount lending, is also worth noting. Feliz (2021, p. 38), Mishkin (2019, p. 423), and Labonte (2020, p. 6) reported that it plays a critical role In monetary policy. Indeed, healthy banks can use the primary credit facility to borrow as much money as they desire at very short maturities (typically overnight). Banks are not charged an interest rate in return for the privilege of a discount rate, which the Fed fixes at a slight premium to the prime rate (Feliz, 2021, p. 38; Mishkin, 2019, p. 423; Labonte 2020, p. 6). Mishkin (2019, p. 423) therefore stated that the mentioned discount rate is typically 100 basis points (one percentage point) higher. This is because the Fed encourages banks to lend to each other in the federal funds market to monitor another bank's credit risk. Therefore, Feliz (2021, p. 38), Mishkin (2019, p. 423), and Labonte (2020, p. 6) referred to it as a "lender of last resort". The discount window's direct lending and other credit facilities were negligible in normal financial conditions but provided significant liquidity during the financial crisis.

Feliz (2021, p. 38) and Mishkin (2019, p. 426) further noted that a deposit-taking institution must hold a minimum level of reserves on transaction accounts and other types of deposit liabilities. These include cash and balances at a Federal Reserve Bank. All banks are required to maintain the minimum reserve requirements determined by the Federal Reserve Board (Feliz, 2021, p. 38). Mishkin (2019, p. 426) observed that, when reserve requirements increase, deposits available to cover a given monetary base are reduced, in reducing the money supply. In addition, increasing reserve requirements causes the policy interest rate to rise also, as does the demand for reserves. A reduction in reserve requirements, by contrast, decreases the key interest rate and expands the money supply. Indeed, according to Feliz (2021, p. 38), prior to the global financial crisis, reserve requirements played a pivotal role in the conduct of monetary policy, influencing banks' demand for reserves. Currently, reserves in the banking system are much larger. As a result, for many banks, the minimum reserve requirements no longer play a significant role in the demand for reserves. Among other ramifications, the Board of Governors consequently announced in March 2020 that it would reduce the minimum reserve requirements to zero, meaning that this instrument is no longer active (Feliz, (Feliz, 2021, p. 38).

Mishkin (2019, p. 426) and Labonte (2020, p. 6) also examined the issue of interest on reserves. Mishkin stated that this monetary policy instrument was not introduced by the Fed until 2008, so its history is brief. Both required and excess reserves are subject to interest payments by the central bank. For the past several years, this has been the primary method of maintaining the policy rate (Labonte, 2020, p. 6). Banks are willing to lend reserves, such as the policy rate, to each other at certain interest rates. Labonte reported that those rates are affected when the opportunity cost for holding reserves at the Fed decreases (2020, p. 6). Mishkin (2019, p. 426) concluded that the Fed has therefore solely used interest on reserve assets to adjust the key interest rate downward and not as a tool of monetary policy. In times of major economic decline, the Federal Reserve can undertake unconventional monetary policy, which is discussed below.

2.1.4.5 Unconventional Monetary Policy

During periods of major economic decline, conventional monetary policy, which expands the money supply and lowers interest rates, is insufficient. Mishkin (2019, p. 428) discussed two reasons for that. On the one hand, because of major economic decline, the economy and investment spending both collapse as the financial system is unable to effectively use capital. On the other hand, the negative shock to the economy causes the zero lower bound (ZLB) problem to occur. In other words, the central bank is unable to lower its policy rate (in the case of the Fed, the key interest rate) because it has reached a level of zero, as what occurred at end of 2008 (see Figure 1). Mishkin examined that financial institutions will be reluctant to earn a lower return on lending in the policy rate market than on holding cash, which has zero yield. As a result, the FFR is unlikely to drop below zero. Both reasons prompt central banks to use non-interest rate instruments, so-called non-conventional monetary policy instruments, to provide stimulus to the economy. Mishkin (2019, p. 428) introduced four forms of these non-conventional monetary policy instruments:

1. "Liquidity provision"
2. "Asset purchases"
3. "Forward guidance"
4. "Negative interest rates on bank deposits with a central bank"

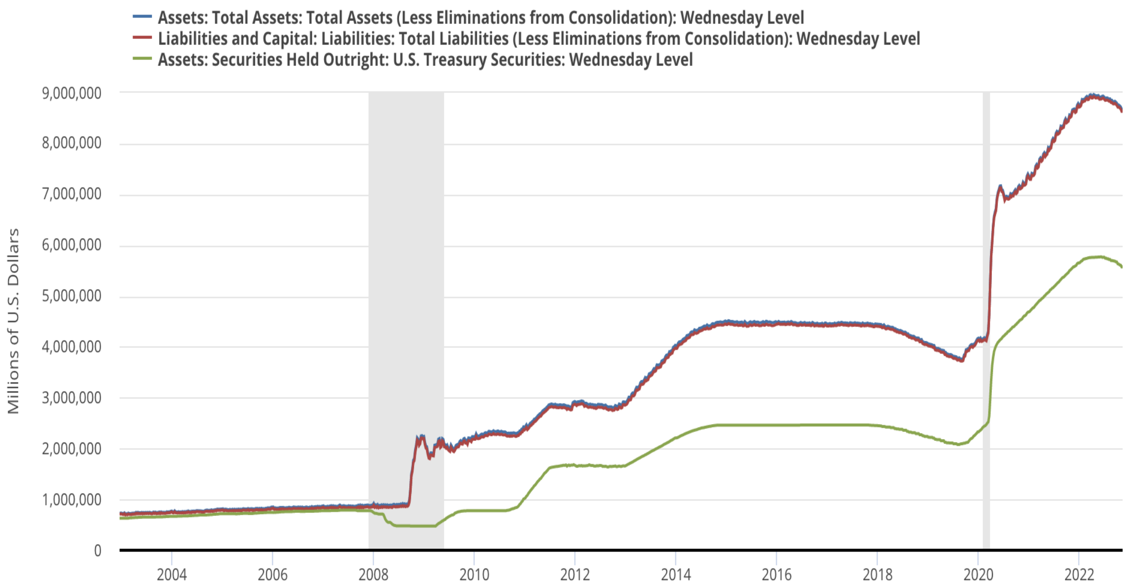
The latter is not discussed further, as the Federal Reserve did not employ it.

Mishkin (2019, p. 428) reported that conventional monetary policy measures failed to heal financial markets during the recent financial crisis. After that, the Federal Reserve increased its lending facilities on an unprecedented scale to infuse financial markets with liquidity. This was largely achieved through discount window expansion, term auction facility, and new lending programs. Discount window lending refers primarily to the discount rates reduced during the crisis. According to Mishkin, the Fed instituted a term auction facility (TAF) under which it lent out at an interest rate determined through competitive auctions. With new lending programs, the provision of liquidity support into the financial system extended far more widely than the provision of lending to banking institutions in the traditional sense.

As part of its open market operations, Mishkin (2019, pp. 428–430) examined how the Fed normally solely purchases government bonds, especially those with short maturities. However, Eberly et al. (2019, pp. 4–5), Engen et al. (2015, p. 1), Kuttner (2018, p. 122), Mishkin (2019, p. 430), and Swanson (2021, p.1) stated that, during the 2008 financial crisis, the Fed launched two new large-scale asset purchase programmes (LSAPs) to lower interest rates on certain types of loans. These large-scale asset purchases are also referred to as quantitative easing (QE) and are discussed in the following chapter. That supply of liquidity and large-scale asset purchase stimulus led to the expansion of the

Federal Reserve's balance sheet, as Figure 2 illustrates, on an almost unprecedented scale (Mishkin, 2019, pp. 428–430).

Figure 2: Fed's Balance Sheet



Note: The size of the FED's balance sheet increased by a factor of 8 after the Financial Crisis in 2008. Gray bars indicate recessions as determined by the NBER. Source: FRED®, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/WALCL; https://fred.stlouisfed.org/series/WLTLECL; https://fred.stlouisfed.org/series/WSHOTSL, accessed September 20, 2022.

The Fed's balance sheet can be defined according to accounting principles. The value of its assets coincides with that of its liabilities and capital, as Table 1 demonstrates.

Table 1: *Simplified Federal Reserve Balance Sheet as of June 15, 2022, Trillions of $*

Assets		**Liabilities and Capital**	
Treasury Securities	$2.2	Currency	$2.2
Mortgage-backed securities (MBS)	$2.7	Bank Reserves	$3.2
Loans/Emergency Facilities	<$0.1	TGA	$0.8
Repos	$0	Reserve Repos	$2.4
Liquidity Swaps	<$0.1	Other	$0.3
Other	$0.3	Total Liabilities	$8.1
		Paid-in Capital	<$0.1
		Surplus	<$0.1
Total	$8.9	Total	$8.9

Note: This Table shows the 2022 Fed Rate Hikes from March to November. As mentioned above, the FFR was raised by 3% in the last six months. In raising the FFR, the Fed aimed to reduce aggregate demand and lower inflation. Adapted from "2022 Fed Rate Hikes" by Tepper, T., 2022, November 2, Federal Funds Rate History 1990 to 2022. Forbes Advisor. https://www.forbes.com/advisor/investing/fed-funds-rate-history/.

The term "forward guidance",[4] according to Eberly et al. (2019, pp. 4–5), Kuttner (2018, p. 121), Mishkin (2019, p. 432), and Swanson (2021, p.1), describes announcements by the FOMC on the anticipated future course of the federal funds rate over future quarters or years. Kuttner (2018, p. 126) specifically reported that its distinctive characteristics do not differ qualitatively from those of other forms of Fed communication that hint at future policy. Compared to conventional policy, forward guidance communicates a more explicit path for interest rates. In addition to the change in the current key interest rate, forward guidance influences expectations about future interest rates. Consequently, it also impacts longer-term interest rates to be applied, such as the slope of the yield curve.

Kuttner (2018, p. 142) concluded that the evidence shows quantitative easing and forward guidance to have successfully reduced long-term interest rates. Furthermore, quantitative easing has tangibly affected firms and financial intermediaries in micro data studies. Models at the macrolevel, Kuttner argued, suggest that rates were reduced in a noticeable manner because of the rate reduction. In the absence of the unconventional policy, the adverse side effects would be less severe than the long-term consequences of the protracted recession in the United States. As a result, unconventional policies likely provided more benefits than costs.

2.1.5 Quantitative Easing and the Money Supply

The Fed was criticized for not achieving its goals of stability and low inflation (Selgin et al., 2012, p. 570). This resulted several advocated changes, including alterations to the policy rule (Eberly et al., 2019, pp. 4–5; Engen et al., 2015, p. 2; Kiley, 2018; Kuttner, 2018, p. 122; Mishkin, 2019, p. 430; Salter, 2018, p. 5; Swanson, 2021, p.1) and unconventional monetary policy. Dell'Ariccia et al. (2018, p. 150) observed that an important aspect of quantitative easing is the Fed's aforementioned purchase of many securities. The Fed generally maintains this program by buying long-term government bonds, financing it by increasing commercial banks' reserve accounts at the bank. In other words,

[4] Statement first included in explicit, forward-looking language (Evans, 2012, p. 4)

even when the policy rate and thus the yield on short-term bonds are at zero, the Fed can provide monetary stimulus by lowering long-term bond yields through support for long-term bond prices. Macroeconomic models have formalized this mechanism.[5]

Until the 2008 global financial crisis, the Fed's balance sheet increased slightly over time, as Figure 2 demonstrates. Selgin et al. (2012, p. 570) and Mishkin (2019, p. 407) highlighted that the Federal Reserve was at the forefront of adopting an unconventional monetary policy during that crisis, initially purchasing alternative assets to ease capital market distress. As a result, its objectives soon expanded to include creating inflationary levels to stimulate the real economy (Dell'Ariccia et al., 2018, p. 150). These large-scale asset purchases are referred to as quantitative easing (QE) and are illustrated in Table 2. During the financial crisis, the Federal Reserve instituted three rounds of quantitative easing between 2009 and 2014. These phases varied, Labonte (2022, p. 2) explained, in both size and duration. Labonte added that rolling over maturing assets between 2014 and 2018 allowed the Fed to maintain a constant balance sheet size. A certain number of maturing assets was gradually phased out by the Fed beginning in 2018.

Table 2: Federal Reserve Balance Sheet Trends

Trillions of Dollars, 2008-2022

Event (Dates	End Size	Change
Financial Crisis (9/08-12/08)	$2.2	+$1.3
QE1 (3/09-5/10)	$2.3	+$0.4
QE2 (11/10-7/11)	$2.9	+$0.6
QE3 (10/12-10/14)	$4.5	+$1.7.
Roll Off (9/17-8/19)	$3.8	-$0.7
Repo Turmoil (9/19-2/20)	$4.2	+$0.4
COVID-19 (3/20-5/22)	$8.9	+$1.3

Note: Fed's large-scale asset purchases after the Financial Crisis, also referred to as quantitative easing (QE), as explained by Labonte (2022, p. 2).

Except the period of 2019 to March 2020, Labonte (2022a, p. 2) clarified that the federal funds rate has been close to zero in every period of asset purchases. Through QE, the Fed could stimulate additional interest rates during periods of severe recession. It could do so by cutting interest rates on government bonds and mortgages when short-term interest

[5] For examples, see Gertler & Karadi (2011, p. 1) and (H. Chen et al., 2012, p. 1)

rates remained constrained by zero lower bound interest rates. Labonte (2022, p. 2) also explained that repo market volatility convinced the Fed in 2019 to hold more bank reserves to run its large reserve system. This prompted the Fed to start doing repurchase agreements and asset purchases, as well as further expand the balance sheet. At the onset of the COVID-19 pandemic, repo lending and asset purchases accelerated, and contingency facilities began to be implemented. The latter development increased the growth rate of balance sheet totals. Responding to high inflation, Labonte highlighted, in November 2021, the Fed decided to scale back its asset purchases (i.e., less assets to purchase per month). It ended asset purchases in March 2022. At that point, total assets had more than doubled compared to the pre-pandemic period. In June 2022, the Fed began tapering its balance sheet, which is known as quantitative tightening. In so doing, it drained up to $30 billion of Treasury securities and $17.5 billion of MBS from the balance sheet every month in perpetuity. However, the balance sheet is not projected to return to pre-pandemic levels. Labonte concluded that QE aimed to lower long-term interest rates and bring further liquidity to the financial system. With QE, long-term interest rates could lower as the yield on the Fed's securities purchases declined, lowering interest rates in the economy. The lower yields on MBS reduced mortgage rates, which boosted demand for real estate. Indeed, by increasing bank reserves, QE has increased liquidity. Kuttner (2018, p. 124) asserted that there is a general misunderstanding that quantitative easing was designed to boost banks' reserves and the money supply. Based on that theory, Kuttner wrote that providing banks large quantities of cheap liquidity would encourage them to lend, in turn increasing the money supply more broadly. The Fed, by contrast, focused on the asset side of the balance sheet.

2.1.6 Changes in Policy and Actions over Recent Decades

Feliz (2021, p. 38) highlighted that, for nearly 20 years, the FOMC has conducted monetary policy by adjusting short-term interest rates to achieve the board's dual mandate. The committee has done so by affecting financial conditions. That monetary policy framework endeavours towards a systematic and transparent policy adjustment in response to the perceived and prospective evolution of employment and inflation. Following the extraordinary global economic shocks that have occurred since 2007, the Federal Reserve expanded its toolkit to include fewer conventional methods when needed. The previous chapter expanded on these actions.

2.1.6.1 Before the Financial Crisis

Mishkin (2019, p. 450) reported that, from the mid-1980s to 2006, the Federal Reserve had achieved excellent macroeconomic outcomes. These included low and stable inflation, with no explicit nominal target inflation anchor. Despite the absence of an explicit strategy, the Federal Reserve had a coherent monetary policy strategy. While this method included a nominal anchor, it was not unambiguous. At the core of this anchor was the Federal Reserve's overriding concern to control inflation over the long term. The Federal Reserve was concerned with long-term inflation control, but this was implicit rather than explicit. To combat inflation risks, monetary policy used a combination of regular "pre-emptive strikes" (Mishkin, 2019, p. 450) by relying on an extensive pool of information. From 1994 to 1995, Mishkin (2019, p. 451) discussed, the Fed raised interest rates before a rise in inflation became perceptible. As a result, inflation not only remained the same but fell slightly after the action taken by the Fed's pre-emptive monetary policy. The author concluded that the policy was also used for economic downturns before the financial crisis; this was referred to as the "just do it" policy (Mishkin, 2019, p. 451).

2.1.6.2 2007-09 Financial Crisis

Feliz (2021, p. 31) reported that the global financial crisis that began in 2007 intensified sharply in 2008, when banks faced liquidity shortages. In reaction, the Fed increased bank lending as part of its regular discount window. Emergency lending programs were, according to Feliz (2021, p. 32), initiated by the Fed to address the short-term liquidity needs of financial institutions, relieve market pressures, and support credit flow to businesses and households. Moreover, to counteract the pressure on global dollar funding, the Federal Reserve entered into dollar liquidity swap agreements with a selection of foreign central banks. Feliz added that another way the Fed responded to the crisis was by adjusting the FFR. Beginning in autumn 2007, the FOMC lowered its target for the FFR and moved it from a level of 5.25% to a range of 0–.25% by the end of 2008 (see Figure 1). By lowering the rate, the Fed provided significant financial market stimulus. Despite those decisions, a protracted and severe recession resulted. Because of the near-zero FFD, the FOMC adopted two unconventional measures to strengthen the economy and contain disinflationary pressures: forward guidance and LSAPs. According to Feliz, the FOMC has used forward guidance, described in the previous chapter, in its policy rate as an additional policy measure to influence expectations about future monetary policy. A series of other programs led the Federal Reserve to issue longer-term securities as part of its large-scale asset purchases. From late 2008 to October 2014, Feliz explained, these securities were issued to lower longer-term interest rates, improve financial market conditions, and strengthen the economy. In response to FOMC's purchase programmes and reinvestment of maturing and prepaid securities, the Federal Reserve's total assets increased from $870 billion in August 2007 to $4.5 trillion by the end of 2014. That represents 25% of the nominal GDP (Feliz, 2021, p. 33)

2.1.6.3 2015-2019

Feliz (2021, p. 33) reported that forecasts expected inflation to rise to 2% in 2015. As a result, following its macroeconomic policy targets, the FOMC decided to begin normalising the monetary policy stance. Feliz highlighted that the aim was to normalise short-term interest rates as well as bring the size and composition of the Federal Reserve's balance sheet to more standard levels. A final step adopted by the FOMC was publicising the principles and plans for normalising monetary policy. This involved the interest rate being raised from near zero, followed by the size and structure of the balance sheet's adjustment to normal levels. To achieve this, Feliz emphasised, the target range for the policy rate was gradually raised between December 2015 and December 2018, and the FFR target range in 2018 was raised from 2.25– to 2.5%. Feliz further observed that the FOMC progressively removed reinvestments from maturing and early redeemed securities as part of its balance sheet policy in late 2017. Consequently, the Federal Reserve's balance sheet fell to just under 20% of nominal GDP at the beginning of 2019. Due to the increased risk in the low interest rate environment, economic shocks became able to push the key interest rate to the effective lower limits. As the COVID-19 pandemic began in March 2020, Feliz concluded, the FOMC quickly lowered the target range. They also turned to additional tools, forward guidance, and balance sheet policies that had been tried and tested for years.

2.1.6.4 2020 and Beyond

2020: The COVID-19 pandemic is essentially a global human health crisis. Feliz (2021, p. 34) and Labonte (2020, p. 1) highlighted that it sparked profound economic collapses, including numerous employment losses and a drastic decline in GDP. It also caused major tensions in financial markets around the world. In addition, Feliz (2021, p. 34) explained, the programs introduced during the COVID-19 pandemic supported the flow of credit to households. Labonte (2020, p. 2) stipulated that the Federal Reserve took monetary policy actions and acted as a lender of last resort in response to COVID-19. It assumed this role by taking several measures to promote economic and financial stability. In this regard, Labonte (2020, p. 3) argued, the Fed stimulated banks to contract debt at the Fed's discount window to cover the liquidity requirements. It extended the maturity of discount window loans to 90 days and reduced the discount rate. Furthermore, to bring liquidity to the market, the Fed recommended that banks use intraday credit. To stimulate the economy, Labonte (2020, p. 22) explained, the Fed cut the FFR at the start of the pandemic from a band of 1.5% to 1.75% and 1% to 1.25%. In addition, the FOMC implemented a near-zero policy interest rate with the range reduced to 0%–0.25% in March 2020. The rate reached zero lower bound for the second time in a row—the previous occurring during the financial crisis of 2007–2009 described above. The FOMC introduced a forward guidance to indicate its intention to maintain the near-zero target range until the unemployment and inflation goals were essentially met (Feliz, 2021, p. 34). Labonte (2020, p. 22) discussed that there is no firm commitment or market transactions to support forward guidance. Furthermore, by guaranteeing lower future short-term interest rates, the Fed can lower long-term rates. Feliz highlighted four other decisions the Federal Reserve made in addition to these steps:

1. Restoring of market functioning through open market operations
2. Implementation of the measures to increase liquidity conditions on the short-term funding markets
3. Working in concert with the U.S. Treasury Department on measures to aid in facilitating lending more directly
4. Incentivising banks to use their extensive capital and liquidity buffers accumulated during the past decade to sustain the economy during this critical juncture.

As a result, Feliz (2021, p. 34) and Labonte (2020, p. 8) noted, all these initiatives expanded the Federal Reserve's balance sheet. By mid-2020, the level of assets amounted to nearly $7 trillion, equal to 35% of nominal GDP (see Figure 2), and grew to reach $7 trillion by the end of that year. Labonte (2021, p. 24) further stated that the Fed increased its securities holdings by an average of $100 billion, $70 billion, and $80 billion per month in the three QE rounds following the economic crisis. In April 2020 alone, the Fed's securities holdings grew by around $1.2 trillion. Typically, Labonte would assume that QE causes a rapid increase in inflation because it leads the money supply to increase rapidly. This crisis ultimately became the opposite of what was expected, with inflation remaining below the Fed's 2% target despite QE. As mentioned in chapter 2.1.4.3, Fed rates were routinely targeted by repurchase agreements before the 2008 financial crisis. Labonte (2020b, p. 1) explained that repo rates increased in September 2019 in response to a spike in interest rates, which led the Fed to cease using repos. Therefore, on March 15, 2020, the Fed announced that it would continue to offer overnight and longer-term repos of $500 billion. According to Labonte, these repos were larger and lasted longer than those offered in September 2019.

2021: Numerous unanticipated economic developments arose due to the COVID-19 pandemic. Labonte (2021, p. 1) cited an increase in price inflation as one such factor, explaining that prices rose more quickly than usual in 2021. This occurred both monthly and annually for several months and was based on a variety of measures, including the Consumer Price Index (CPI) and the Personal Consumption Expenditures (PCE) index. Furthermore, the Federal Reserve introduced unprecedented levels of monetary stimulus. As a result, Labonte stated, a sustained and significant inflation rate would be problematic from a policy perspective. Although some inflation measures were higher than others in 2021, the increase had not met either criterion. With the policies in place at the time, inflation was assumed to return to the Fed's 2% target in 2022, according to the Fed and other experts (Labonte, 2021, p. 1). Inflation is a concern because it could further pose a conflict between the Fed's two statutory objectives. Labonte (2021b, p. 1) explained that a tighter policy may be instituted in response to higher inflation. Alternatively, a stimulus policy may be retained in the case of a reduced job market. Labonte further argued that the Fed would be unlikely to unwind its monetary stimulus in the short term. In July 2021, the central bank announced that it would not raise interest rates above zero until employment and inflation returned to the level the committee assessed as maximum. As an additional consideration, then, it would have been further unlikely to raise rates above zero until such a time (Labonte, 2021b, p. 1).

2022: According to Labonte (2022a, p. 1), on 16 March 2022, the Fed raised the FFR by 0.25 percentage points. This was the first time interest rates had been raised above zero since the Fed had set rates near zero in response to the sharp decline in employment when the COVID-19 pandemic began. With the economy recovering, Labonte explained, the Fed maintained this target. They did so despite the unemployment rate falling to 3.8% and inflation rising to 6.1% by the beginning of March 2022, the highest level since 1982. Furthermore, the Fed considered further rate hikes as an indication, largely because inflation was above its target. In June, the CPI had changed by over 8% per year from March 2022 (Labonte, 2022b, p. 1). Labonte further observed that the Fed began raising rates in

March 2022, lifting them from 0.25% to 1.5–1.75%. In raising the FFR, the Fed aimed to reduce aggregate demand and lower inflation. Labonte (2022c, p. 1) recently reported that there has been an increase in prices every month since February 2021, as measured by the (CPI) and (PCE) indexes. In 2021, PCE inflation totalled 4.2%. The annual change in PCE inflation (measured as a 12-month change) had exceeded 6% since February 2022. In fact, the last time PCE inflation reached this high peak was in the early 1980s at the end of the "Great Inflation" (Labonte, 2022c, p. 1). The Fed decided to address inflation and has raised the federal funds rate by three percentage points in the last six months, as Table 3 indicates.

Table 3: 2022 Fed Rate Hikes: Taming Inflation

FOMC Meeting Date	Rate Change (bps)	Federal Funds Rate (FFR)
Nov 2, 2022	+75	3.75% to 4.00%
Sept 21, 2022	+75	3.00% to 3.25%
July 27, 2022	+75	2.25% to 2.5%
June 16, 2022	+75	1.5% to 1.75%
May 5, 2022	+50	0.75% to 1.00%
March 17, 2022	+25	0.25% to 0.50%

Note: This Table demonstrates the 2022 Fed Rate Hikes from March to November. As mentioned above, the FFR has been raised by three percentage points in the last six months. In raising the FFR, the Fed aimed to reduce aggregate demand and lower inflation. Source: Tepper, T., 2022, November 2, Federal Funds Rate History 1990 to 2022. Forbes Advisor. https://www.forbes.com/advisor/investing/fed-funds-rate-history/.

Pursuant to Labonte (2022c, p. 1), sustained, persistent, and substantial inflation is required for it to be classified as problematic from a policy perspective. All three criteria are met in the case of 2022's inflation. Next, the influence of monetary policy conduct on financial markets is discussed before linking the Fed's actions to inflation.

2.1.7 Influence on Markets

According to Fama's 1970 study (as cited in Fawley & Neely, 2014, p. 75), the efficient market theory implies that only the unexpected part of a monetary policy change should affect asset prices, and very quickly. This is because financial markets are forward-looking. Several empirical studies[6] have, as observed by Bekaert et al. (2013, p. 2), explored the relationship between monetary policy and the stock market. According to the literature, expansionary (contractionary) monetary policy impacts the stock market positively (negatively). Bernanke & Kuttner (2005, p. 1221) noted that inflation, output, and employment are macroeconomic variables that can be used to determine monetary policy objectives. These indicators are, however, only indirectly impacted by monetary policy tools. Changes in the federal funds rate, for example, have the greatest direct and instantaneous effect on financial markets. Policymakers attempt to influence economic behaviour such that it helps them achieve their ultimate goals by influencing asset prices and yields (Bernanke & Kuttner, 2005, p. 1221). Previous studies by Campbell, Fisher, Justiniano, and Melosi (as cited by Lakdawala & Schaffer, 2019, p. 1) suggested that the FOMC's communication of monetary policy decisions has an additional “Delphic” component. Specifically, it contains a signal about the forecast of economic activity. Lakdawala and Schaffer (2019, p. 1) therefore divided the policy surprises into exogenous and Delphic shocks and studied the response of stock prices. In addition, Chortareas and Noikokyris (2017, p. 1) provided an empirical result on the international propagation mechanism of U.S. monetary policy shocks to global equity markets. Similarly, Eksi and Tas (2017, p. 1) examined the Federal Reserve's monetary policy actions’ impact on equity returns since the Fed began taking its unconventional policy steps. Later, Swanson (2021, p. 1) analysed the effects of unconventional monetary policy by showing the effects of forward guidance and LSAPs on treasury yields, stock prices, and exchange rates. Using time-varying VAR models, Kumar et al. (2022, p. 1) subsequently explored the effect of option-implied measures of equity and bond market volatility on government bond term premiums and macroeconomic variables. In addition, both Bekaert et al. (2013, p. 1) and Bruno and Shin (2015, p. 1) investigated how monetary policy impacts bank leverage, cross border flows and the exchange rate. Inoue and Rossi (2019, p. 419) also explored monetary policy, focusing on whether unconventional monetary policies affect the transmission of monetary policy to international financial markets. They also sought to determine whether monetary policy influences exchange rates. Accordingly, it can be argued that the impact of monetary policy on equity markets has received concise attention. The findings of these investigations are discussed next.

[6] Studies by Thorbecke (1997)04/12/2022 23:53:00, Rigobon & Sack (2003), and Bernanke & Kuttner (2005).

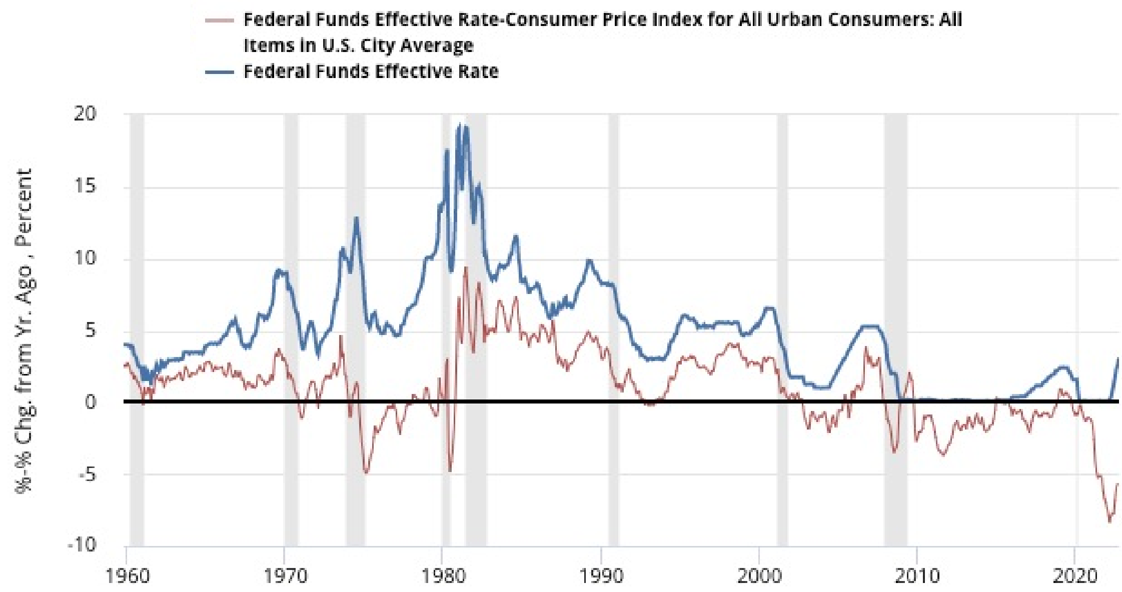
Bernanke Kuttner's (2005, p. 1253) study demonstrated that the stock market reacts relatively strongly and consistently to surprise monetary policy actions, using federal funds futures data to measure policy expectations. They further uncovered that, for broad stock market indices, unexpected interest rate cuts of 25 basis points would generally result in a rise in share prices in the order of 1%. Additionally, these findings were shown to be reliable when excluding outliers. Furthermore, the period selection was considered for assessing the stock market's reaction. However, they emphasised that monetary policy surprises account for only a small part of stock price variability. Chortareas and Noikokyris (2017, p. 19) mainly concluded that local monetary policy conditions are crucial for determining the intensity of the transmission of U.S. monetary policy to global equities. Lakdawala and Schaffer (2019, p. 1) discovered that stock prices are, on average, more likely to fall in response to exogenous shocks (unexpected changes in monetary policy unrelated to macroeconomic fundamentals) compared to Delphic shocks (surprising changes in policy due to the Fed's asymmetric knowledge of the state of the economy). Eksi and Tas (2017, p. 146) found that LSAPs have a far stronger impact on equity markets from a monetary policy perspective than the traditional monetary policy instrument of the federal funds rate. The authors showed that the Fed's unconventional policy actions in December 2008 increased its policies' impact by seven-fold. After the LSAP program concluded at the end of 2014, the S&P 500 index climbed to 2058.9 from 797.87 at the beginning of 2009 (Eksi & Tas, 2017, p. 146). Among the factors responsible for this dramatic increase was, Eksi and Tas speculated, monetary policy. Swanson (2021, p. 26) affirmed that yields on government bonds are affected by forward guidance on the day of the announcement. This stands apart from the very longest maturities, which peak around the 5-year mark. However, LSAPs are generally more efficient at longer maturities, such as 10 and 30 years. This is because their effects increase with maturity, and bonds with shortest maturities are not affected by LSAPs. However, Swanson estimated, all these effects tend to be temporary and return to zero after a period of approximately two to three months. Swanson (2021, p. 26), additionally reported that forward guidance has no impact on corporate bond yields, which applies in both impact and longer horizons. LSAPs, by contrast, have a highly significant impact on these yields. LSAPs' impact on corporate bonds, though, is smaller than that on government bonds. As a result, corporate bond yields rise following an increase in bond purchases by the FOMC. Swanson concluded that forward guidance and LSAPs mattered for equity prices and exchange rates in approximately equivalent proportions. Inoue and Rossi (2019, p. 419) noted the ineffectiveness of conventional measures around the zero lower bound recently forced central banks to resort to unconventional monetary policy measures. These unconventional measures include, as mentioned in earlier chapters, changing the size and composition of central banks' balance sheets and/or announcing the future path of short-term interest rates (see Chapter 2.1.4.4). To analyse how monetary policy shocks dynamically affect exchange rates, Inoue and Rossi (2019, p. 445) identified monetary policy shocks as shifts in the entire yield curve. The authors further stated that, on average, both conventional and unconventional periods experience comparable effects of monetary policy shocks on exchange rates. Conversely, monetary policy easing causes the U.S. dollar to depreciate. The author explained that exchange rates react differently depending on people's expectations of interest rate path and risk rewards in the short, medium, and long run. The variations therein depend on the effects of monetary policy. Even at long maturities, real interest rates change because of the monetary policy transmission mechanism.

2.1.8 Link with Inflation

With the Federal Reserve's statutory mandate, the committee considers a 2% inflation rate, measured by the annual PCE Price Index change, as the most consistent in the longer run. Numerous unanticipated economic developments have occurred as a result of the COVID-19 pandemic. One such development has been an increase in price inflation. As a measure of inflation, a basket of goods is used to determine how prices change over time. An index measurement of price inflation, such as the CPI or PCE, is therefore commonly used to track inflation. In the following, the link between monetary policy decisions and inflation is discussed in greater detail.

According to Labonte, 2022, p. 21), as long as unemployment or price levels are below the Fed's targets, the Fed will stimulate the money supply and tighten policy if price levels are higher. Previous chapters mention Fed policy decisions regarding the control of inflation. This raises the question of whether these decisions help to fight inflation. In this regard, Ireland (2000, p. 432) observed that, from 1980 to 2000, the Federal Reserve attempted to address inflation by pursuing an active policy of managing short-term nominal interest rates. By maintaining a stable interest rate in the presence of exogenous shocks to the demand for money, Ireland explained, the real economy is shielded from the effects of such a shock. The Board of Governors of the Federal Reserve System (U.S.) et al. (2019, p. 4) asserted that conventional and unconventional monetary policy tools are only effective with a substantial time lag. As a result, the FOMC's ability to contain inflation during a recession is limited. According to the authors, though, it is possible to strengthen the recovery of the labour market and raise inflation to 2% over time. That can be accomplished using the unconventional monetary policy tools they studied in their paper, even if the policy rate is constrained by the ELB during the recession. In this regard, Houcine et al. (2020, p. 628) described a solution to the liquidity trap into which many economies fell during the 2008 financial crisis. Specifically, global central banks used unconventional monetary policy tools to affect expected inflation rates. The author concluded how much expected inflation was impacted by credit volume changes and that these impacts were insignificant. Since unconventional monetary policy tools were designed to stabilise financial markets rather than stimulate inflation expectations, this was attributed to them. Based on Houcine et al.'s results, the U.S. Federal Reserve's zero-interest policy adopted in December 2008 stimulated inflation rates. Labonte (2022a, p. 1) remarked that the Fed has initiated a series of increases in the Federal Funds Rate during every economic recovery since 1958. Furthermore, if the economy continues to strengthen, the Fed will increase FFRs to phase out the monetary incentives used in the previous recession to stimulate consumer spending. Figure X shows that, at the onset of the COVID-19 pandemic, the Fed reduced the FRR to zero for the first time since during the financial crisis in 2008. The Fed's intention in these two cases had been to stimulate the economy as much as possible to overcome two of the most severe recessionary periods since the Great Depression (Labonte, 2022a, p. 1). Moreover, during both crises, the Fed adopted other unusual stimulus measures like the unconventional monetary policies mentioned in earlier chapters. When adjusted for inflation, Figure 3 demonstrates that interest rates currently have an even more stimulative aspect when compared to historical levels.

Figure 3: FFR vs. Inflation Adjusted FFR

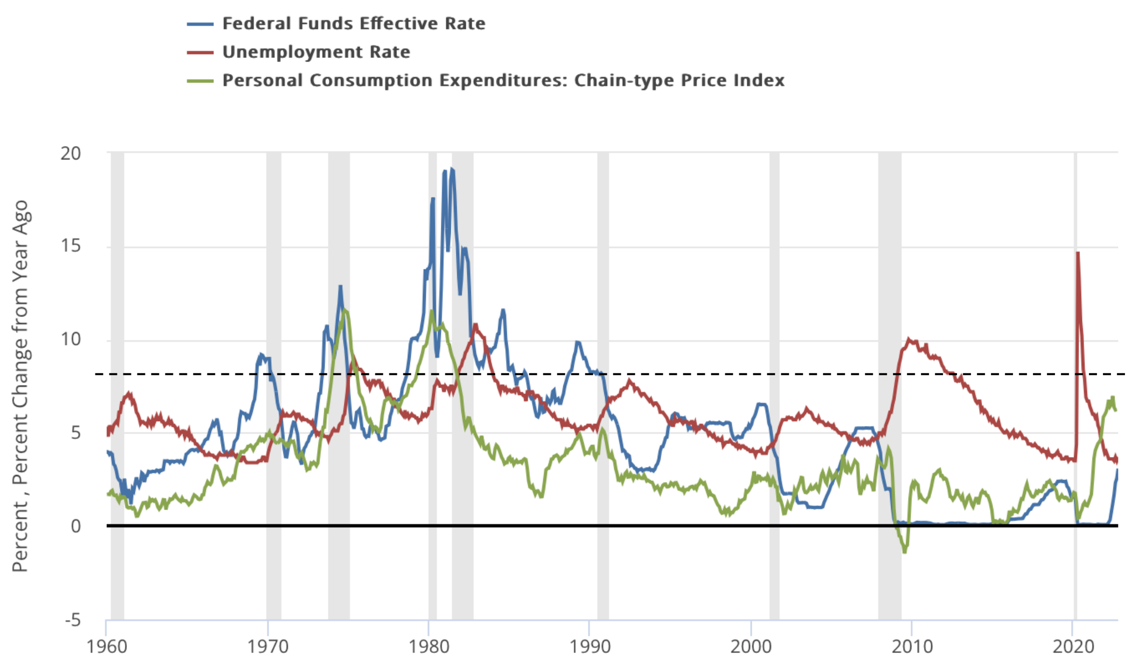


Note: The figure shows the FFR and the FRR, adjusted for Inflation, From 1960 to 2022. Gray bars indicate recessions as determined by the NBER. Source: FRED®, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/FEDFUNDS; https://fred.stlouisfed.org/series/CPIAUCSL; accessed September 30, 2022.

As Figure 3 illustrates, The FFR appears negative at present (close to -6%) when adjusted for inflation. Consequently, investors' compensation has a lower real purchasing power than the original amount borrowed. The figure also shows that, according to the Fed's current agenda, real interest rates would remain in the negative even after further FFR hikes this year. In addition, it indicates that inflation did not fall in 1970 when nominal interest rates were high because real interest rates were low. Nominal interest rates also rose at times but not quickly enough to keep pace with inflation. In turn, real rates were low or even negative at times. The high inflation period eventually ended when monetary policy was tightened to the point that real rates were no longer low. The average effective federal funds rate rapidly increased from about 11% when he took office to about 18% in April 1980. It peaked at over 19%; between July 1981 and November 1982, there was another recession. The federal funds rate hovered around double digits through 1982, mainly because inflation had to drop considerably before it could be maintained at a stable level. Following the 2008 financial crisis, the Fed faced the opposite problem—even at zero, nominal rates were not low enough to prevent inflation from falling below its 2% target. As a result, its monetary policy strategy emphasised raising low inflation over preventing high inflation.

Labonte (2022a, p. 2) reported that interest rates have historically been raised before employment levels hit low points. This was either because inflation was already high or the Fed was concerned that it would become excessive, as Figure 4 indicates. Fed policy changed in 2020 when it pledged to respond only to “shortfalls of maximum employment levels” (Labonte, 2022a, p. 2).

Figure 4: FFR, Inflation, and Unemployment Rate



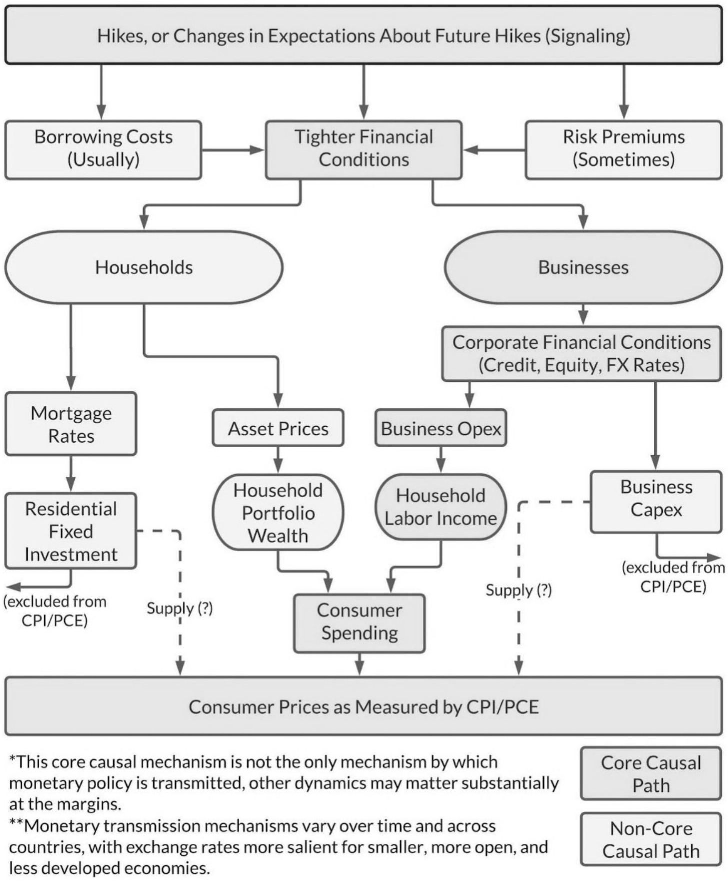
Note: The figure shows the FFR, the Inflation Rate, and the Unemployment Rate from 1960 to 2022. Gray bars indicate recessions as determined by the NBER. Source: FRED®, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/FEDFUNDS; https://fred.stlouisfed.org/series/UNRATE; https://fred.stlouisfed.org/series/PCEPI ; accessed September 30, 2022.

Labonte (2022a, p. 2) reported that the current inflation rate is the third highest in the period considered in Figure 4. As also evidenced in Figure 4, inflation often exceeded the Fed's 2% target at the beginning of monetary tightening, only rising above 4% in the 1970s and early 1980s. That was a period marked by persistently high inflation that averaged at 6.6% between 1969 and 1983. According to Labonte (2022a, p. 2), the FFR may have been high during this period, but inflation-adjusted rates were negative, as is the case today. In this regard, Hetzel (2021, p. 3) stated that the FOMC used the recovery from the Great Recession to revise its policy framework. Indeed, there is a danger that the public’s expectation of inflation will become unanchored to the downside because of the ZLB.

2.1.8.1 How the Fed slows Inflation

Figure 5 depicts that the Fed can slow inflation through monetary policy. Food and rent are the most prominent cyclical inflation components. As a result, the Fed's ability to influence the labour market is key to its influence over short-run inflation dynamics. Understanding the Fed's influence on the labour market enhances understanding of how the Fed influences inflation.

Figure 5: How the Fed slows Inflation



Note: The figure shows how the Fed slows inflation. Source: Amarnath, S. (2022, 1. Juni). What Are You Expecting? How The Fed Slows Down Inflation Through The Labor Market. Employ America. https://www.employamerica.org/researchreports/how-the-fed-affects-inflation/

A higher interest rate and tighter financial conditions cause businesses to decrease their spending on labour, reducing total household income. Figure 5 illustrates this mechanism. The result is a decrease in consumer spending, which lowers price pressure. A further important insight the figure provides is that a tightening of financial conditions requires almost no interest rate increase from the Fed. It is sufficient to signal that monetary policy will be tighter than market participants expected, with financial conditions adjusted accordingly, as the next chapter discusses in greater detail. As the first part of the figure demonstrates, higher interest rates result in higher borrowing costs and risk premiums, thus tightening financial market conditions. Under asset pricing theory,[7] the discounted value of the future cash flows generated by an asset is used to determine the asset's present value. Generally, higher risk-free interest rates, which are in effect the FFR, would entail higher discount rates, lowering present values for assets.

2.1.8.2 Money Growth and Inflation

Labonte (2022a, p. 2) argued that increases in the money supply have historically served as an indicator of the inflation rate. Underlying this is the theory that inflation is driven by "too much money chasing too few goods" (Labonte, 2022b, p. 2). In addition, Labonte observed, the money supply grew more strongly than ever before after the financial crisis, yet the inflation rate generally remained below the target value before rising significantly again in 2021. Monetary supply increased relatively quickly after 2008 because the monetary base, consisting of bank reserves and cash, grew rapidly and was under the Fed's control. A faster rise in the money supply would typically raise inflation. However, Labonte explained, the interest on reserves (IOR) allows the Fed to tie up bank reserves to keep them from causing inflation.

Monetarist theory (Friedman and Schwartz, 1963, as cited by Esteban Posada et al., 2020, p. 1) is one of the best-known theoretical frameworks for understanding the relationship between money growth and price level. According to the theory, Esteban Posada et al. (2020, p. 2) noted, money market equilibrium results from the equality of the real money supply (M/P) and the demand for money (L). That demand is in turn a function of real income (Y) and the nominal interest rate (R):

$$\frac{M}{P} = L(Y, R) \tag{2}$$

By rewriting and fully differentiating (1), Esteban Posada et al. (2020, p. 2) showed that price developments can be determined as a function of changes in the supply and demand for money:

$$\frac{dP}{P} = \frac{dM}{M} - \frac{dL}{L} \tag{3}$$

Considering the money demand function, the money demand elasticities, with respect to income and interest rate, can be calculated as follows:

$$\frac{dL}{L} = \frac{Y}{L}\frac{\partial L}{\partial Y}\frac{dY}{Y} + \frac{R}{L}\frac{\partial L}{\partial R}\frac{dR}{R} \tag{4}$$

[7] (Drake & Fabozzi, 2010, p. 2)

Replacing equation (3) with formula (2) allows price development to be deduced as a function of the quantity of money and income and the nominal interest rate's growth rate:

$$\frac{dP}{P} = \frac{dM}{M} - \frac{Y}{L}\frac{\partial L}{\partial Y}\frac{dY}{Y} - \frac{R}{L}\frac{\partial L}{\partial R}\frac{dR}{R} \quad (5)$$

By re-designating the terms in (4), the price level's elasticity in relation to its determinants and the expected variables is obtained from the following:

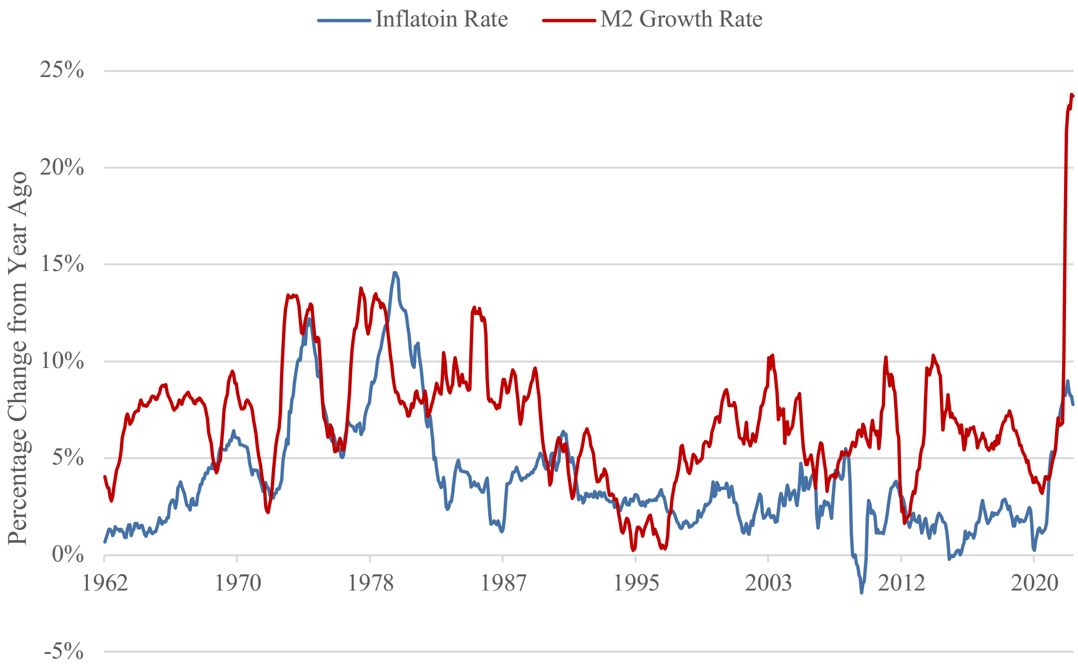
$$\frac{dP}{P} = \beta_1\frac{dM}{M} - \beta_2\frac{dY}{Y} - \beta_3\frac{dR}{R} \quad (6)$$

Esteban Posada et al. highlighted the long-run relationship between price level change and its determinants, which equation (5) highlights. There is a virtually complete transmission of money growth to prices because parameter β_1 is the elasticity of inflation to money growth (see equation 4). The authors observed that the parameter β_2 indicates the sensitivity of money demand to changes in real income and should be negative ($\frac{Y}{L}\frac{\partial L}{\partial Y} > 0$), while β_3 ($\frac{R}{L}\frac{\partial L}{\partial R} < 0$), should be negative.

Milton Friedman[8] once said that "inflation is always and everywhere a monetary phenomenon in the sense that it is and can be produced only by a more rapid increase in the quantity of money than in output". According to Mishkin (2019, p. 536), decades with higher money growth rates tend to have higher inflation rates on average considering the quantity theory of money in the long run. Mishkin also, though, analysed whether the quantity theory of money provides a good explanation of short-run inflation fluctuations. Figure 6 depicts the short-term relationship between money supply growth and inflation. It does so using the annual U.S. inflation rate from 1965 to 2017 plotted against the annual money supply growth rate (M2) for the previous two years. A two-year lag is incorporated into the money growth rate to account for the time required for changes in money growth to affect inflation. Money supply growth and inflation do not have an exceedingly strong relationship on an annual basis. For many years, it was common for money supply growth to be high but inflation to be low. The data presented in Figure 6 illustrates that the quantity theory of money is not a good theory in the short run but is a good theory in the long run, as Mishkin concluded. Conversely, Milton Friedman's statement could be argued as being true in the long- but not the short term.

[8] See Friedman (1970, p. 24)

Figure 6: Annual U.S. Inflation and Money Growth Rates, 1962–2022

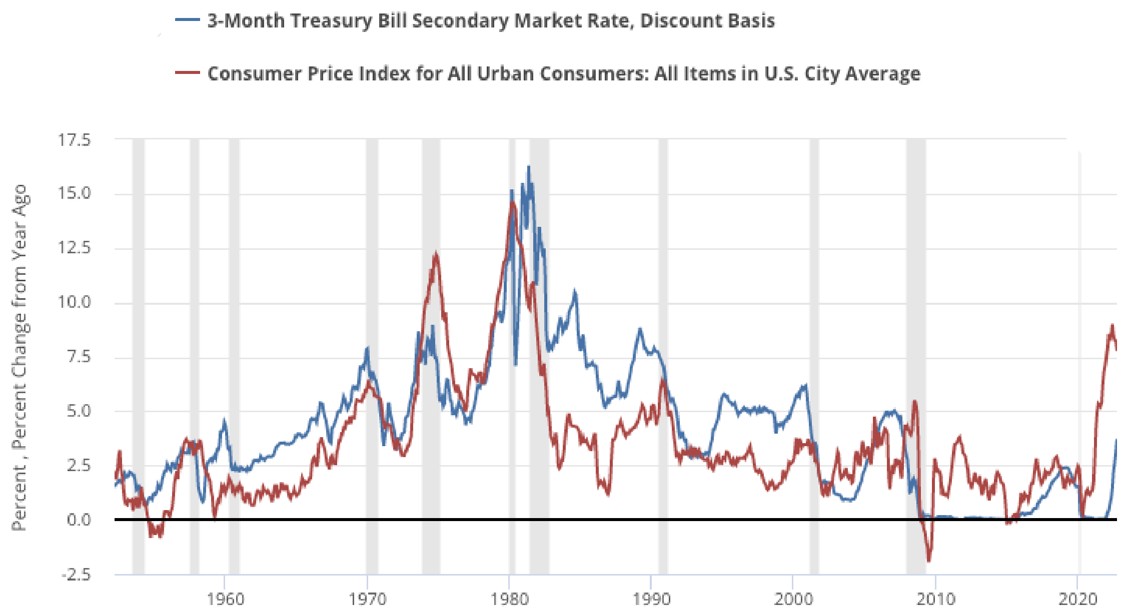


Note: The figure shows the Inflation Rate and M2 Growth Rate from two years earlier from 1962 to 2022. Source: FRED®, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PCEPI; https://fred.stlouisfed.org/series/M2SL, accessed October 15, 2022.

2.1.8.3 Expected Inflation and Interest Rates

In the context of the previous chapter, expected inflation cannot be ignored. The current section elaborates on the concept. The Federal Reserve's policy assumes expected inflation, not expected money supply growth, to be the main cause of inflation. Mishkin (2019, p. 591) commented that the Fed attempts to avoid inflation, which is why it is quite concerned about prices being considered stable and downplays any case of rising prices. According to Mishkin, expected inflation is especially important for workers and firms, as they care about wages in the real term. Real wages are important because goods and services can be bought with wages. Furthermore, Mishkin showed that expected inflation can change if the Fed tolerates an inflation rate of more than two percentage points. Households and businesses then assume that the Federal Reserve is pursuing policies that allow inflation to rise in the future and will want to increase wages and prices by this additional amount. Therefore, Mishkin argued that "when expected inflation rises, interest rates will rise" (2019, p. 149). Figure 7 demonstrates the relationship of expected inflation and interest rates on three-month Treasury. This relationship is predicted by the Fisher effect, which is described below.

Figure 7: Expected Inflation and Interest Rates Over Time



Note: The figure shows that the interest rate on three-month Treasury bills generally moves in tandem with expected inflation, as the Fisher effect predicts. Gray bars indicate recessions as determined by the NBER. Source: FRED®, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DTB3; https://fred.stlouisfed.org/series/CPIAUCSL, accessed October 15, 2022.

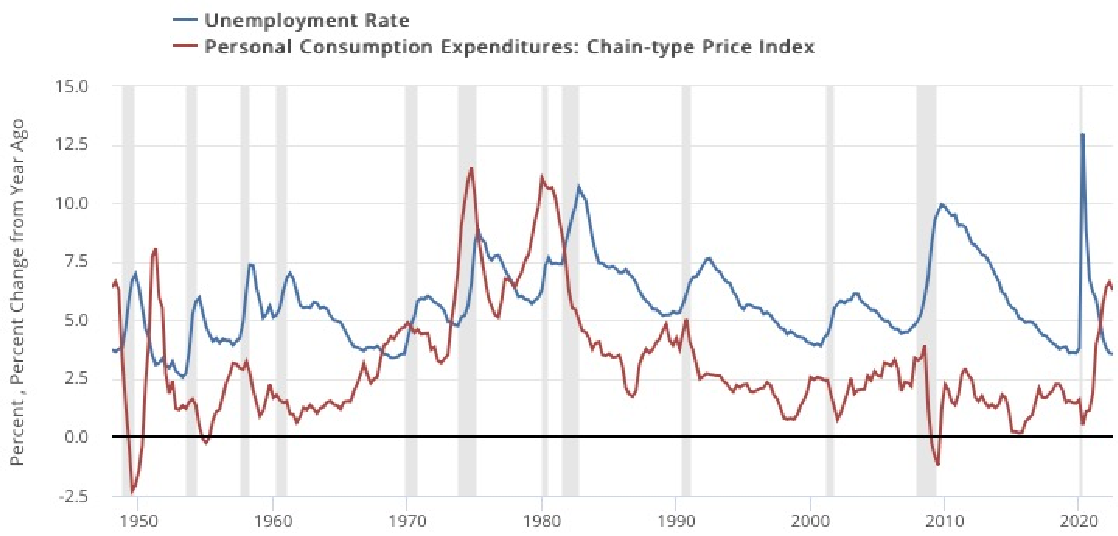
2.1.8.4 The Fisher Effect

According to the neutrality of money principle, Mankiw and Taylor (2017, p. 580) observed, an increase in the money supply's growth rate increases the inflation rate but does not affect real variables. An important application of this principle is money's effect on interest rates. According to Mankiw and Taylor, in the long run, money is neutral. Therefore, a change in the growth of the money supply should have no effect on the real interest rate. After all, the real interest rate is a real quantity. For the real interest rate to remain unchanged, the authors explained, the nominal interest rate must adjust. The Federal Reserve increasing money supply growth results in higher inflation and nominal interest rates. The relationship between interest rates and inflation was first put forward by Fisher (1930). It postulates that the nominal interest rate in any period is equal to the sum of the real interest rate and the expected rate of inflation. This is termed the Fisher Effect. Fisher further hypothesised that the nominal interest rate could be decomposed into two components, a real rate plus an expected inflation rate. He claimed a one-to-one relationship between inflation and interest rates in a world of perfect foresight. In that construct, real interest rates are unrelated to the expected rate of inflation. Rather, they are determined entirely by the real factors in an economy, such as the productivity of capital and investor time preference. However, Mankiw and Taylor (2017, p. 580) argued that the adjustment of the nominal interest rate to the inflation rate must be viewed from a long-term perspective. The authors claimed that the Fisher effect does not apply in the short term when unexpected inflation occurs. Rather, a nominal interest rate is part of a credit contract and is typically fixed at the beginning of the credit transaction. If unexpected inflation occurs in the meantime, the credit transaction's nominal interest rate cannot reflect this price increase. Thus, in essence, the Fisher effect postulates that the nominal interest rate adjusts to the expected rate of inflation. In the long run, expected inflation moves in the same way as actual inflation, but in the short run it may look different. Figure 7 clearly shows the close connection between the two variables.

2.1.8.5 The Phillips Curve

Phillips (1958) found a negative correlation between the unemployment and inflation rates. Years with a low unemployment rate tended to have a low inflation rate. Phillips concluded that two important macroeconomic variables—the inflation and unemployment rates—are linked in a way that economists had not observed closely before that point. Samuelson and Solow (1960) demonstrated a similar negative correlation between the inflation and unemployment rates for the United States. They attributed that correlation to the association between low unemployment and high aggregate demand and the notion that a high demand level has a pull on wages and prices. Milton Friedman (1968), by contrast, showed what monetary policy cannot do is select a particular combination of inflation and unemployment on the Phillips curve. Friedman could not identify any cause for a long-run functional link between the inflation and unemployment rates. In the long run, Friedman concluded, there are no alternatives to choose between the inflation and unemployment rates. The growth of the money supply only determines the inflation rate level. Regardless of the inflation level at a given moment, the unemployment rate tends toward the natural rate of unemployment. Figure 8 illustrates that, over the first two decades, a decline in unemployment generally translated to rising inflation, and a rise in unemployment generally translated into a fall in inflation. There have been less obvious relationships between the two variables in recent decades.

Figure 8: Inflation and Unemployment



Note: The figure shows the relationship between inflation and the unemployment rate. Gray bars indicate recessions as determined by the NBER. Source: FRED®, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UNRATE; https://fred.stlouisfed.org/series/PCEPI, accessed October 23, 2022.

As Meade and Thornton (2012, p. 214) reported, the FOMC minutes show that most policymakers consider inflation the consequence of excess demand when the real economy stands at or near full employment. The general reliance on an aggregate demand/supply view of inflation notwithstanding, the authors observed that opinions differed widely on several measures. These included the usefulness of the gap between actual and potential output or actual unemployment and the NAIRU as a measure of excess demand. From this finding, Meade and Thornton concluded that the Phillips curve exhibited a far lower significance in the actual formation of monetary policy than the classical macroeconomic model or the widely used policy reaction functions would suggest.

2.1.9 Business Cycle and Interest Rates

This chapter discusses the business cycle, the origins of recessions, and the possible causes and effects of these fluctuations in the economy.

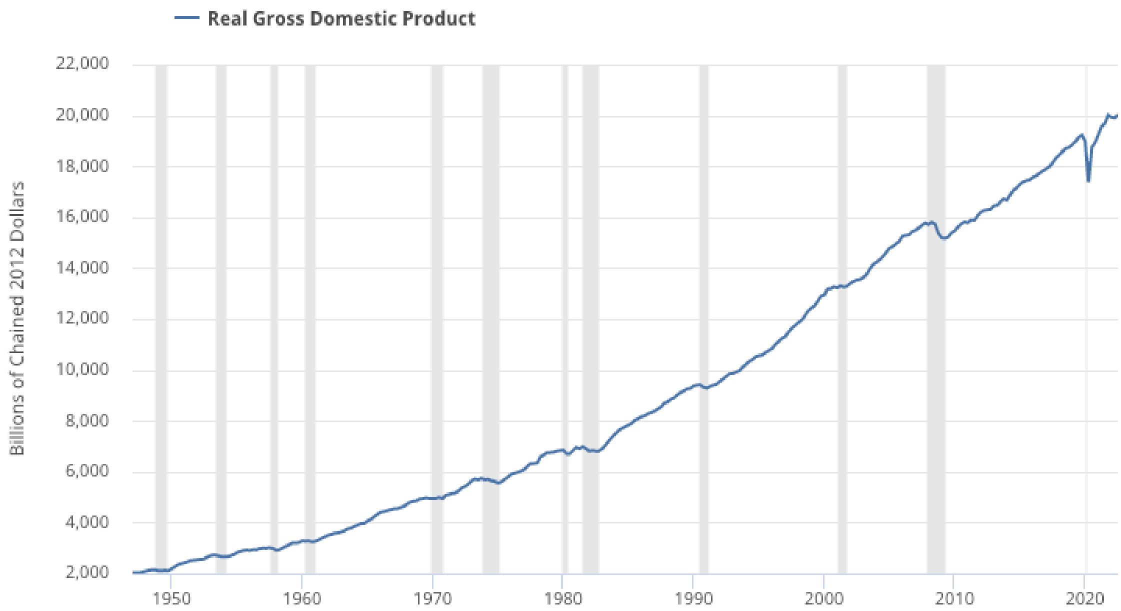
As economic activity fluctuates over time, it typically occurs in spurts of increased activity, called expansions, and decreased activity, called recessions. Burns and Mitchell (1946, pp. 56–114) outlined the theoretical basis for measuring business cycles. They examined how different economic variables had changed as the economy grew. In addition, they investigated why economic variables tend to move together during economic slowdowns. An important economic indicator, regarded by both academic researchers and the public at large, is the real gross domestic product (GDP). It measures total economic output adjusted for inflation. Labonte (2022, p. 1) and Mankiw and Taylor (2017, p. 621) highlighted that the business cycle describes how an economy alternates between growth and recession phases. When the economy passes through the business cycle, a range of economic indicators, in addition to GDP, tends to change. During economic growth, employment, incomes, industrial production, and sales rise in parallel with the increase in real GDP. Furthermore, the rate of inflation tends to rise during economic growth. Nonetheless, the upswing from 2009 to 2020 demonstrated that inflation can remain at a low level even when the economy is growing (Labonte, 2022, p. 1). The opposite tends to be the case in a recession (Mankiw & Taylor, 2017, p. 621). These indicators do not change simultaneously but at around the same time. These variations in economic activity have been defined as a “cycle”, but the business cycle is neither periodic nor regular. The irregular pattern of the business cycle makes forecasting recessions and expansions extremely difficult. During an upswing, short-term declines in economic activity can occur within an upswing phase and vice versa.

2.1.9.1 Dating the Business Cycle

Chauvet and Hamilton (2005, p. 2) showed that the dating of business cycles is based on the peaks and troughs of economic performance. Labonte (2022, p. 1) argued that “a single business cycle is dated from peak to peak or trough to trough”. A recession refers to the period between a peak in economic activity and the subsequent trough. The economy is in an expansion phase between the trough and the peak. Expansion represents the economy’s normal state; periods of recession are typically of short duration. The National Bureau of Economic Research’s (NBER) Committee for the Determination of Business Cycles is considered the identifier of the business cycle in the United States (*Business Cycle Dating | NBER*, n.d.). According to Chauvet and Hamilton (2005, p. 2), researchers and the general public both regard these dates, obtained from NBER, as authoritative. According to the NBER's definition, recession does not mean that real GDP falls for two consecutive quarters, which is often used as an indicator. Instead, the NBER uses a broader definition of recession as a period characterised by a significant drop in economic activity that affects the entire economy (*Business Cycle Dating*, n.d.). Chauvet and Hamilton (2005, p. 2) discussed the quasi-official dates, noting that they were determined by the NBER's Business Cycle Dating Committee. This makes a qualitative judgment about the state of the economy by reviewing a variety of economic indicators, including real GDP, aggregate employment, real sales, and industrial production. Figure 9 presents real

GDP between the first quarter of 1947 and the third quarter of 2021, including recessions identified by the NBER.

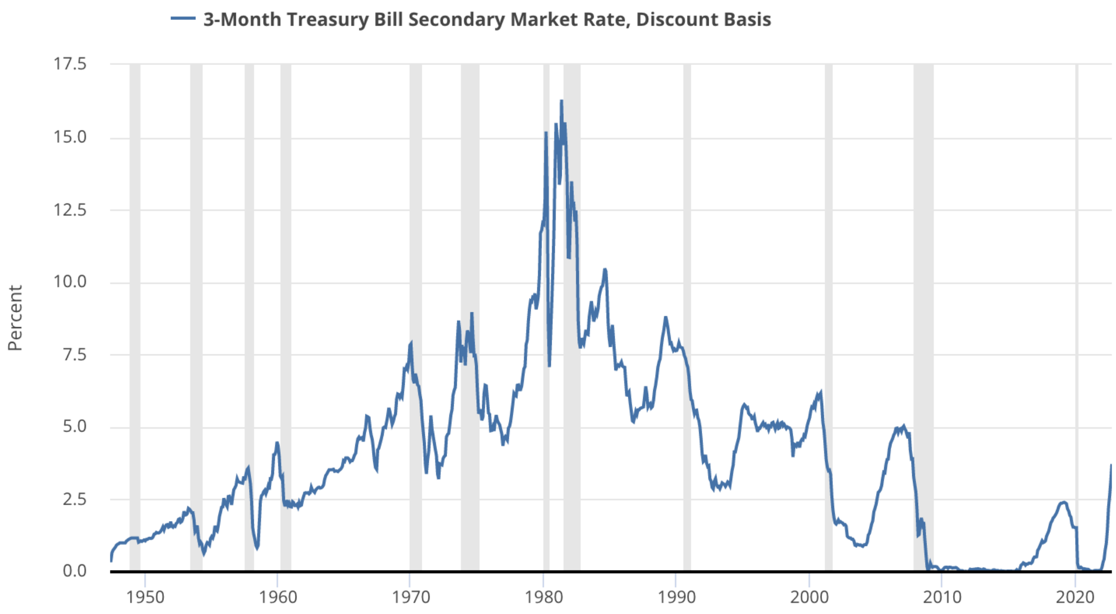
Figure 9: Real GDP and Recessions



Note: The figure depicts the development of real GDP between the first quarter of 1947 and the third quarter of 2021. Gray bars indicate recessions as determined by the NBER. Source: FRED®, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GDPC1, accessed October 23, 2022.

Figure 9 reveals that, in general, economic growth has lasted longer than contraction, particularly in the period after the Second World War. Between 1945 and 2019, marking the end of the last economic cycle, average economic expansion lasted about 65 months. In contrast, the average recession spanned about 11 months. At 128 months, the 2009–2020 economic upswing lasted longer than ever before. In the United States, the last recession before the COVID-19 pandemic, namely the Great Recession, began in December 2007 and ended in June 2009, a total of 18 months. Labonte (2022, p. 1) explained that, in total, there have been 12 other recessions in the United States since the 1850s that lasted at least as long as the Great Recession. However, all these recessions occurred before the onset of the Great Depression in the 1930s. As Figure 8 indicates, the COVID-19 recession technically lasted only two months. However, calling the end of a recession does not mean that the economy has returned to its pre-recession level, as the economy needs time to recover from its trough (*Business Cycle Dating | NBER*, n.d.). According to Mishkin (2019, p. 151), expanding the business cycle and increasing income both lead to a higher interest rate. Figure 10 illustrates the development of the interest rate for three-month U.S. Treasury bills from 1951 to 2017. It also highlights the phases of the business cycle in which recessions occurred (shaded areas). As the figure illustrates, the interest rate tends to rise during economic upswings and fall during recessions.

Figure 10: Business Cycle and Interest Rates



Note: The figure shows the relationship between the 3-month U.S. *Treasury bill and recessions (grey bars). Source: FRED®, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/TB3MS , accessed October 23, 2022.*

2.1.9.2 Recession

As stated previously, the NBER's Committee on Business Cycle Data compiles the standard recession chronology in the United States. The weighting of that indicator is explicitly ambiguous and can change over time. However, there is one certainty: recession is a term that evokes a variety of concerns. During a recession, many people suffer job losses, investors experience asset price declines, and entrepreneurs are placed at risk of bankruptcy. The NBER defined recessions as periods of significant decline in economic activity which last more than a few months and extend across the entire economy (*Business Cycle Dating | NBER*, n.d.). The NBER further stated that, following that definition, depth, spread, and duration may be used interchangeably. The extreme conditions uncovered by one criterion can partly offset the weaker conditions uncovered by another, though each criterion must meet some degree. In determining the timing of turning points, the committee takes a retrospective approach. It waits to report peaks and troughs until sufficient information is available, ensuring that no major changes need be made in the chronology of the business cycle. In determining the timing of a business cycle peak, the committee waits until it is certain that a recession is in place. As Chauvet and Hamilton (2005, p. 2) emphasised, the NBER announced the end of the 2001 recession in July 2003. The authors explained that the delays occurred because the committee wanted to be certain before making an official statement. Table 4 shows the periods of recession since World War 2 according to the NBER definition.

Table 4: Periods of recession since World War 2

Recession Start	Recession End	Length of Recession (Months)	Length of Following Expansion (Months)
February-45	October-45	8	37
November-48	October-49	11	45
July-53	May-54	10	39
August-57	April-58	8	24
April-60	February-61	10	106
December-69	November-70	11	36
November-73	March-75	16	58
January-80	July-80	6	12
July-81	November-82	16	92
July-90	March-91	8	120
March-01	November-01	8	73
December-07	June-09	18	128
March-20	April-20	2	30*
	Average	*10*	*64*
	Median	*10*	*53*

Note: This Table demonstrates the periods of recession since World War 2 as defined by the NBER. Source: FRED®, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USREC, accessed October 29, 2022.

Since the Second World War, the average recession has lasted 10 months. 2020 produced the shortest recession in history at only two months, followed by an average expansion of 64 months (see Table 4). Chauvet and Hamilton (2005, p. 2) determined the probability law for GDP growth per se without any dependence on the NBER data. They also determined parameters, such as how long recessions last and how pronounced they are in terms of GDP growth, from the GDP data alone. They did so by applying the maximum likelihood estimation procedure. Chauvet and Hamilton explored the potential use of this algorithm as a neutral alternative to the NBER Committee's explanations of business cycle data, considering that the data were heavily revised on a regular basis. However, throughout the rest of the paper, whenever a recession is referred to, the NBER's definitions and periods are used.

Given that a recession evokes a multitude of concerns, the forecasting thereof is often of vital importance for both public and private decision-makers. In the literature, yield curve inversions are considered an extremely good predictor of recessions, which the next chapter elaborates on.

2.2 Inverted Yield Curve and the Economic Downturn

The term spread represents the divergence between interest rates for short- and long-term government bonds. It is often considered an indicator of the economic cycle. Inversions of the yield curve, in particular negative term spread, are regarded as an early warning sign. The subsequent chapters discuss the yield curve in greater detail.

2.2.1 Interpreting Yield Curves

In spite of their similar risk, liquidity, and tax characteristics, Mishkin (2019, pp. 175–176) observed, bonds with varying maturities have different interest rates. The same is not true for a curve indicating the yields of bonds with different terms but the same risk, liquidity, and tax aspects. According to Mishkin, that case is referred to as a yield curve, and it describes the term structure of interest rates for certain types of bonds, such as government bonds. The author introduced three types of yield curves: upward sloping, flat, and downward sloping. The latter are often called inverted yield curves. Long-term interest rates tend to be higher than short-term ones in upsloping yield curves, which are the most common scenario. Mishkin noted that the yield curve of a short-term bond exhibits short- and long-term interest rates at the same level. In contrast, the yield curve of an inverted bond shows long-term interest rates lower than short-term interest rates. Mishkin further wrote that a sharply rising yield curve indicates a rise in interest rates on short-term bonds in the future. Short-term interest rates will no longer considerably increase or decrease in the future if the yield curve increases moderately. According to the flattening yield curve, short-term interest rates should decline moderately in the coming years. As a result of an inverted yield curve, short-term interest rates are expected to decline sharply as well. Kumar et al. (2022, pp. 8–9) overviewed the term premium and stated that the long-term interest rate is calculated by adding together the average future short-term rates and the term premium (7):

$$i_t^m = \frac{1}{m} E_t \left\{ \sum_{j=0}^{m-1} i_{t+j} \right\} + \emptyset_t^m \tag{7}$$

with $\emptyset_t^m$ being the annualised term premium for a period of m, i_t^m the annualised interest rate for a period of m, and $E_t \frac{1}{m}\{\sum_{j=0}^{m-1} i_{t+j}\}$ the average interest rate for the short-term term. Therefore, the term premium equals the following:

$$\emptyset_t^m = i_t^m - E_t \frac{1}{m}\left\{\sum_{j=0}^{m-1} i_{t+j}\right\} \tag{8}$$

The authors subsequently bifurcated as follows on the right-hand side:

$$\emptyset_t^m = i_t^m - E_t \frac{1}{m}\left\{i_t + \sum_{j=1}^{m-1} i_{t+j}\right\} \tag{9}$$

In this case, they concluded that i_t is a one-period interest rate at time 0. The slope of the yield curve (term spread) can therefore be represented as follows:

$$(i_t^m - i_t) = \left(\frac{1}{m} E_t \left\{\sum_{j=0}^{m-1} i_{t+j}\right\} - i_t\right) + \left[i_t^m - \frac{1}{m} E_t \left\{\sum_{j=0}^{m-1} i_{t+j}\right\}\right] \tag{10}$$

According to Kumar et al. (2022, p. 9), the slope comprises the term premium and the difference between the short rate at present and the short rate expected in the future. Kumar et al. found that higher slopes or steeper yield curves are normally associated empirically with lower GDP growth and greater recession risk. This mechanism is elaborated on in the next chapter.

2.2.2 The Yield Curve as a Forecasting Tool for Inflation and the Business Cycle

In their paper, Kumar et al. (2022, p. 9) explained that the phenomenon mentioned above has yet to be explained by a clear theory. In response to changing economic conditions, the authors hypothesised that changes in the slope reflect changes in the expected component. Furthermore, long-term interest rates should change little if inflation expectations are well anchored. Mishkin (2019, p. 185) stated that inflation and real output fluctuations can be forecasted using the yield curve because it contains information about future interest rates. Earlier chapters discussed the correlation between rising interest rates and economic booms and recessions. It was also noted that an economy likely to enter a recession is indicated by a flat or downward-sloping yield curve. Indeed, the yield curve has been found to be an accurate predictor of the business cycle. The nominal interest rate is, according to Mishkin, composed of a real interest rate and expected inflation. Consequently, the yield curve contains indications of both the development of both nominal interest rates and inflation. Thus, a steep yield curve predicts a future increase in inflation, whereas a flat or downward sloping yield curve signals a decrease in future inflation.

Because the yield curve is useful for forecasting economic activity and inflation, Mishkin highlighted that the slope of the yield curve is a tool used by many economic researchers. In addition, a steep yield curve indicates loose policy, and a flat or downward sloping yield curve indicates tight policy. As a result, yield curve slope is often also considered a useful indicator of the monetary policy stance. When considering the standard asset-pricing theory[9] (as cited in Andolfatto & Spewak, 2018, p. 1), the real interest rate is a measure of the expected rate of consumption growth over a certain period. For that reason, policymakers can avoid yield curve inversion in the near term by being cautious when raising rates. Alternatively, a rise in policy rates must be accompanied by an increase in nominal interest rates over the longer term.

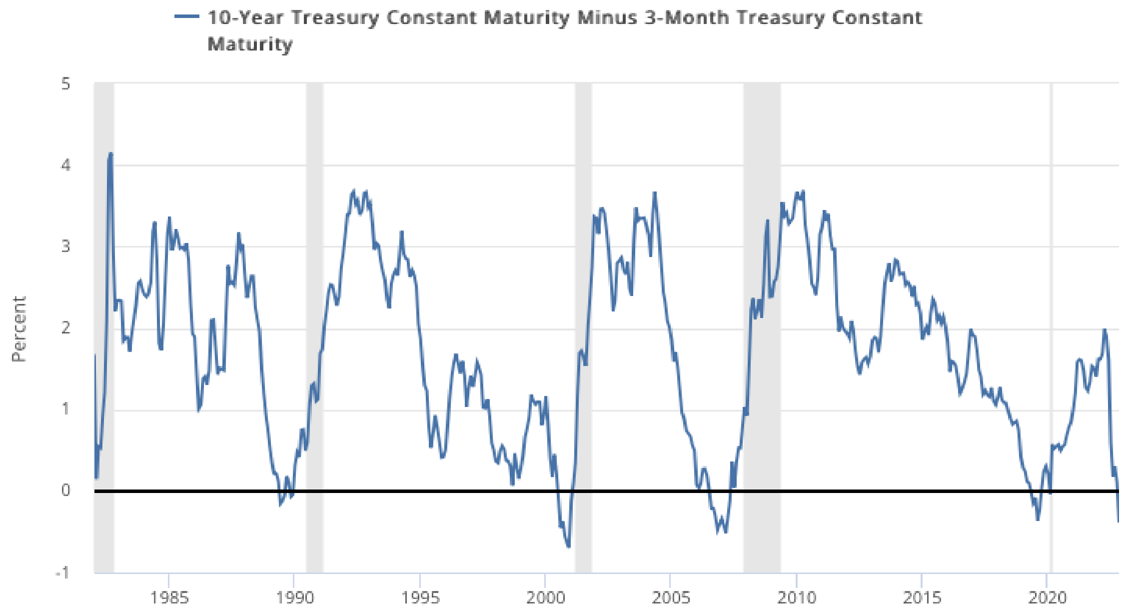
2.2.3 Yield Curve as a Leading Recession Indicator

The difficulties that have afflicted the global economy since the financial crisis began have made the forecasting of future financial crises more important than ever. One of the indicators most often relied upon to indicate recessions has been the maturity yield curve. Its downward slope is associated with an increased probability of a period of negative or sharp decline in real economic growth. Iqbal et al. (2019, p. 61) asserted that assessing recession risk has a long tradition, as an inverted yield curve has led to all recessions since 1969–1970. That an inverted yield curve can indicate a recession has been demonstrated empirically by several researchers[10] over several decades. Estrella and Hardouvelis (1991, pp. 555–575) were the first to study a recession forecasting model with a binary dependent variable for recession and an interest rate explanatory variable. Similarly, Estrella and Mishkin (1996, pp. 4–5) explored the outcomes of several financial variables in predicting recessions in the US. In this case, the authors examined the spread between the interest rates on the ten-year Treasury note and the three-month Treasury bill. In a later paper published by Estrella and Mishkin (1998, p. 45), they investigated the out-of-sample performance of several financial variables as predictors of U.S. recessions. Ahrens (2002, p. 519) evaluated the information in the term structure as a predictor of recessions in eight countries of the OECD using Markov-switching models. He confirmed the term structure's indication of recession. In more detail, In addition, Chauvet and Potter (2001, p. 1) compared forecasts of recessions using four different specifications of the probit model. Moreover, Estrella and Trubin (2006, pp. 1–7) considered whether any explanations for

9 See Robert (1978, pp. 1429-1445)
10 Such as Laurent (1988), Harvey (1988, 1989), Stock and Watson (1989), Chen (1991), and Estrella and Hardouvelis (1991).

the predictive power of the yield curve would justify using the signal for operational purposes. They also investigated the best way to construct the yield curve indicator and subsequently read the indicator in real time. The most accurate forecasts are made using Treasury rates, and the best combination of maturities may be three months and ten years, according to the authors. Figure 11 plots the difference between the yield on 10-year Treasury securities and that on 3-month Treasury securities at a monthly frequency.

Figure 11: Treasury Yield Curve, 1982 to 2022



Note: The figure shows the difference between the yield on 10-year Treasury securities and that on 3-month Treasury securities at a monthly frequency. It also depicts recessions (grey bars). FRED®, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/TB3MS , accessed October 23, 2022.

Based on the empirical academic research mentioned above, Figure 11 illustrates the effectiveness of using the yield curve slope to predict future economic activity. Policymakers and market professionals should, then, take the possibility of a yield curve inversion seriously. A similar pattern is observed when plotting the term spread between the ten-year and the two-year yields (10y–2y; Bauer & Mertens, 2022, p. 2). Several ways to predict recession have been described in the research examined to this point (probit regression, Markov switching, Bayesian methods, etc.) According to Puglia et al. (2020, p. 4), those methods are well established in econometrics. More recent papers have developed new methods, like the one presented by Leamer (2022, p. 1). Such new methods address intra-correlation issues when applying probit models or the application of

Machine Learning (ML) models presented in academic literature[11]. As Puglia et al. (2020, p. 4) observed, machine learning is rooted in statistics and computer science. Furthermore, while it is used in many industrial applications, only in recent years has it found application in macro econometric analysis. Hasse and Lajaunie (2022, p. 6) reported that the yield curve alone is not structural but is dependent upon monetary policy. For that reason, other macroeconomic variables have predictive power and can help improve recession forecasting accuracy. This thesis aims to evaluate recession indicators within a machine learning framework. Consequently, the next chapter addresses ML and the most common models applied when evaluating recession indicators and recession forecasting.

2.3 Machine Learning

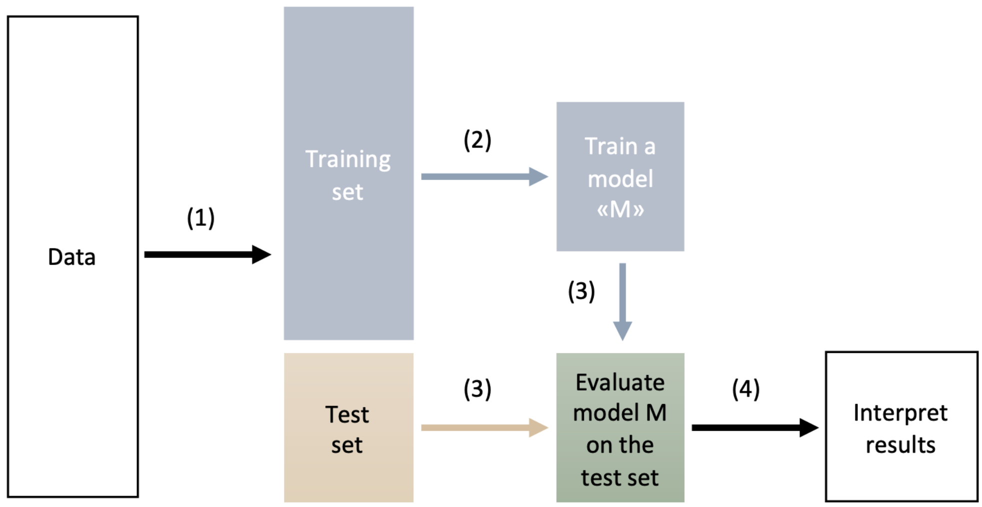
Müller & Guido (2016, p. 1) introduced in their book that machine learning (ML) is the process of deriving knowledge from data. According to the authors, it is an area of research at the interface of statistics, artificial intelligence, and computer science to which it is referred as predictive analytics as well as statistical learning. In recent years, the authors pointed out that the use of machine learning methods has become ubiquitous in everyday life. Modern websites and devices often feature machine learning algorithms, from automatically recommending what movies to watch, what food to order or what products to buy, to personalising online radio and recognising friends in your photos. The authors further explained that ML can be divided into supervised and unsupervised learning. Supervised learning is explained by the authors as an automate decision-making processes that generalizes from known examples. One the one hand, a supervised learning algorithm finds a way to produce the desired output based on an input when the user provides it with pairs of inputs and outputs. In general, supervised learning involves experience-based learning. Supervised learning can be further divided in classification and regressoin algorithms. The regression model predicts continuous outcomes, whereas the classification model identifies an object's category. Unsupervised learning, by contrast, involves showing the input data to the algorithm and asking it to extract knowledge from it. Next, the machine learning framework and procedure is elaborated in more detail, binary classification, as well as the classification models Logistic Regression, Random Forest, and XGBoost, since these are also applied in the thesis.

[11] See Delgado et al. (2022), Gogas et al. (2015), Iqbal et al. (2019), and Puglia et al. (2020)

2.3.1 Machine Learning Framework

As shown in Figure 12, Fazlija (2022) demonstrated a commonly used ML procedure for supervised learning.

Figure 12: Machine Learning Procedure



Note: uihiuziuz

For ML to work and learn a pattern, Fazlija (2022) further highlighted that it must be trained. This learning process starts according to the author with a prepared data set (training data set) that is searched for patterns and correlations by a machine learning algorithm. After a successfully completed learning process, he stated that the trained model is used to evaluate unknown data. Thus, better decisions can be made based on these predictions. Figure 12 shows that first, all the available data is splatted into a training set and a test set. Second, a model is trained on the training set. Next, the trained model is used to predict outputs $\hat{y}_i$ for given inputs x_i. These values are then in turn compared with actual values y_i that came in pairs with the x_i. The error that is made here is called generalization error. Lastly, the results are interpreted that are computed with respect to the given performance measure.

2.3.2 Classification and Regression

Fazlija (2022) pointed out that predictions in ML are split in two classes. One type predicts a label among finitely many, which is called classification, while another type predicts a number out of a continuous range (for instance the real numbers $\mathbb{R}$), which is called regression. Fazlija further discussed that classification and regression tasks often differ by the output the model produces, in one case the output in one of a (finite) set of objects/categories, whereas for regression, it is an outcome from a continuous range, such as a real number. Sometimes there is an ambiguous line between classification algorithms and regression algorithms. Many algorithms can be used for both classification and regression, and classification is just regression model with a threshold applied. Next, the binary classification is discussed, since in transforming the problem of detecting an economic recession, into a mathematical and probabilistic problem, there are only two possible outcomes: there is an economic recession or there is not.

2.3.2.1 Binary Classification

As a practical application of machine learning, binary classification stands out as one of the most common and conceptually simple. Taking the recession outcome into consideration, assuming, as presented by Fazlija (2022), there are only finitely many possible attainable values or categories C_1,..., C_N. A classification problem, as mentioned earlier, is the problem of identifying to which of these categories a new observation belongs, on the basis of a training set of data containing observations whose category membership is known. If there are only two possible categories (N=2), Fazlija highlighted that it is considered a binary classification. Müller & Guido (2016, p. 279) further stated that there might be some types of errors when applying binary classification, like measuring accuracy and that when talking about binary classification, it is typically refer to two classes as positive and negative, with the idea that the positive class is being emphasized. Further, the authors brought up the issue of imbalanced datasets, which are characterized by a much higher frequency of one data class than the other. In an imbalanced setting, accuracy is therefore an inadequate measure for quantifying predictive performance. As a result, alternative metrics, which provide better guidance when selecting models, are discussed next.

2.3.2.2 Evaluation metrics for binary classification

Müller & Guido (2016, p. 279) explained that confusion matrices are among the most comprehensive ways of representing binary classification results. In this regard, Fazlija (2022) pointed out that depending on the circumstances, applying different performance criteria might be necessary. Next the confusion matrices is elaborated in more detail. Müller & Guido (2016, p. 279) explained that using a confusion matrix, the output is a two-by-two array, where the rows are the true classes, and the columns are the predicted classes. As illustrated in Figure 13, the matrix explains the meaning of the entries by counting how often samples that belong to the row correspond to the column.

Figure 13: Confusion Matrix

		Predicted class	
		P	N
Actual class/True label	P	True positives (TP)	False negatives (FN)
	N	False positives (FP)	True negatives (TN)

Note: Source: Fazlija (2022)

According to Müller & Guido (2016, p. 281), the confusion matrix's main diagonal is composed of entries that indicate correct classifications, while the other diagonals tell us how many samples of one class were incorrectly classified as samples of another. The authors stated that these designations get in the form of FP, FN, TP and TN and result within a confusion matrix seen in Figure 13. In addition, the information in the confusion matrix can summarized in different ways. Therefore, some important notions need to be explained in more detail. In this regard, Müller & Guido (2016, pp. 279–283) examined the following notions: accuracy, precision, recall (=sensitivity), and f1-score, which are defined as follows:

Accuracy: $$accuracy = \frac{TP + TN}{PTP + TN + FP + FN}$$

Müller & Guido (2016, p. 282) looked at the accuracy of predication as the ratio of the number of correct predictions (TP and TN) to the number of samples (all entries of the confusion matrix summed up). There are several other ways to summarize the confusion matrix, with the most common ones being precision and recall.

Precision: $$precision = \frac{TP}{TP + FP}$$

Precision measures how many of the samples predicted as positive are actually positive. Precision is used as a performance metric when the goal is to limit the number of false positives. Recall, on the other hand, measures how many of the positive samples are captured by the positive predictions.

Recall: $$recall = \frac{TP}{TP + FN}$$

Recall is used as performance metric when it is needed to identify all positive samples; that is, when it is important to avoid false negatives. While precision and recall are very important measures, looking at only one of them will not provide the full picture. One way to summarize them is the f-score or f-measure, which is with the harmonic mean of precision and recall.

F1-score: $$f_1\text{–}score = \frac{precision \times P}{TP + FN}$$

As it takes precision and recall into account, it can be a better measure than accuracy on imbalanced binary classification datasets.

2.3.2.3 Imbalanced classes

As mentioned earlier, the issue of imbalanced datasets, which are characterized by a much higher frequency of one data class than the other, is of relevance when discussing the behavior of classifiers at different thresholds. Many machine learning models will tend to predict towards the class that is more often represented. Fazlija (2022) highlighted possible strategies of how to deal with imbalanced data. He stated that additional data could be added, different performance metrics instead of accuracy could be used, and by applying resampling. Therefore, Müller & Guido (2016, p. 282) discussed the receiver operating characteristics curve (ROC) curve.

2.3.2.4 ROC Curve

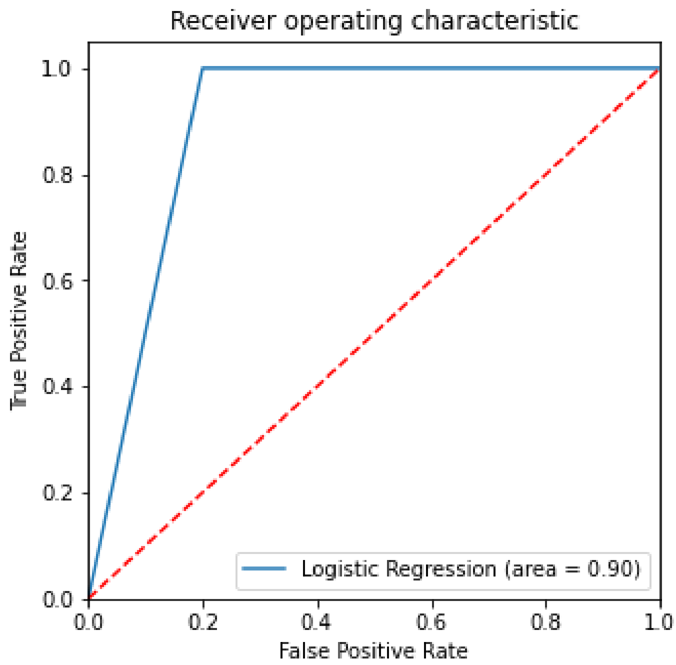
Before explaining the ROC curve in more detail, the definitions, as explained by Fazlija (2022) of the true positive rate (TPR) and the false positive rate (FPR) are presented.

TPR ≡ recall!: $$TPR = \frac{TP}{TP + FN}$$

$$\mathrm{FPR} = \frac{FP}{FP + TN}$$

According to the Müller & Guido (2016, pp. 292-293), the ROC curve takes into account all possible thresholds for a given classifier, but rather than reporting precision and recall, it demonstrates the false positive rate (FPR) against the true positive rate (TPR). As demonstrated in Figure 14, each point on the ROC curve represents one combination of TRP and FPR.

Figure 14: ROC AUC Curve



Note: ROC AUC Curve. Source: Fazlija (2022)

Fazlija (2022) demonstrated that the classifier boundary deciding between one class, or another is to be determined by a threshold value. Therefore, it can be said, that for every threshold it will get different rates of true positive and false positive and thus a whole graph that we call ROC curve. According to Müller & Guido (2016, p. 293), there should be no false positives or high recognition rates on the top left of the ROC curve. They explained that an ideal classifier will have a low false positive rate and a high recognition rate. With a 0.9 hit rate, the authors demonstrated that a much higher FPR (only slightly increased) can be achieved than with a zero threshold. They concluded that as an alternative to the default working point, the point at the very top left might be a better choice. Fazlija (2022) further addressed the area under the curve (AUC), which measures the area beneath the ROC curve by making an integral of the signal. He explained that the red line is the baseline of 0.5, where the true positive rate (TPR) is equal to the false positive rate (FPR) and the closer the AUC returns near the value 1, the better the classifier is.

2.3.3 Classification Models

There is no single machine learning model that works best on all problems/datasets (as demonstrated by the no free lunch theorem)[12]. In general, different models have strengths

[12] See Wolpert & Macready (1997, p. 67)

and weaknesses that differ from one another. In the literature[13], the ML models for predicting economic recession like Logistic Regression, Random Forest, XGBoost, Support-Vector Machine classifier, and Neural networks have found their application. As for the purposes of this thesis the ML model's accuracy is of relevance that is achieved by employing in-sample and out-of-sample criteria. Therefore, the following three ML models suited for binary classification, namely Logistic Regression, Random Forest, and XGBoost are chosen and will be elaborated next in more detail.

2.3.4 Logistic Regression

Using a given set of dependent variables and a probability value between 0 and 1, logistic regression is a machine learning classification technique which is used to predict categorical dependent variables (Cox, 1958, p. 1). The following equation 11 demonstrated by Müller & Guido (2016, p. 213) shows how the logistic regression makes predictions.

$$\hat{y} = w[0] * x[0] + w[1] * x[1] + \ldots + w[p] * x[p] + b > 0 \qquad (11)$$

In equation 11, the authors stated that w[i] and b are coefficients learned from the training set, while x[i] are the input features. This equation, in the view of the authors, makes sense when x[i] are numbers. This model is suited to problems in which the dependent variable is categorical. A further assumption mentioned by the authors is that there are no outliers in the data. This approach is popular because it is easy to implement, however it ignores the possible correlations between class labels.

2.3.5 Random Forest

Breiman (2001, pp. 5–6) described random forest as an ensemble decision tree-based classification method. According to the author, each tree in the forest is formed using values from a random vector which is sampled independently for all trees within the forest. In equation 12 Breiman explained the rationale behind the decision tree-based classifier.

$$\{\mathrm{h}(\mathrm{x}, \Theta_k), \mathrm{k} = 1, \ldots\} \qquad (12)$$

In random forests, Breiman (2001, p. 6) pointed out that $\{\Theta_k\}$ are independent identically distributed random vectors and each tree votes for the most popular class at input x based on a set of unit votes. Advantages of this algorithm are that it is fast, and the ensemble of relatively weak classifiers combine to create a highly generalizable model that is simple to tune and avoid over- and underfitting.

[13] See Delgado et al. (2022), Gogas et al. (2015), Iqbal et al. (2019), and Puglia et al. (2020)

2.3.6 Gradient Boosting (XGBoost)

(T. Chen & Guestrin, 2016, pp. 785–786) introduced XGBoost as a popular and efficient open-source implementation of the gradient boosted trees algorithm. Gradient boosting was first introduced by Friedman (2001, pp. 1189–1193). Friedman further stated that Gradient Boosting can be used for classification as well as regression. According to (T. Chen & Guestrin, 2016, pp. 785–786), extreme gradient boosting (XGBoost) is a learning algorithm that merges several weak learners into one powerful one using decision trees as a base. Since several models are incorporated into the final prediction, it is called an ensemble learning algorithm. In this regard, (Puglia et al., 2020, p. 5) stated that XGBoost has been shown to possess a number of advantages over previous alternatives, notably speed and scalability.

2.3.7 Overfitting

Müller & Guido (2016, p. 28) addressed the concern of overfitting in a machine learning scheme. The authors stated that the process of overfitting entails building a model that contains too much information for the information there is available. According to the authors, overfitting is fitting a model excessively closely to the idiosyncrasies of the training set and obtaining a model that works well with the training set but cannot be generalised to new data. Therefore, overfitting should not be disregarded in the evaluation of the models in the following chapter.

3 Quantitative Analysis

As this thesis aims at evaluating recession indicators within a machine learning framework, the models Logistic Regression, Random Forest, and XGBoost discussed in the previous chapter are tested by employing in-sample and out-of-sample tests, as the accuracy of the chosen models is of relevance. This is achieved with selected indicators that are evaluated for their performance in the next chapter. Prior to this, the data and methodology will be discussed.

3.1 Data

This thesis will analyse different recession indicators to obtain a diversified deliverable for a ML framework by employing in-sample and out-of-sample tests. The indicators presented in the following are from the US, as the focus of this thesis is on this specific country. For this thesis, the NBER recession dates, 10-year, 2-year, and 3-month Treasury yields are used as well as the respective spreads. It needs to be clarified that the NBER recession data, as discussed in earlier chapters, either takes a 0 for no recession or a 1 for a recession. In the application of the ML models, primarily the 10-year and 3-month yields as well as the respective spread were considered in the beginning, which as explained in the literature review are very good recession indicators. Since the indicators previously referred to have very little data, additional indicators were fed into the models to have balance and more data. In this respect, it is of relevance whether the models are more accurate due to the expansion of other indicators. The indicators added are unemployment rate, inflation rate, and industrial production as well as a recession probability that derives from a model of the Federal Reserve Bank of New York that uses the slope of the yield curve to calculate the probability of a recession in the US twelve months ahead. All the data for the other indicators are taken from the Federal Reserve database and are on a monthly basis and from 31.05.76 to 31.08.22. Table 5 shows the data used for the ML framework together with some descriptive statistics.

Table 5: Data used for ML Framework

	Date	10 Year Treasury Yield	2 Year Treasury Yield	3 Month Treasury Yield	Spread 10y3m	Spread 10y2y	Rec_prob	Unemployment Rate	Inflation Rate	Industrial Production	NBER_Rec
0	31.05.76	7.900	5.200	5.342	0.013	0.800	0.013	7.600	5.493	3.693	0.000
1	30.06.76	7.860	7.060	5.410	2.299	0.980	0.021	7.800	5.124	3.516	0.000
2	31.07.76	7.830	6.850	5.230	2.456	1.140	0.051	7.800	5.248	3.427	0.000
3	31.08.76	7.770	6.630	5.140	2.490	1.170	0.050	7.600	5.320	3.040	0.000
4	30.09.76	7.590	6.420	5.080	2.372	1.430	0.046	7.700	5.262	2.852	0.000
...	...	...	...	...	...	...	...	...	...	...	...
551	30.04.22	2.750	2.540	0.760	1.978	0.280	0.060	3.600	6.515	4.406	0.000
552	31.05.22	2.900	2.620	0.980	1.904	0.140	0.061	3.600	6.976	3.906	0.000
553	30.06.22	3.140	3.000	1.490	1.624	-0.140	0.071	3.500	6.363	3.980	0.000
554	31.07.22	2.900	3.040	2.230	0.626	-0.350	0.091	3.700	6.223	3.943	0.000
555	31.08.22	2.900	3.250	2.630	0.216	-0.340	0.095	3.500	6.244	5.326	0.000
	count	556.000	556.000	556.000	556.000	556.000	556.000	556.000	556.000	556.000	556.000
	mean	5.948	5.023	4.238	1.566	0.919	0.116	6.208	3.153	1.319	0.104
	std	3.335	3.798	3.581	1.284	0.898	0.160	1.724	2.333	3.567	0.306
	min	0.620	0.120	0.010	-3.505	-2.130	0.001	3.500	-1.467	-17.424	0.000
	0.25	3.000	1.570	0.940	0.707	0.250	0.016	5.000	1.698	0.109	0.000
	0.5	5.645	4.865	4.425	1.637	0.850	0.053	5.900	2.430	2.135	0.000
	0.75	8.073	7.495	6.103	2.541	1.513	0.156	7.300	3.900	3.379	0.000
	max	15.320	16.460	16.300	4.146	2.830	0.954	14.700	11.594	14.066	1.000

Note: Data used for the ML Framework. Source: own representation based on FRED®, Federal Reserve Bank of St. Louis.

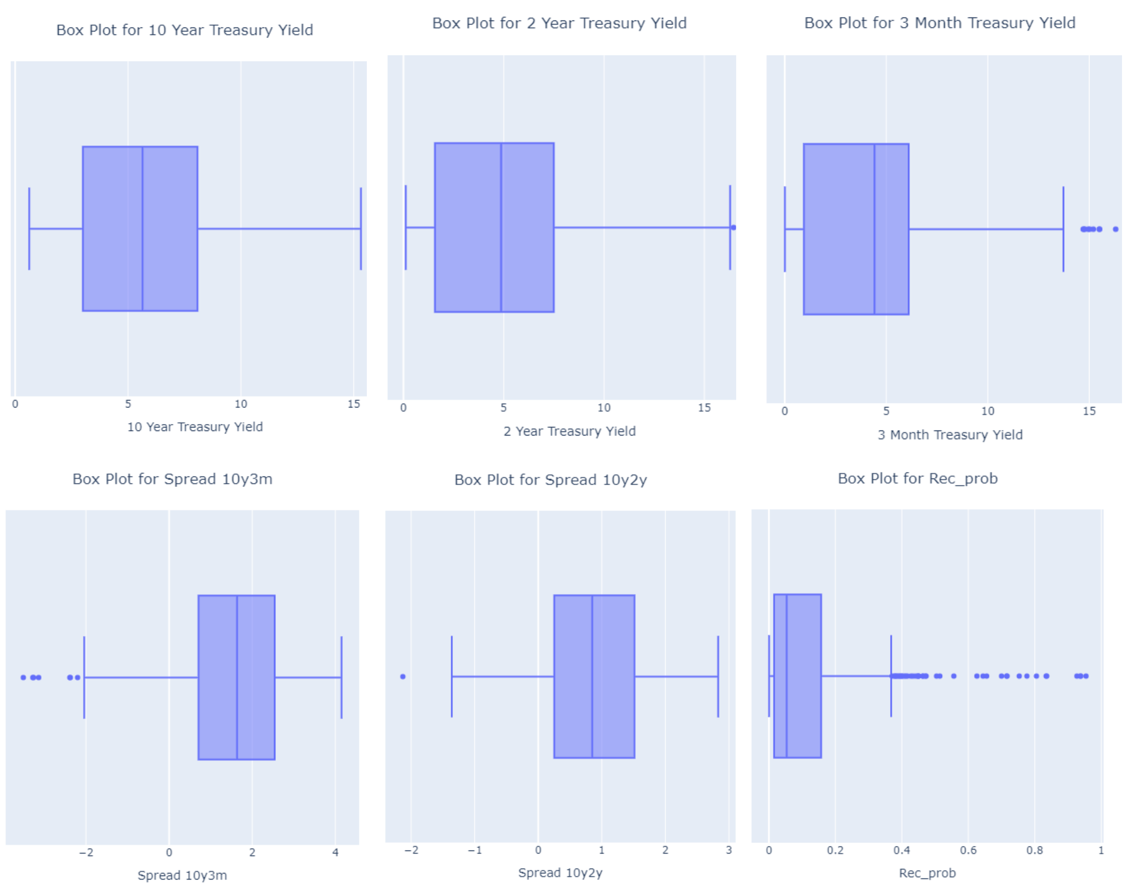
3.1.1 Exploratory Data Analysis (EDA)

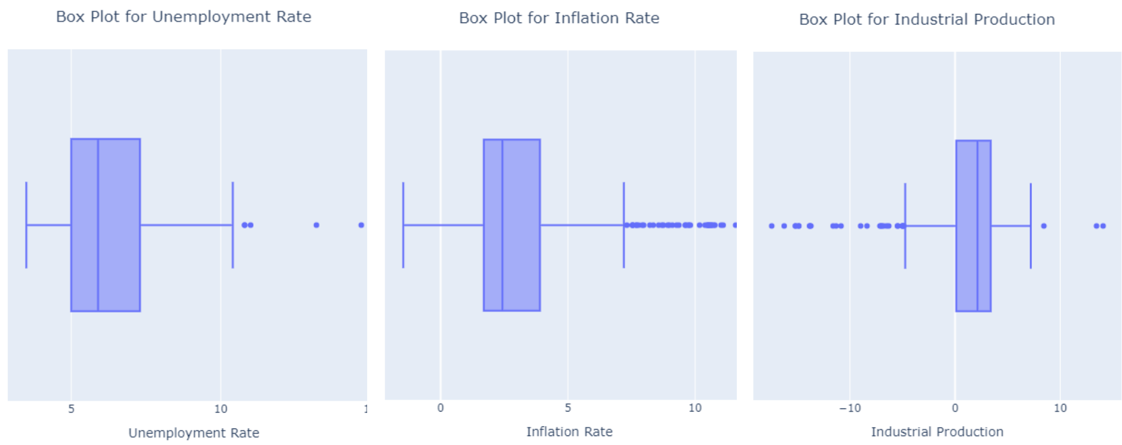
In the next part, an exploratory data analysis is presented in more detail. First the box plots are presented, following by a few line charts and in the end the yearly averages for all indicators. As mentioned before, all the data are on a monthly basis from 31.05.76 to 31.08.22.

3.1.1.1 Box Plots

The following box plots suggest outliers and show the spread of each indicator. It can be observed that there is a greater variability for all the yields presented. For the 3-month Treasury yield there are as well larger outliers in comparison to the other two Treasury yields. It can also be observed that the shorter the maturity of the Treasury yield, the more right skewed it is. The median weights of the three yields are similar. The 10y3m spread, as well as the recession probability, unemployment rate, inflation rate and industrial production have a few outliers.

Figure 15: Box Blots for Selected Indicators



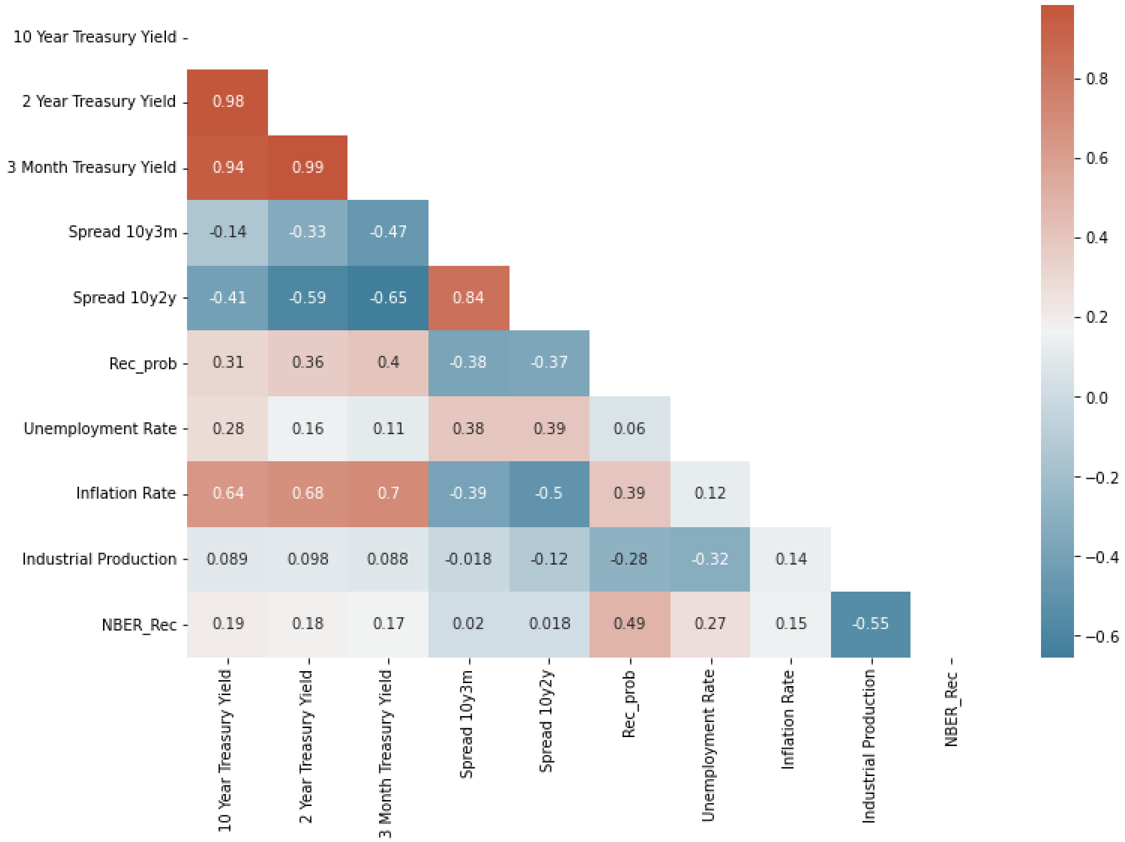


Note: Box Plots. Source: own representation based on FRED®, Federal Reserve Bank of St. Louis.

3.1.1.2 Historical Correlation

Correlation is essentially a statistical tool used to calculate the movement between assets classes in relation to each other. It is an important measure that can be utilized in evaluating the correlation and at which coefficient level individual indicators such as Treasury yields or economic indicators move in the same or opposite direction. In this paper, recession indicators for correlation were used to calculate how closely linked are these indicators considered in our ML models. To understand the correlation coefficient results, it is considered that a -1 value equates to a low or perfectly negative correlation, while a +1 value represents a strong or perfectly positive correlation. In other words, if perfect positive correlation exists both indicators will move in the same direction by the matching percentage, while perfectly negative correlated indicators will proportionally complement each other in terms of gains and losses. On the other hand, when the value of the coefficient is zero, there exists no correlation. Finally, a medium correlation is positive coefficients that are less than +0.5 in value. Therefore, twenty different correlation coefficients were generated to cover the correlations between each indicator in relation to each other. All the different correlations calculated are represented within the correlation heatmap in Figure 16.

Figure 16: Correlation Heatmap



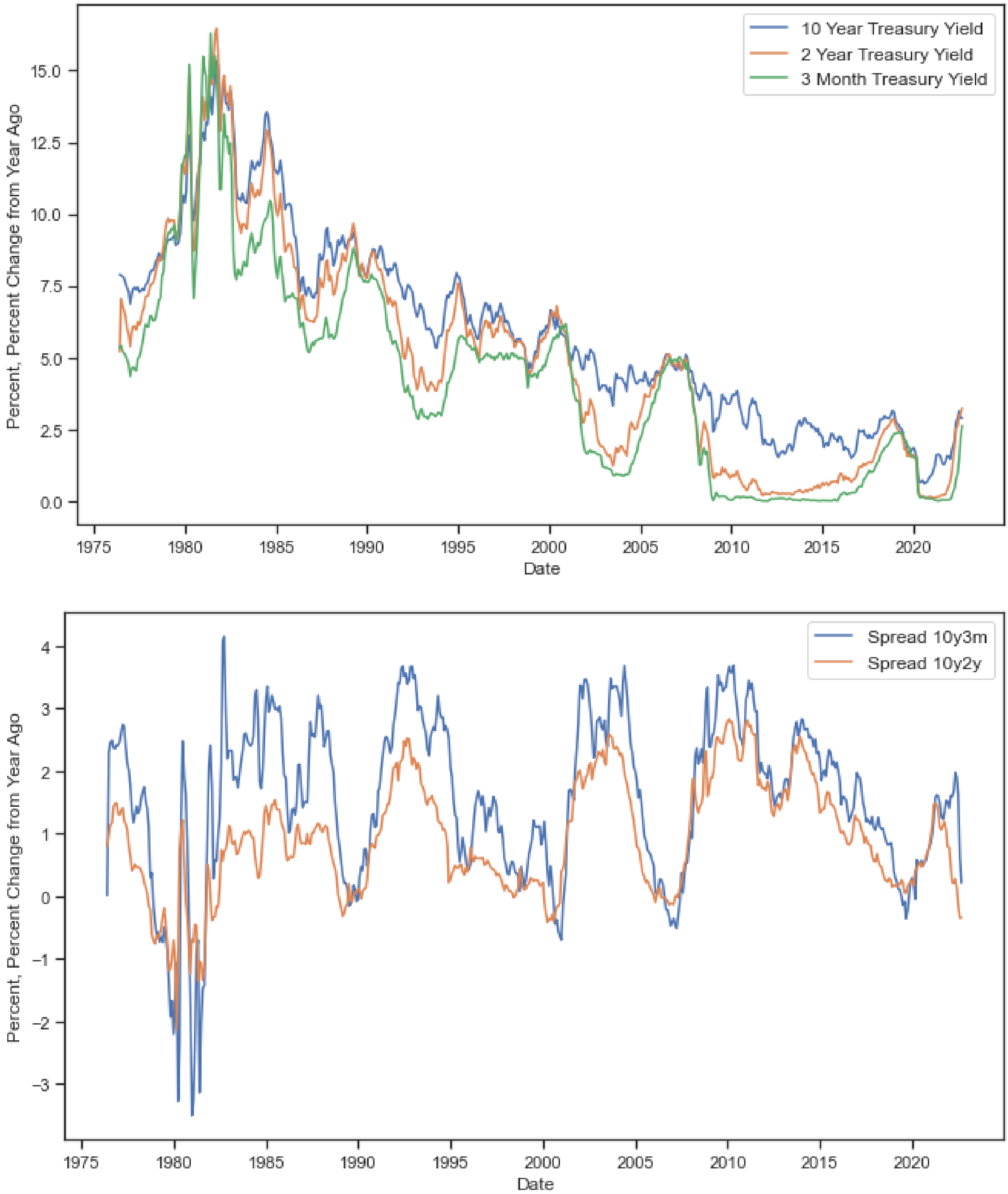
Note: Correlation Heatmap. Source: own representation based on FRED®, Federal Reserve Bank of St. Louis.

The correlation between the 10-year Treasury yield and the other two Treasury yields is calculated at a coefficient of 0.98 and 0,94, which represents a strong correlation between the three indicators, as expected. The correlation between the 2-year Treasury yield and the 3-month Treasury yield is calculated at 0.99, which is the strongest correlation calculated in Figure 16, meaning that the two Treasury yields are the most likely to move in the same direction considering similar levels of volatility. The relationship of the three Treasury yields mentioned before and the 10y3m and 10y2y spread are closely correlated. In fact, the correlation between the 10-year Treasury yield and the two spreads seems to be lower than for the other two Treasury yields. The 3-month Treasury yield shows the highest correlation between the two spreads among the Treasury yields. As expected, the correlation between the two spreads itself represents a strong and positive correlation calculated at a coefficient of 0.84. Recession probabilities are slightly positive correlated with the Treasury yields and slightly negative correlated with the two spreads. Considering the relationship of spreads as early recession indicators, the correlation is reasonable. When it comes to the economic indicators, it can be observed that the unemployment rate has a low positively correlation with all the indicators, besides of industrial production, that has a negative correlation. Inflation is positively correlated with the 10-year, 2-year, and 3-month Treasury yield with coefficients of 0.64, 0.68, and 0.7. When evaluating the correlation between industrial production and the other indicators a low to very low correlation that is close to a zero correlation can be seen. The recessions defined by the NBER have the strongest correlation with industrial production, which is calculated at a coefficient of -0.55 and the recession probability with a coefficient of 0.49. In the following, some line charts, scatterplots, and other diagrams are presented to illustrate some of the indicators

3.1.1.3 Treasury Yields and the Corresponding Spreads

. First the monthly percent change from year ago of the Treasury yields and the corresponding spreads across Date are shown, as illustrated by Figure 17. The strong correlation for the Treasury yields mentioned before can be observed clearly. It can be also said that the three Treasury yields lowered down with time and that they might have a seasonal effect. All yields peaked in the 1980s and it can be observed that all three have risen again considerably in the last two years. Examining the spreads across date, that plots the difference between the yield on 10-year Treasury yields and the yield on 3-month Treasury as well as the difference between the10-year Treasury yields and the yield on 2-year Treasury, it shows the strong correlation between the spreads and that the spreads lowered down around the 1980 dramatically but was somehow cyclic until 2005. If one considers the informative value of the spreads with regard to recession recognition and compares them with the recession data of the NBER, the spreads have always inverted shortly before a recession, as referred to in Section 2.2.3. The inverting of the spreads has happened again this year, as seen in Figure 17 below.

Figure 17:Comparison Treasury Yields and the Corresponding Spreads across Date

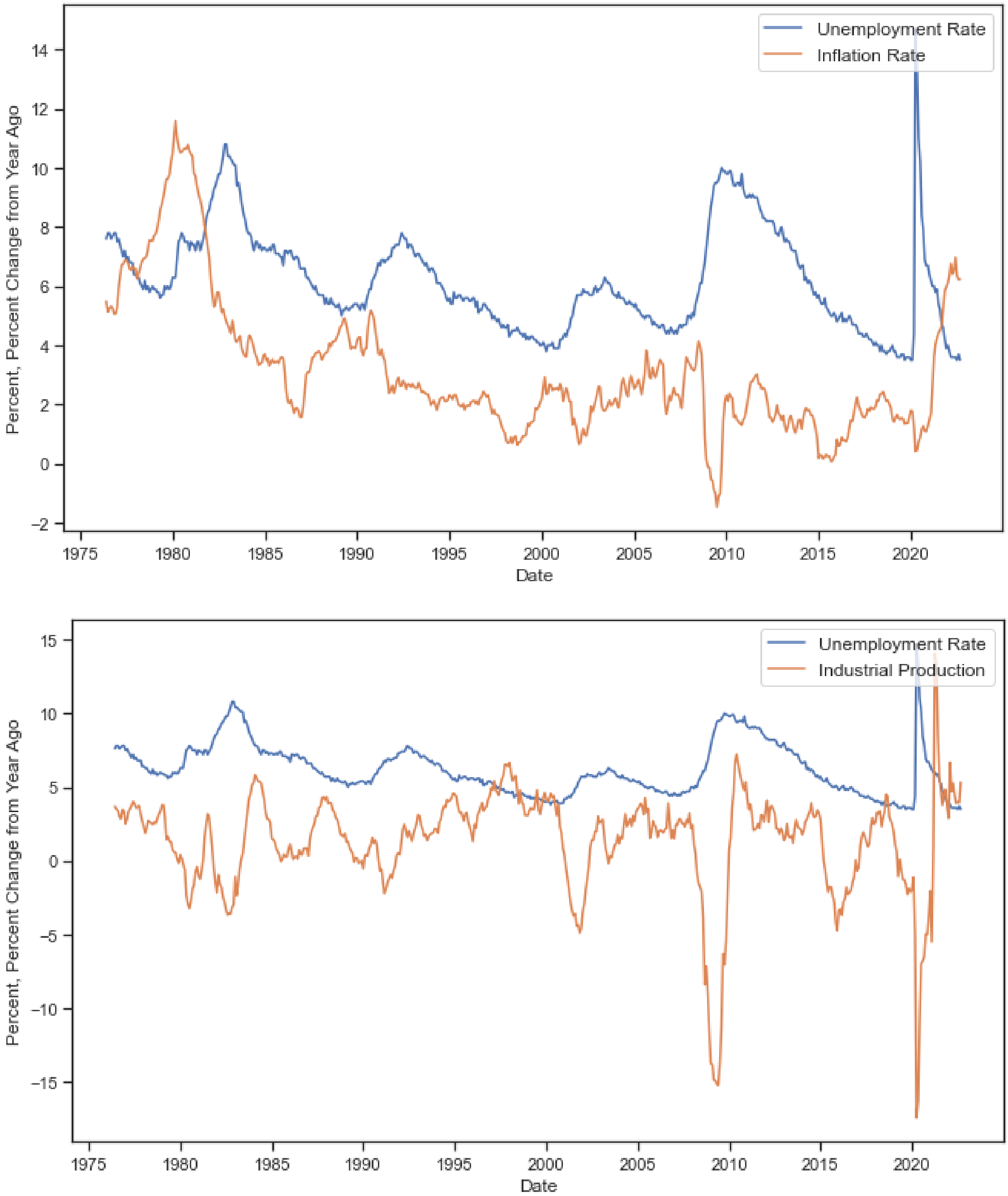


Note: Comparison Treasury Yields and the Corresponding Spreads across Date. Source: own representation based on FRED®, Federal Reserve Bank of St. Louis.

3.1.1.4 Unemployment, Inflation, and Industrial Production

Figure 18 demonstrates a comparison of the unemployment vs. the inflation rate and the unemployment rate vs. the industrial production. It can be said that inflation has historically had an inverse relationship with unemployment, which is also describe as the Phillips Curve discussed in Section 2.1.8.5. There have been less obvious relationships between the two variables in recent decades. Even industrial production seems to have an inverse relationship with unemployment. Furthermore, unemployment seems to have increased after 2020 which might be due to Covid-19 and a lockdown implemented across the country.

Figure 18: Comparison Unemployment vs. Inflation and Unemployment Rate vs. Industrial Production

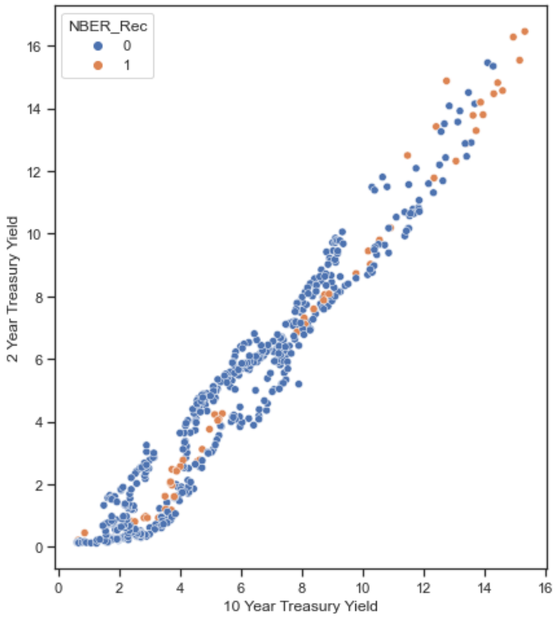


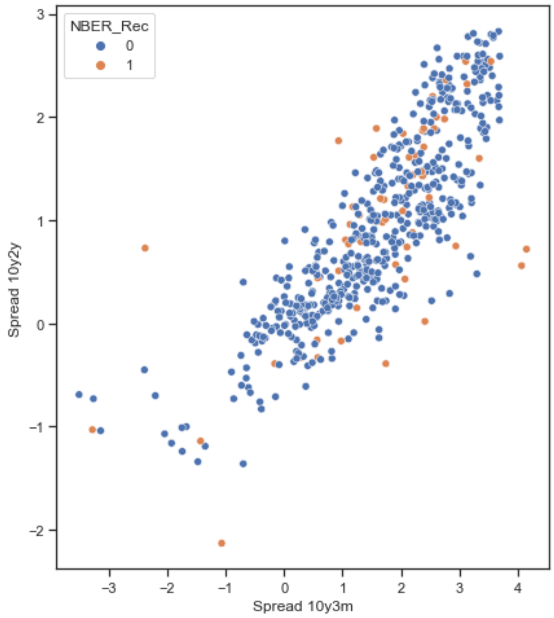
Note: Comparison Unemployment vs. Inflation and Unemployment Rate vs. Industrial Production. Source: own representation based on FRED®, Federal Reserve Bank of St. Louis.

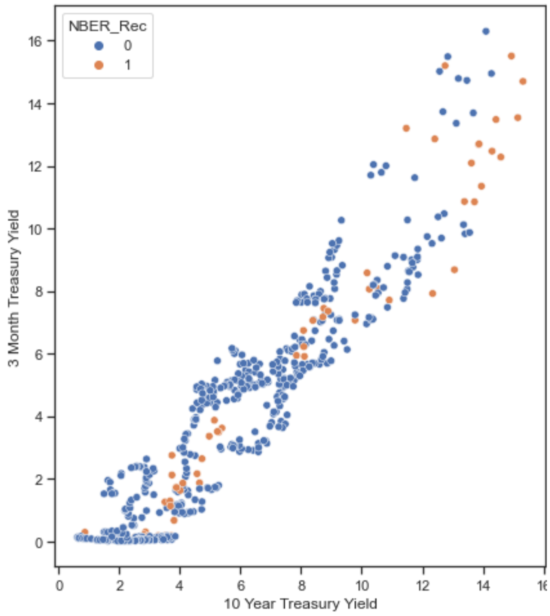
3.1.1.5 NBER Recessions, Treasury Yields, and Corresponding Spreads

Figure 19 demonstrates the correlational relationship between the Treasury yields and the corresponding spreads with an additional third variable that indicates a categorical value, in this case the NBER recession outcome of the value 1 (recession) and 0 (no recession). All the graphs show a positive correlation, so the compared indicators above have a positive association when taking the categorical values of the NBER recession data into consideration. What can be further observed is that NBER recessions were more positive for higher 2-year, 3-month and 10-year Treasury yields. It is also demonstrated that the higher the shorter Treasury yield compared with the 10-year Treasury yield is, the more likely a recession occurs (see Section 2.2.3).

Figure 19: Comparison NBER Recessions, Treasury Yields, and Corresponding Spreads





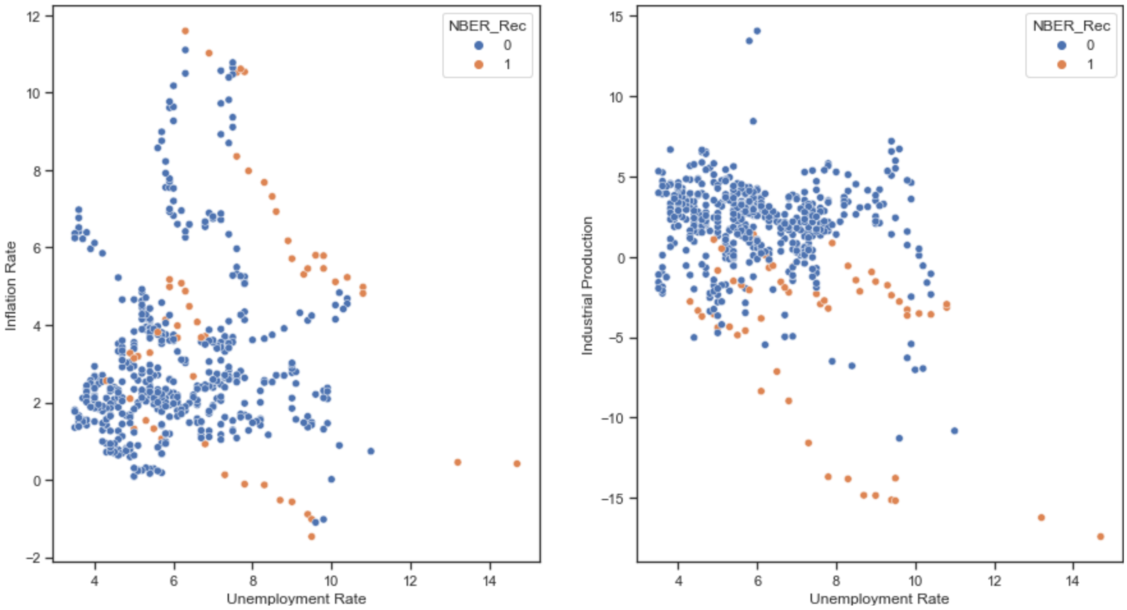


Note: Comparison NBER Recessions, Treasury Yields, and Corresponding Spreads. Source: own representation based on FRED®, Federal Reserve Bank of St. Louis.

3.1.1.6 NBER Recession and Economic Indicators

Figure 20 illustrates the correlational relationship between the unemployment rate, the inflation rate, and industrial production. As before, the additional third variable NBER recession was included. It can be observed that the high unemployment rate generally has more positive NBER recessions, as discussed in Section 2.1.8.5. The figure further demonstrates that with inflation around 2%, fewer recessions tend to occur, as referred in Section 2.1.8. High industrial production seems to be associated with no recessions and the lower the industrial production it has more positive NBER recessions (see Section 2.1.9).

Figure 20: NBER Recession and Economic Indicators

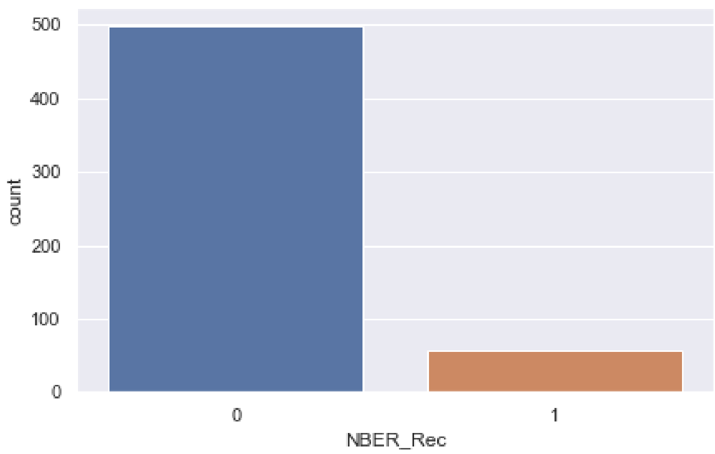


Note: Comparison NBER Recessions, Treasury Yields, and Corresponding Spreads. Source own representation based on FRED®, Federal Reserve Bank of St. Louis.

3.1.1.7 NBER Recession

As discussed in Section 2.3.2.1, when applying binary classification, the issue of imbalanced datasets, which are characterized by a much higher frequency of one data class than the other, is of relevance. Figure 21 demonstrates the NBER recession dataset, which consist of O's (no recession) and 1's (recession). As demonstrated in Figure 20, the NBER recession dataset is unbalanced, as there were much more periods without a recession than otherwise. This needs to be considered as for the ML framework the models will emphasize the positive class.

Figure 21: The NBER Recession Data Count

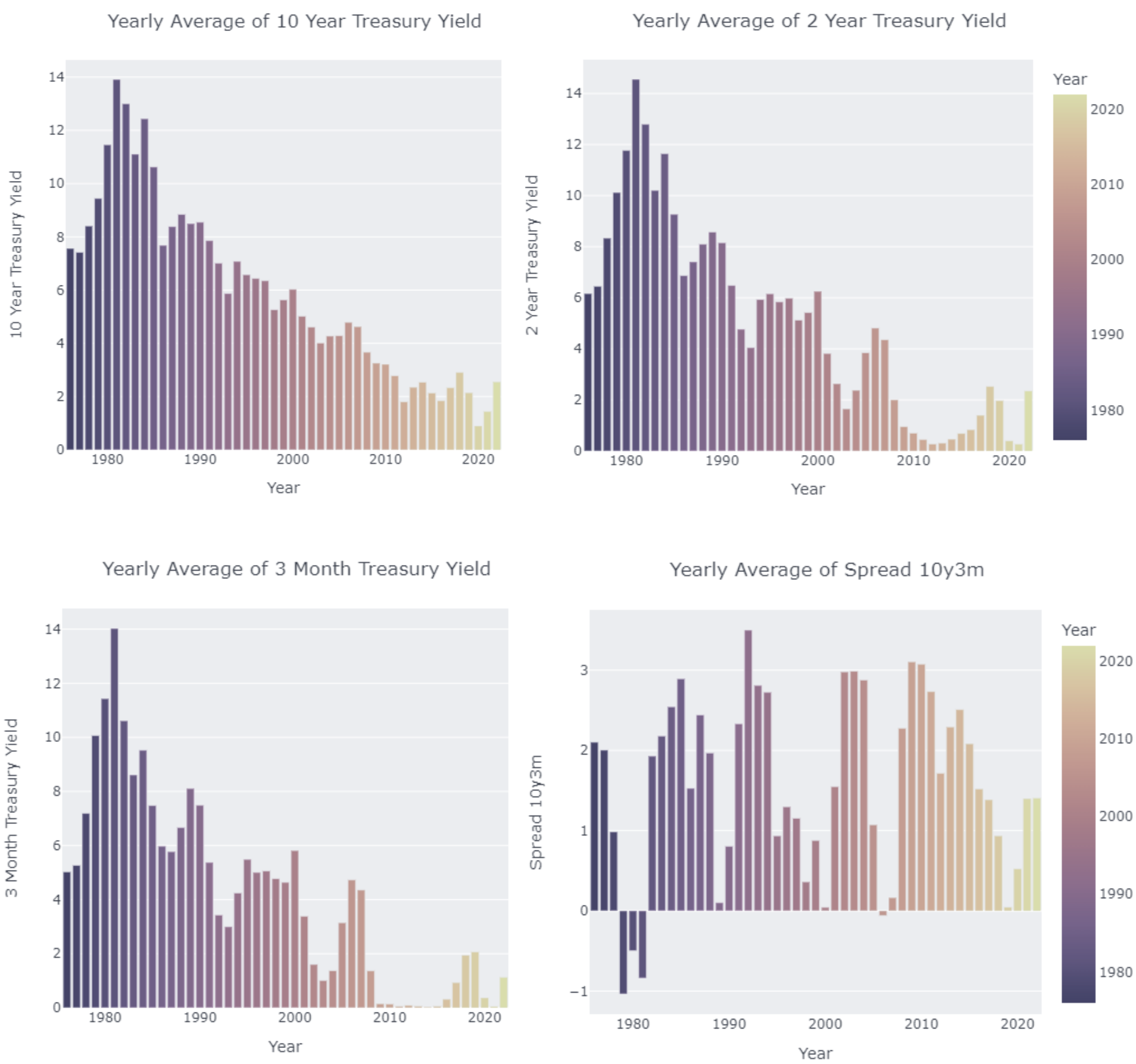


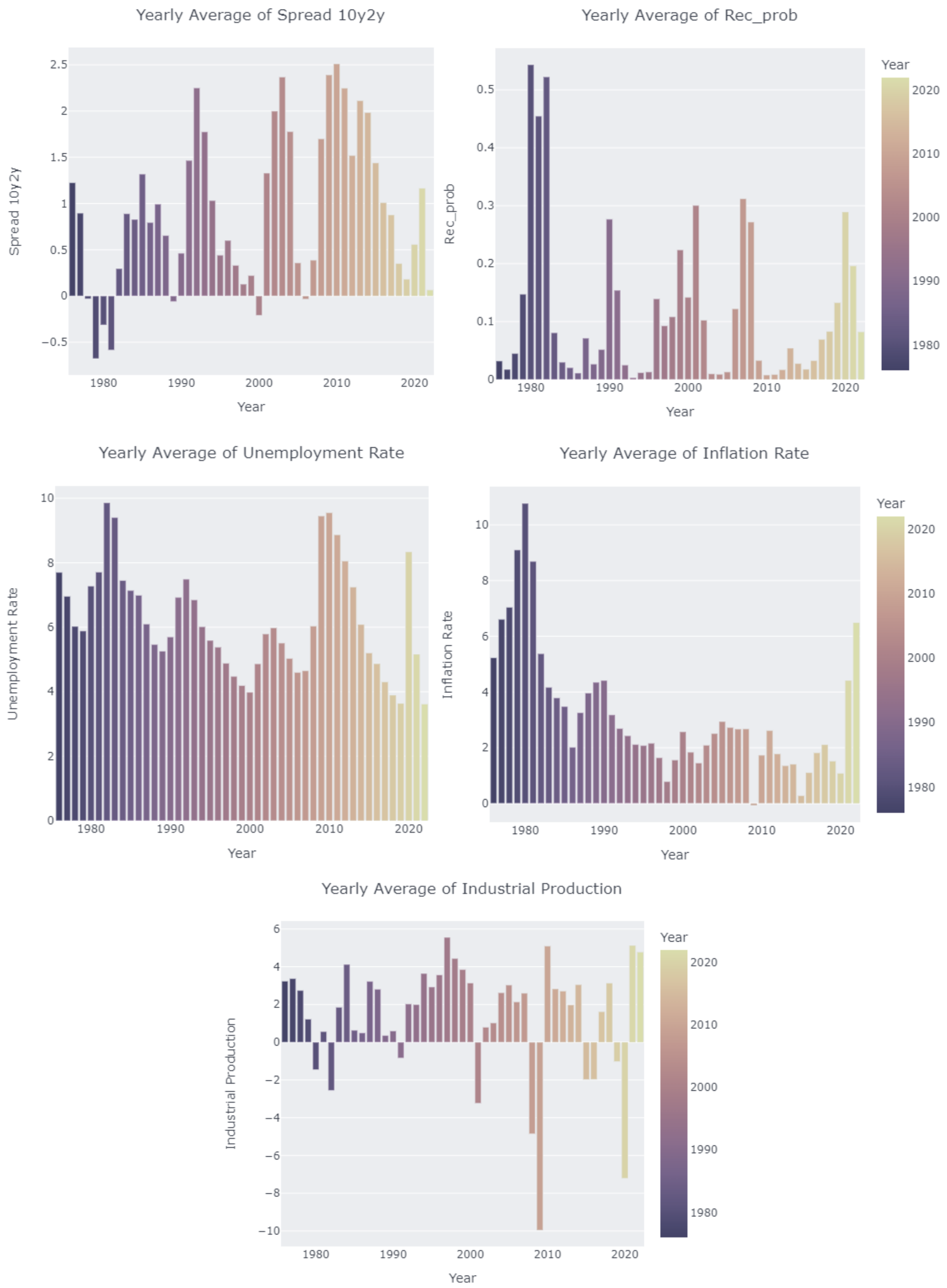
Note: The NBER Recession Data Count. Source: own representation based on FRED®, Federal Reserve Bank of St. Louis.

3.1.1.8 Yearly Averages for all Indicators

For the purpose of completeness, the yearly averages of the respective indicators is shown below. As the indicators selected for the ML framework are specified and described, the methodology is further elaborated in the following chapter.

Figure 22: Yearly Average of all Indicators





Note: Yearly Average of all Indicators. Source: own representation based on FRED®, Federal Reserve Bank of St. Louis.

3.2 Methodology

For the ML framework, the selected models applied are Logistic Regression, Random Forest, and XGBoost. This chapter will explain how the indicators were evaluated with the different ML models described before. Therefore, Table 6 shows the ML procedure that was applied when evaluating the recession indicators. Three jupyter notebooks were created for different combination of indicators used in each of them. Notebook A takes only the 10-year and 3-month Treasury yield, the 10y-3m spread, and the NBER recession dataset into consideration. Notebook B additionally uses the 2-year Treasury yield as well as the 10y-2y spread. Finally, Notebook C adds economic indicators.

Next, the individual steps are described in more detail, as shown in Table 6. In a first step, the unbalanced data (1) is used in every notebook first to see how the models perform. Although the unbalanced dataset would therefore most likely affect the training and bias the prediction, it is exactly why this step is carried out in order to show the differences in performance when applying the other steps. With the unbalanced data, a binary classification (b) is applied, where the unbalanced dataset is randomly spitted (c) into training (75%) and test set (25%), as presented in Section 2.3.1. In addition, the data is scaled (c) in a further step. After scaling the data, the models are built (d) and evaluated (e). Steps (a) to (e) are repeated for step (2), where the unbalanced dataset is balanced by using a data transformer called smote. Lastly, features extraction (3) is applied by principal components analysis. For the feature extraction the steps (a) to (e) are applied as well. The explained procedure is then also applied in Notebook B and Notebook C for the added indicators to see differences in the model's performance.

Table 6: Evaluation of Recession Indicators within ML Framwork

Indicators used		
NOTEBOOK A: -10-year and 3-month Treasury yield -10y-3m Spread -NBER Recession Dataset	*NOTEBOOK B:* -10-year, 2- year, and 3-month Treasury yields -10y-3m and 10y-2y Spread -NBER Recession Dataset	*NOTEBOOK C:* -10-year, 2- year, and 3-month Treasury yields -10y-3m and 10y-2y Spread -Economic Indicators -NBER Recession Dataset

Steps	**Actions**
1	*Unbalanced Data*
a)	*Binary Classification*
b)	*Spliting the Data*
c)	*Scaling the Data*

d)	*Building the Models*
e)	*Evaluating the Models*
2	*Balancing Data*
a) ... e)	*Binary Classification…Evaluating the Models*
3	*Feature Extraction*
a) ... e)	*Binary Classification…Evaluating the Models*

Note: Methodology of the Evaluation of Recession Indicators within ML Framework. Source: own representation.

3.3 Results

After explaining the methodology, in this chapter the results, specifically the evaluations made in step (e) mentioned before, are explained. Therefore, the classification reports of each model is shown for every notebook in Appendix 1-3. The respective confusion matrices and ROC curves can be found in Appendix 1-3 as well. First, the results of the evaluations of Appendix 1 is discussed, beginning with the results of the unbalanced data and ending with the results after feature extraction. The same approach is used for the results presented in Appendix 2 and 3.

3.3.1 Results Notebook A

The Notebook in Appendix 1 shows the jupyter notebook with the python codes needed to evaluate the indicators chosen and explained before. The indicators chosen for notebook A are the 10-year and 3-month Treasury yield, 10y-3m Spread, and the NBER recession dataset. It needs to be mentioned that for this notebook, dates from January 1959 are selected. The reason for this was that with the few indicators, the problem of sufficient data would otherwise arise. For the other two notebooks, data from 31.06.76 - 31.08.22 were chosen as described above. In a further step, the results of the evaluation with non-balanced and balanced NBER data, as well as that with feature extraction, are discussed.

3.3.1.1 Unbalanced Data Results

Looking at the results in Appendix 1, it is clear to observe that for the unbalanced data the model's accuracy is very high. However, caution is required here. Considering the ratio of the number of recessions and the number of non-recessions, which in this case is 0.87, this mark should be used by the models as a comparison value. Taking that into consideration and based on the metrics described in Appendix 1, the best performed models are the random forest model with an accuracy of 0.89 and the logistic regression model with an accuracy of 0.88. However, these figures can be deceptive if a closer look is taken at the confusion matrix, as seen in Appendix 1. Therefore, the models were very accurate in detecting the non-recession values but performed very poorly in detecting the recessions. This indicates that the problem is with the unbalanced data, as stated in Section 2.3.2.3. Therefore, the results of the balanced data are presented below.

3.3.1.2 Balanced Data Results

Appendix 1 provides after the results presented before, the performance of the models using smote. Smote is a data transformer that in this case was able to create synthetic data for oversampling the group that is underrepresented in the NBER recession dataset. Before smote, the count of the label '1' was 72. After using smote the count of the label increased to 501, as the count of the label '0'. Having a look at Appendix 1 and the performances achieved using smote, it is observed that the accuracy decreased for the logistic regression model and the XGBoost. The random forest model performed the same with an accuracy of 0.89 as in the unbalanced dataset before. In comparison to the unbalanced dataset, each model performed better detecting the recession and non-recession data. Although the random forest model performed best when taking accuracy as a measure, still the logistic regression model and the XGBoost were able to detect the recession values better.

3.3.1.3 Feature Extraction Results

To have another comparison to the results mentioned before, PCA feature extraction was used for the process of the data given to create numerical features. The results in Appendix 1 show that by feature extraction, the model preforming best is random forest, with an accuracy of 0.85, followed by logistic regression, with an accuracy of 0.68. Especially logistic regression and XGBoost performed worse in comparison with the application of smote. However, the feature extraction XGBoost was able to detect recession better than in all other examples. Random Forest was able to determine the number of non-recessions better through feature extraction than smote, but had to give in the accuracy of recession detection.

3.3.2 Results Notebook B

The Notebook in Appendix 2 shows the jupyter notebook with the python codes needed to evaluate the indicators chosen and explained before. The indicators chosen for

Notebook B were the 10-year, 2-year, and 3-month Treasury yield, 10y-2y and 10y-3m Spread, and the NBER recession dataset. As only the 2-year yield curve and the 10y-2y spread were implemented, the discussion about the results is kept short. As demonstrated in Appendix 2, with the new data, there is a knew ratio of the number of recessions and the number of non-recessions, which in this case is 0.89, this mark should be used by the models as a comparison value. What can be said by observing the results is that for the unbalanced data the model's accuracy are all very high. Based on the metrics in Appendix 2, the best performed models were random forest with an accuracy of 0.95 and logistic regression with an accuracy of 0.92. In comparison to notebook A, the model logistic regression and random forest were able to detect in notebook B the recession much better. Only the XGBoost Model was not able to detect any recessions. By applying smote, the XGBoost model and logistic regression have lost in accuracy. However, the model XGBoost and logistic regression performed very well on recession detection. Based on the metrics shown in Appendix 2, the best performed models are therefore random forest with an accuracy 0.96 and logistic regression with 0.87. For the feature extraction, the models logistic regression and XGBoost performed again very weakly. The random foreset model in comparison outperformed the other two models by far. It achieved a accuracy of 0.96, whereas the logistic regression achieved 0.42 and XBoost 0.29.

3.3.3 Results Notebook C

The Notebook in Appendix 3 shows the jupyter notebook with the python codes needed to evaluate the indicators chosen and explained before. The indicators chosen for notebook C were the 10-year, 2- year, and 3-month Treasury yields, 10y-3m and 10y-2y Spread, chosen economic indicators mentioned in Chapter 2, and the NBER recession dataset. In a further step, the results of the evaluation with rebalanced and balanced data, as well as that with feature extraction, are discussed.

3.3.3.1 Unbalanced Data Results

Looking at the results in Appendix 3, it can be observed that for the unbalanced data the model's accuracy is very high. However, caution is required here. Considering the ratio of 0.89, this mark should be used by the models as a comparison value. Taking that into consideration and based on the metrics described in Appendix 3, the best performed models are the random forest model with an accuracy of 0.94 and the logistic regression model with an accuracy of 0.88. This may be due to the fact that the models can now be better trained with the economic data and therefore also achieve better results. Therefore, the models were more accurate than with less data when it comes to detecting the non-recession values. Next, the results of the balanced data are presented.

3.3.3.2 Balanced Data Results

Appendix 3 provides after the results presented before, the performance of the models using smote. Smote is a data transformer that in this case was able to create synthetic data for oversampling the group that is underrepresented in the NBER recession dataset. Before smote, the count of the label '1' was 72. After using smote the count of the label increased to 501, as the count of the label '0'. Having a look at Appendix 3 and the performances achieved using smote, it is observed that the accuracy decreased for the logistic regression model and the XGBoost. The random forest model performed the even better with an accuracy of 0.96 as in the unbalanced dataset before. These results correlate with the results presented in Appendix 1. In comparison to the unbalanced dataset, each model performed better detecting the recession and non-recession data. Although the random forest model performed best when taking accuracy as a measure, still the logistic regression model and the XGBoost were able to detect the recession values better.

3.3.3.3 Feature Extraction Results

The results in Appendix 3 show that by feature extraction, the model preforming best is random forest, with an accuracy of 0.94, followed by XGBoost, with an accuracy of 0.74. Especially logistic regression and XGBoost performed worse in comparison with the application of smote. However, the feature extraction XGBoost was able to detect recession better than in all other examples. Random Forest was able to determine the number of non-recessions better through feature extraction than smote but had to give in the accuracy of recession detection. These results correlate with the results presented in Appendix 1.

4 Conclusion

This thesis concludes with a discussion of its main findings. In Section 4.1, the research question discussed in the introduction is addressed. In addition, results are discussed and interpreted. It is achieved by integrating the literature review with the quantitative analysis presented in this thesis. There is an explanation of this thesis' limitations in Section 4.2. The implications for future research are discussed in Section 4.3.

4.1 Discussion of Results

This thesis aimed to understand the mechanism behind interest rate levels, the form of the yield curve, inflation, and the economy as well as the stock market. The policy of the FED needed to be understood and analysed given the background of its historical actions. Furthermore, a machine learning framework had to be built for trying to evaluate recession indicators. These topics were addressed by the thesis in order to answer the following question:

- What are the linking changes in the interest rate structure—such as the inversion of the yield curve, inflation, the economy, and the stock market—and can the inverted yield curve forecast if a recession is imminent?
- Which recession indicators are best at forecasting U.S. recessions within a machine learning framework, and which machine learning model performs best?

For the first question, the literature review revealed that the monetary policy in the Fed aims to achieve its statutory mandate objectives: maximum employment, stable prices, and moderate long-term interest rates. Regarding price stability, the literature review showed that the committee makes a particular judgment about a 2% inflation rate measured by the annual change in the Price Index for Personal Consumption Expenditures (PCE). Specifically, it considers a 2% interest rate most consistent over the longer run with the Federal Reserve's statutory mandate. As inflation increased, the Fed hat to increase interest rates as a reaction of high inflation by affecting the money supply and its real impact on the FFR. Longer-term interest rates and asset classes show a responsiveness to changes in the existing and targeted FFR. In this regard, consumer expectations regarding the future development of the key interest rate impact both medium- and longer-term interest rates. If borrowers and lenders currently assume that the FOMC will lower the policy rate substantially in the coming years, medium- and long-term interest rates will reflect these expectations. As a result, interest rates will be lower than they otherwise would have been. Moreover, households and businesses make purchasing decisions based on long-term interest rates, which affect economic performance, employment, and inflation. As the Fed was recently criticized for not achieving its goals of stability and low inflation. This resulted several advocated changes, including alterations to the policy and unconventional monetary policy, that became during the last decade very important. According to the literature, expansionary (contractionary) monetary policy impacts the stock market positively (negatively). Therefore, changes in the federal funds rate, for example, have the greatest direct and instantaneous effect on financial markets. Policymakers attempt to influence economic behaviour such that it helps them achieve their ultimate goals by influencing asset prices and yields. An example on the impact on markets that is corporate bond yields rise following an increase in bond purchases by the FOMC. When it comes to inflation, as long as unemployment or price levels are below the Fed's targets, the Fed will stimulate the money supply and tighten policy if price levels are higher. As economic activity fluctuates over time, it typically occurs in spurts of increased activity, called expansions, and decreased activity, called recessions. This thesis showed that the term-spread can be a very good indicator for predicting recessions. Especially taking into consideration that that inflation and real output fluctuations can be forecasted using the yield curve because it contains information about future interest rates.

For second question, it can be concluded that yield curves and their respective spreads can be good indicators for recession prediction. This thesis showed that with less data, using only the 10y and 3m Treasury yield, the corresponding spread, as well as the NBER recession dataset. ML framework ideally suited for this purpose. In conclusion it can be said that the yield curve alone is not structural but is dependent upon monetary policy. For that reason, other macroeconomic variables have predictive power and can help improve recession forecasting accuracy.

4.2 Limitations of Study

The limitation of the thesis is that it was not possible to forecast whether a recession was imminent or not. Since many mechanisms are interrelated, a prognosis is very difficult. Furthermore, the selection of indicators regarding recession is highly discussed in the literature and other indicators might have also being taken into consideration, as this thesis used the ones discussed in the literature review.

4.3 Implication for Further Reasearch

For a wide implementation, a recession prognose can be made in the future using machine learning. In this respect, the models provide a very exciting environment.

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Appendix

Appendix 1 Jupiter Notebook A

This section shows the Jupiter notebook A. The data is not from an Excel spreadsheet provided separately.

Binary classification

Split the data

```
from sklearn.model_selection import train_test_split
train,test = train_test_split(df,test_size=0.25,random_state=1,shuffle=True)

xtrain= train.drop(labels=["NBER_Rec"],axis=1)
ytrain = train["NBER_Rec"]

Xtest= test.drop(labels=["NBER_Rec"],axis=1)
ytest = test["NBER_Rec"]

print(" counts of label '1' in Train Set: {}".format(sum(ytrain == 1)))
print(" counts of label '0'in Train Set : {} \n".format(sum(ytrain == 0)))
```

```
 counts of label '1' in Train Set: 44
 counts of label '0'in Train Set : 373
```

```
373/44 #### The proportion
```

```
8.477272727272727
```

```
print(" counts of label '1' in Test Set: {}".format(sum(ytest == 1)))
print(" counts of label '0' in Test Set: {} \n".format(sum(ytest == 0)))
```

```
 counts of label '1' in Test Set: 14
 counts of label '0' in Test Set: 126
```

```
126/14   #### The proportion
```

```
9.0
```

Scale the data

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
xtrain_sc = sc.fit_transform(xtrain)
Xtest_sc = sc.transform(Xtest)
```

Build models

Logistic Regression

```
#logistic regression
from sklearn import linear_model
logr = linear_model.LogisticRegression()
logr.fit(xtrain_sc,ytrain)
```

```
LogisticRegression()
```

Random Decision Forest

```
rf = RandomForestClassifier(n_estimators=400,criterion="entropy")
rf = rf.fit(xtrain_sc, ytrain)
```

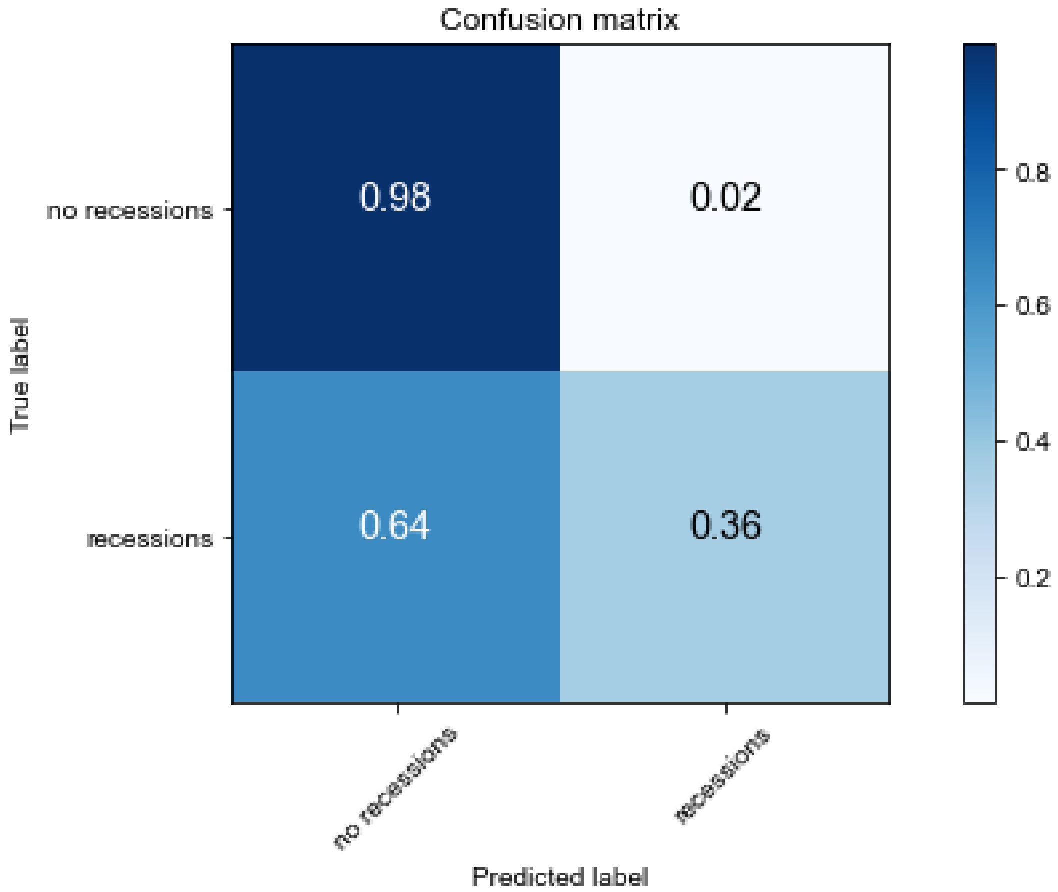
XGBoost

```
xg_reg = xgb.XGBRegressor(objective ='binary:logistic', colsample_bytree = 0.2, learn
ing_rate = 0.1,
                max_depth = 5, alpha = 10, n_estimators = 50)

xg_reg.fit(xtrain_sc,ytrain)

XGBRegressor(alpha=10, base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=0.2,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.1, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=5, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=50, n_jobs=0,
             num_parallel_tree=1, objective='binary:logistic', predictor='auto',
             random_state=0, ...)
```

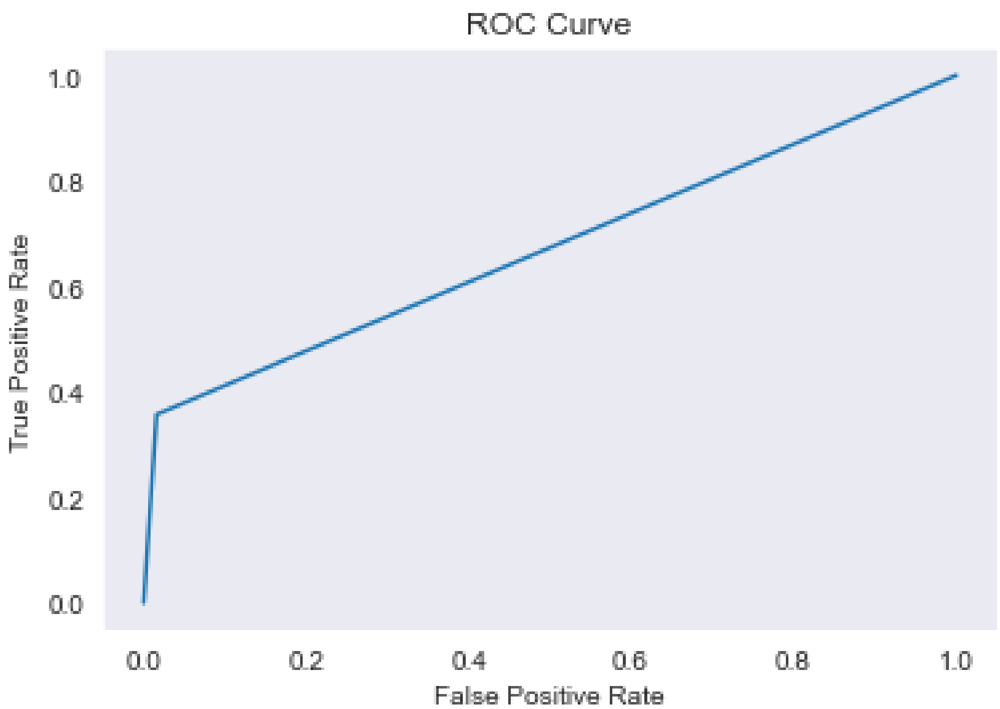
Evaluation of the models

Logistic Regression Evaluation

```
print(" Logisitc Regresion Evaluation")

ypred_logr = logr.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_logr,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_logr)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_logr, target_names=target_names))


 Logisitc Regresion Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```



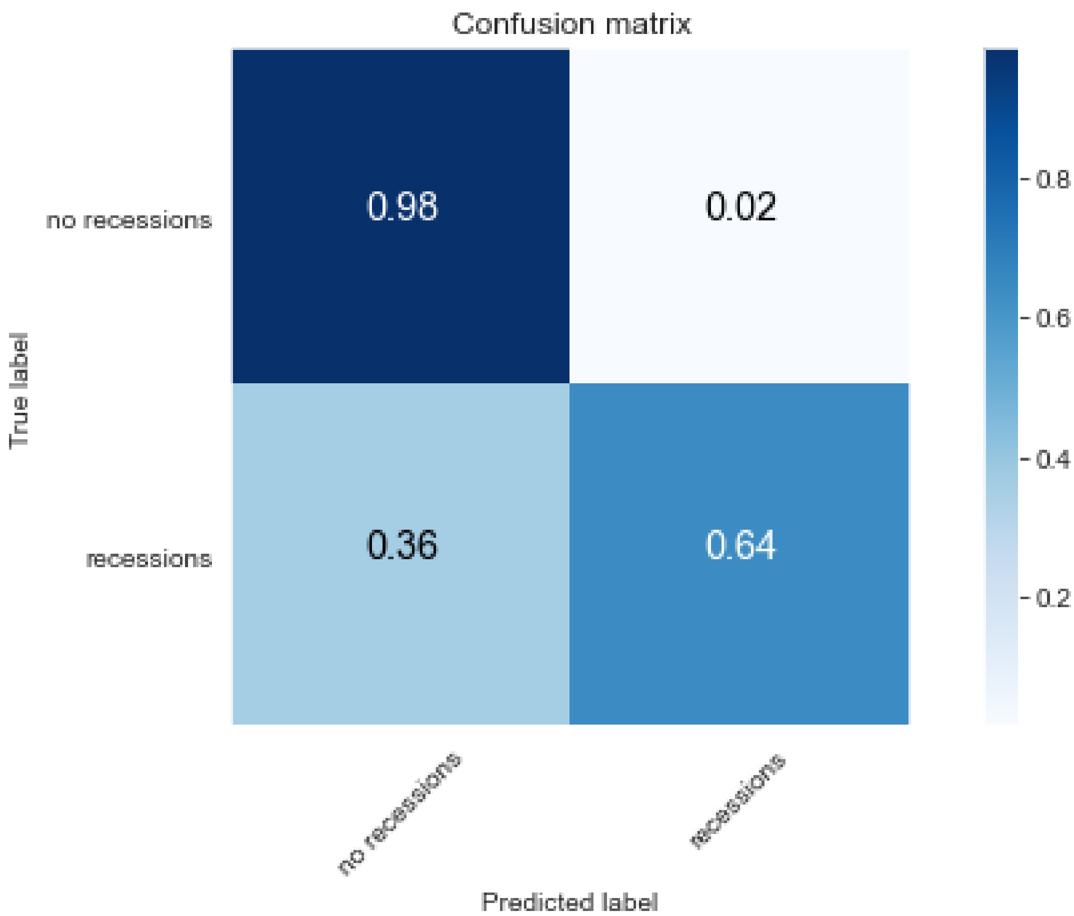

```
 Classificatin Report
               precision    recall  f1-score   support

no recessions       0.93      0.98      0.96       126
```

```
  recessions       0.71      0.36      0.48        14

    accuracy                           0.92       140
   macro avg       0.82      0.67      0.72       140
weighted avg       0.91      0.92      0.91       140
```

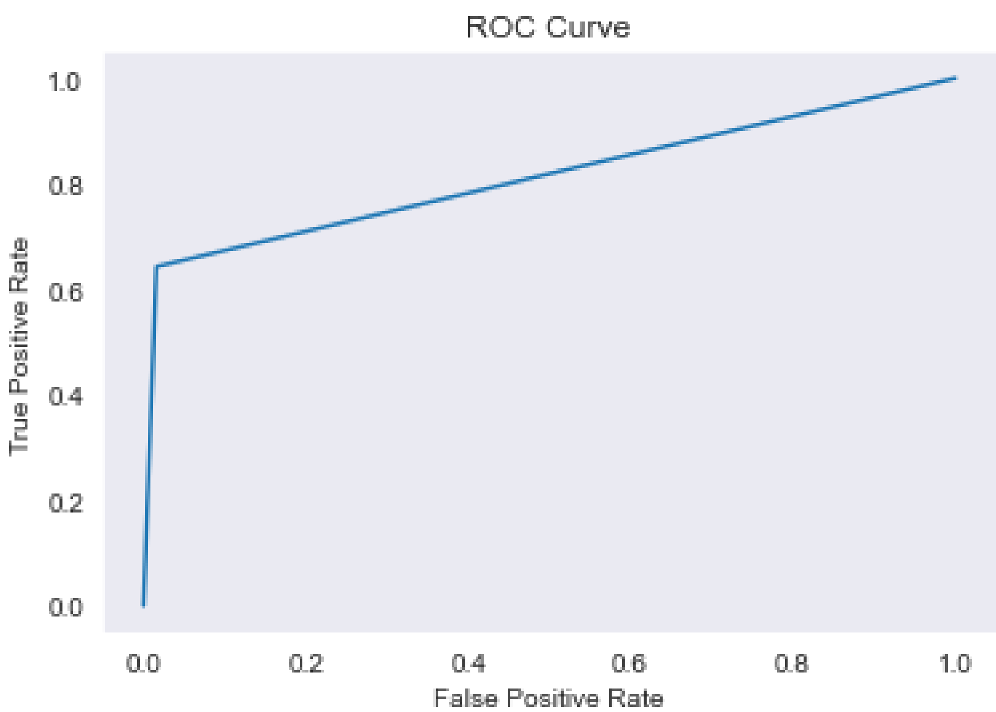
Random Forest Evaluation

```
print(" Random Forest Evaluation")

rf = RandomForestClassifier(n_estimators=300)
rf = rf.fit(xtrain_sc, ytrain)
ypred_rf = rf.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_rf,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_rf)

#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest,ypred_rf, target_names=target_names))
```

```
 Random Forest Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```



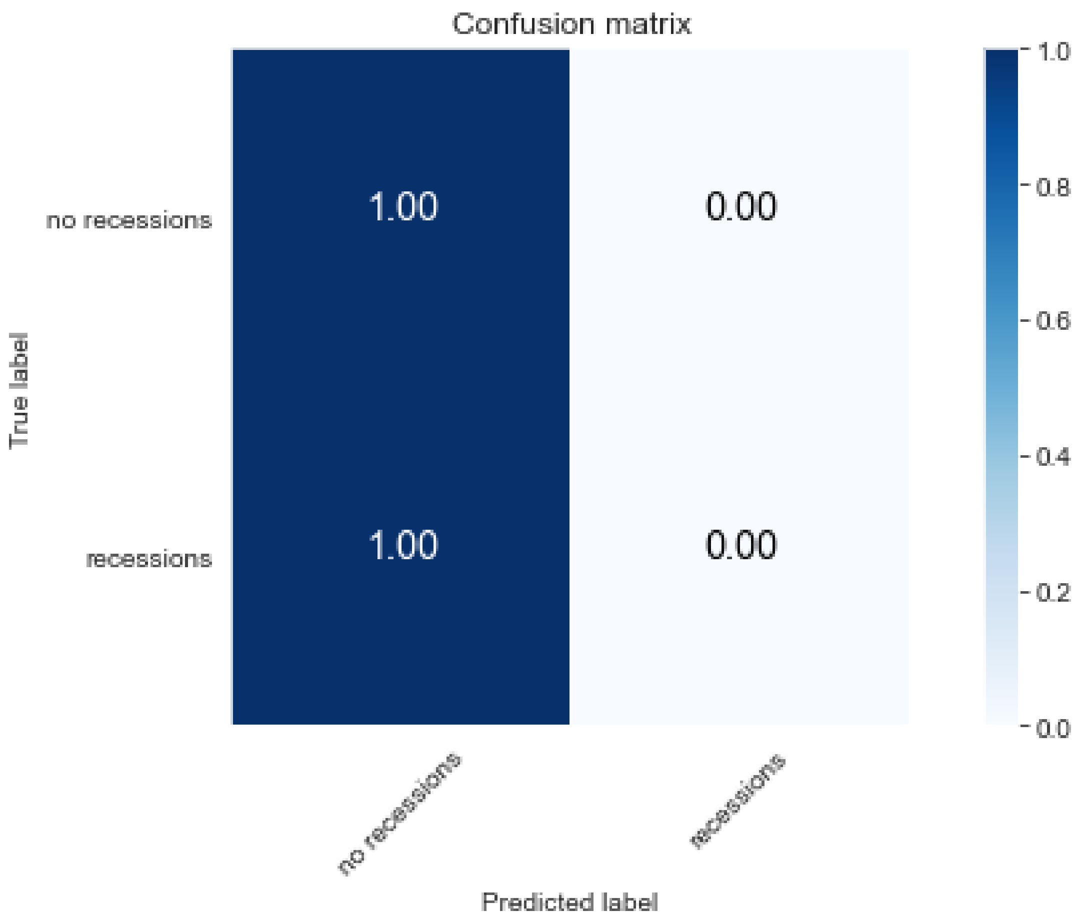

```
 Classificatin Report
               precision    recall  f1-score   support

no recessions       0.96      0.98      0.97       126
```

```
  recessions       0.82      0.64      0.72        14

    accuracy                           0.95       140
   macro avg       0.89      0.81      0.85       140
weighted avg       0.95      0.95      0.95       140
```

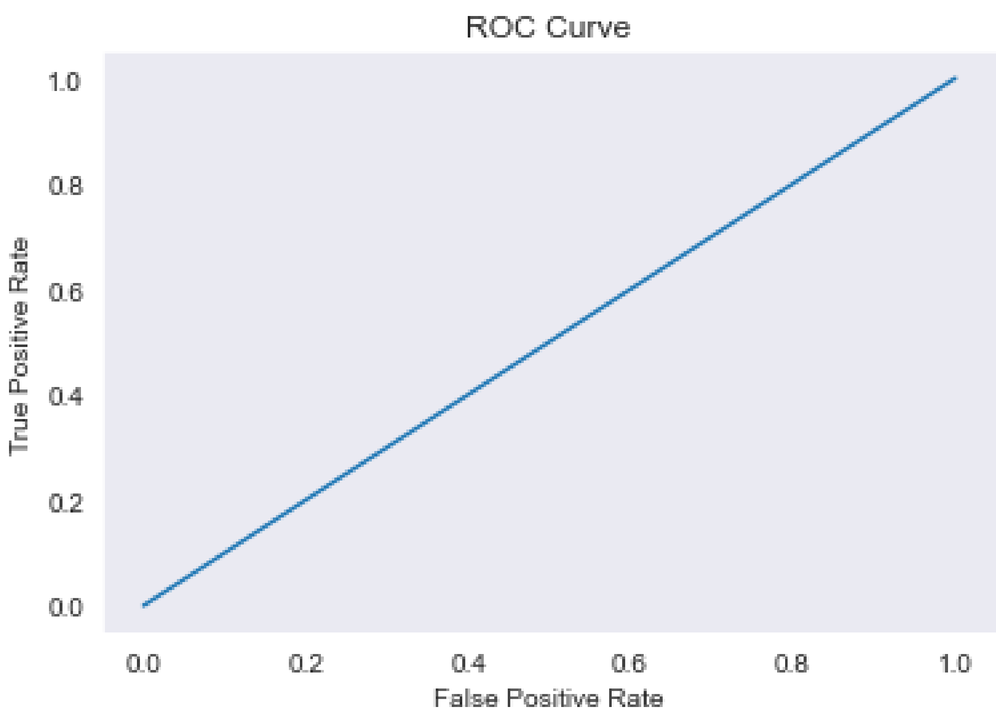
XGBoost Evaluation

```
print(" XgBoost   Evaluation")

ypred_xg= xg_reg.predict(Xtest_sc)

for i,val in enumerate(ypred_xg):
    if val>=0.5:
        ypred_xg[i]=1
    else:
        ypred_xg[i]=0
plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_xg,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_xg)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_xg, target_names=target_names))
```

```
 XgBoost   Evaluation
```



<Figure size 432x288 with 0 Axes>




```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       0.90      1.00      0.95       126
```

```
   recessions       0.00      0.00      0.00        14

     accuracy                           0.90       140
    macro avg       0.45      0.50      0.47       140
 weighted avg       0.81      0.90      0.85       140


C:\Users\doren\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control this behav
ior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\doren\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control this behav
ior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\doren\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control this behav
ior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Conclusion

Based on the metrics above the best performed models are:

- Random Forest with 0.95 accuracy
- Logistic Regressoin with 0.92 accuracy

Models using Balanced Data (SMOTE)

```
print("Before OverSampling, counts of label '1': {}".format(sum(ytrain == 1)))
print("Before OverSampling, counts of label '0': {} \n".format(sum(ytrain == 0)))

from imblearn.over_sampling import SMOTE

sm = SMOTE(k_neighbors=5,random_state = 100)
X_train_res, y_train_res = sm.fit_resample(xtrain_sc, ytrain.ravel())

print('After OverSampling, the shape of train_X: {}'.format(X_train_res.shape))
print('After OverSampling, the shape of train_y: {} \n'.format(y_train_res.shape))

print("After OverSampling, counts of label '1': {}".format(sum(y_train_res == 1)))
print("After OverSampling, counts of label '0': {}".format(sum(y_train_res == 0)))
```

```
Before OverSampling, counts of label '1': 44
Before OverSampling, counts of label '0': 373

After OverSampling, the shape of train_X: (746, 6)
After OverSampling, the shape of train_y: (746,)

After OverSampling, counts of label '1': 373
After OverSampling, counts of label '0': 373
```

Logistic Regression

```
#logistic regression
from sklearn import linear_model
logr = linear_model.LogisticRegression()
logr.fit(X_train_res, y_train_res)
```

```
LogisticRegression()
```

Random Decision Forest

```
rf = RandomForestClassifier(n_estimators=400,criterion="entropy")
rf = rf.fit(X_train_res, y_train_res)
```

XGBoost

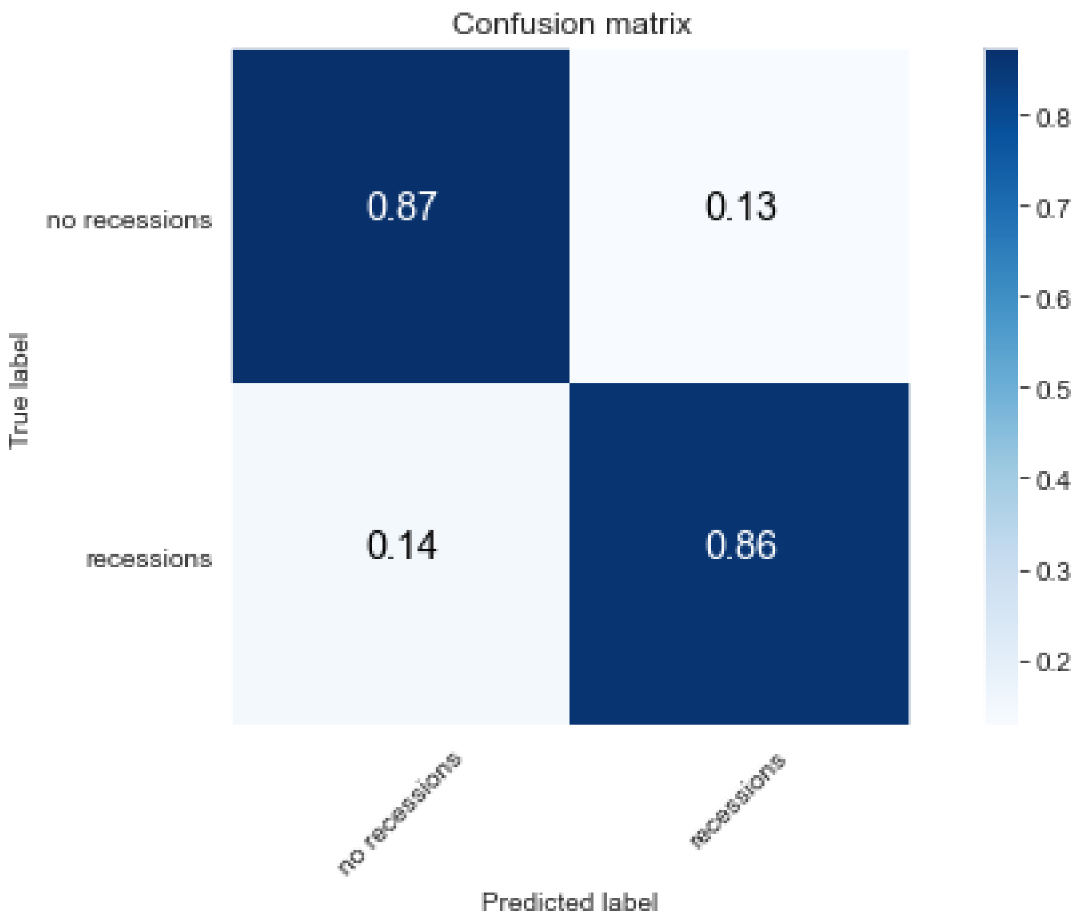
```
xg_reg = xgb.XGBRegressor(objective ='binary:logistic', colsample_bytree = 0.2, learn
ing_rate = 0.1,
                max_depth = 5, alpha = 10, n_estimators = 50)

xg_reg.fit(X_train_res, y_train_res)

XGBRegressor(alpha=10, base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=0.2,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.1, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=5, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=50, n_jobs=0,
             num_parallel_tree=1, objective='binary:logistic', predictor='auto',
             random_state=0, ...)
```

Evaluation of the models

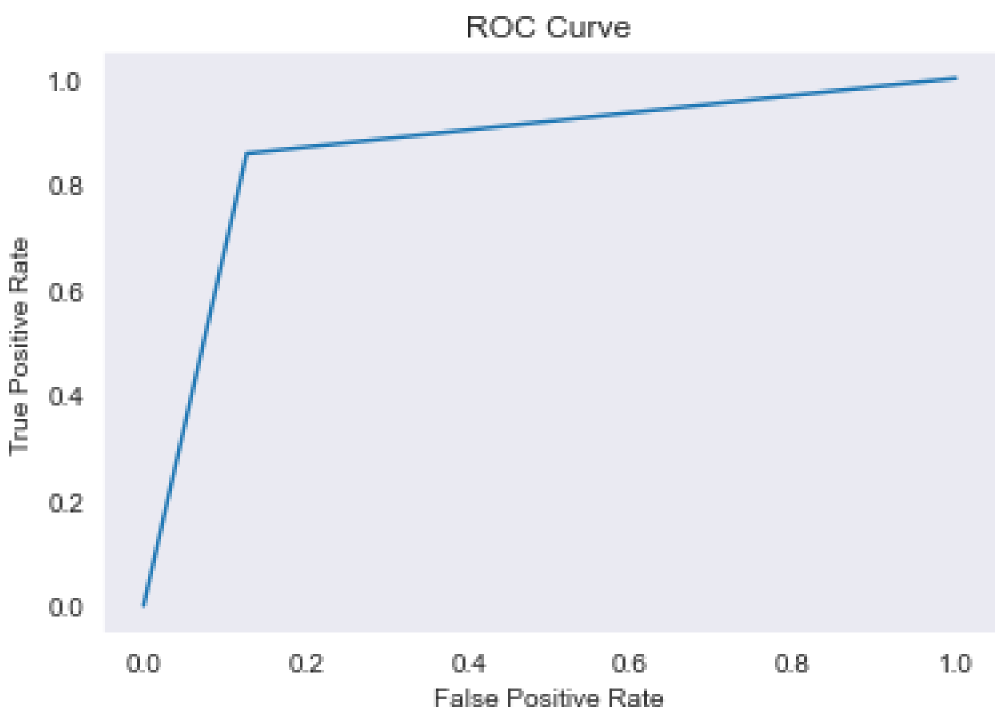
Logistic Regression Evaluation

```
print(" Logisitc Regresion Evaluation")

ypred_logr = logr.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_logr,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_logr)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_logr, target_names=target_names))
```

```
 Logisitc Regresion Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```



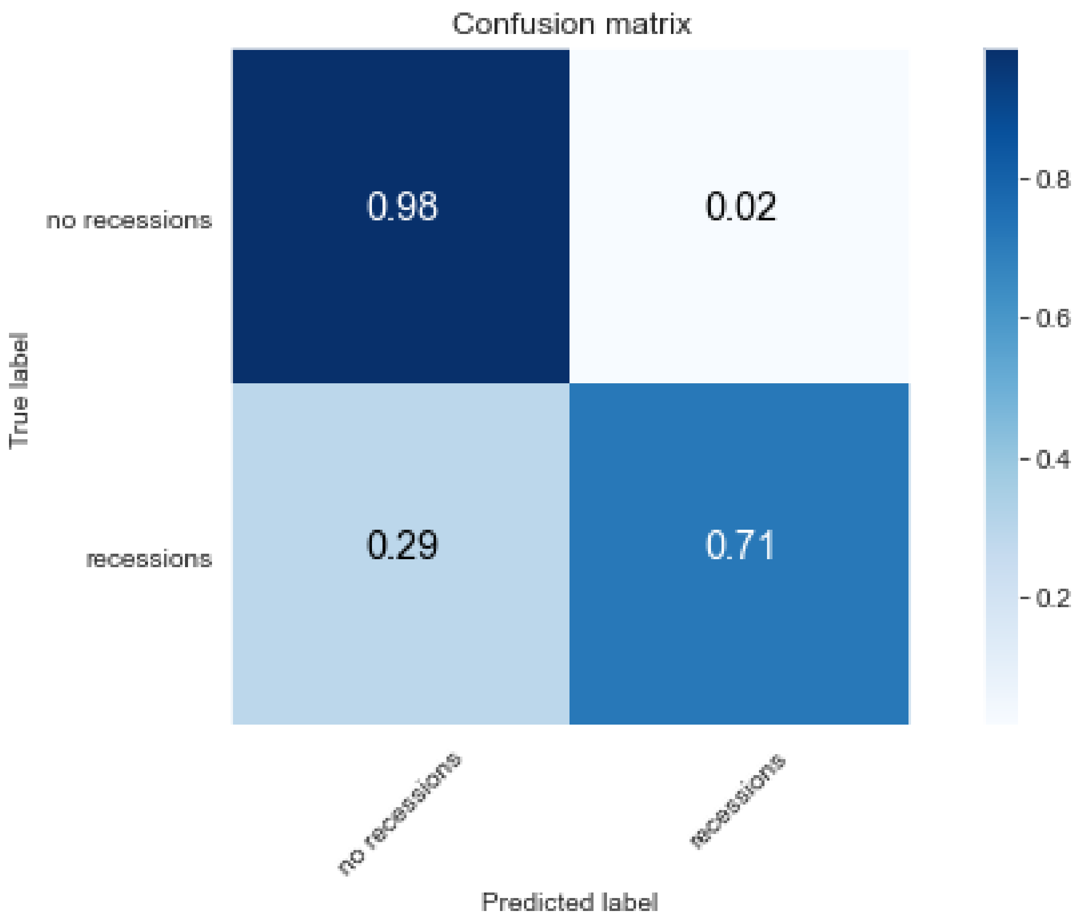

```
 Classificatin Report
               precision    recall  f1-score   support

no recessions       0.98      0.87      0.92       126
```

```
  recessions       0.43      0.86      0.57        14

    accuracy                           0.87       140
   macro avg       0.71      0.87      0.75       140
weighted avg       0.93      0.87      0.89       140
```

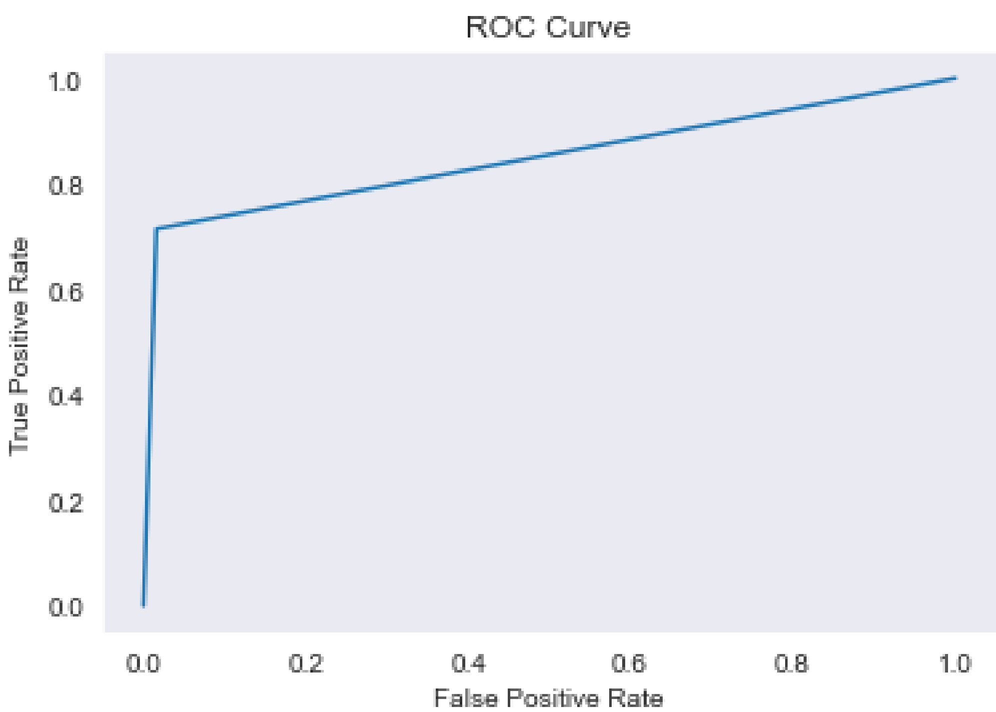
Random Forest Evaluation

```
print(" Random Forest Evaluation")

rf = RandomForestClassifier(n_estimators=300)
rf = rf.fit(xtrain_sc, ytrain)
ypred_rf = rf.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_rf,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_rf)

#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest,ypred_rf, target_names=target_names))
```

```
 Random Forest Evaluation
```



<Figure size 432x288 with 0 Axes>



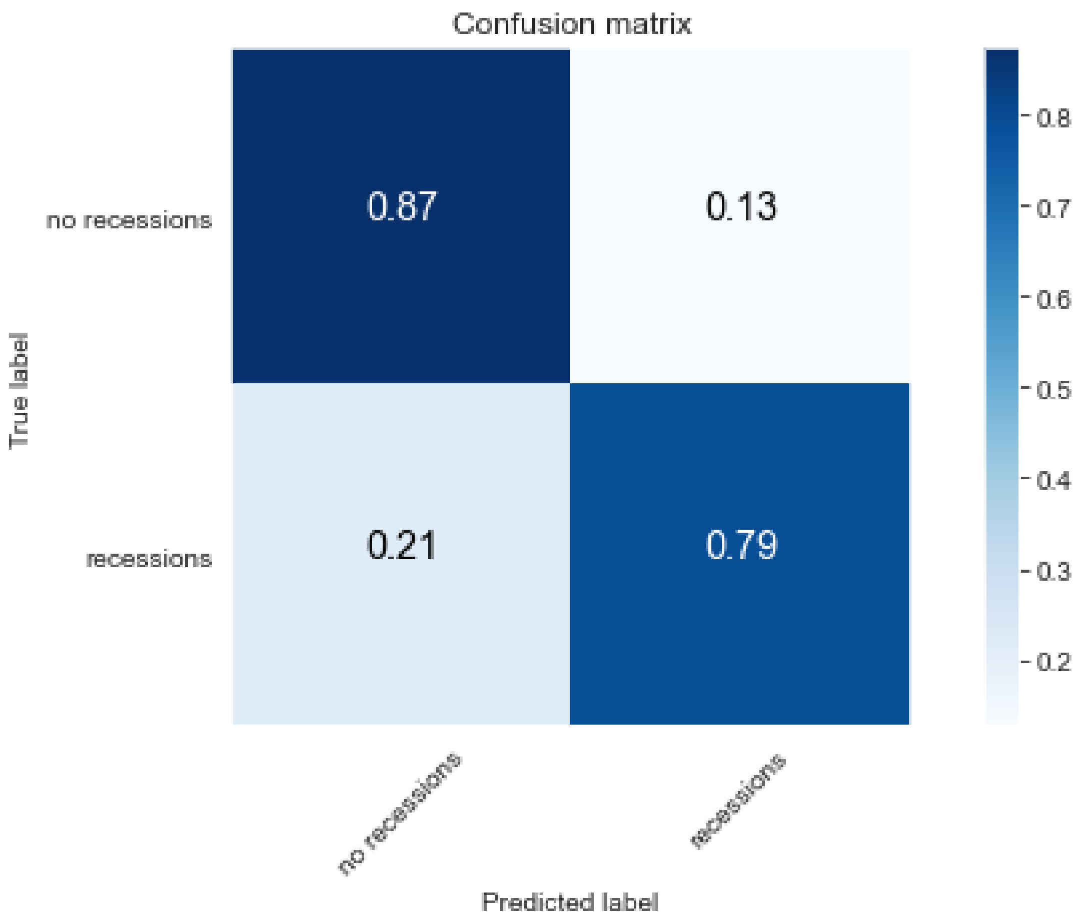

```
 Classificatin Report
              precision    recall  f1-score   support

no recessions      0.97      0.98      0.98       126
```

```
  recessions       0.83      0.71      0.77        14

    accuracy                           0.96       140
   macro avg       0.90      0.85      0.87       140
weighted avg       0.96      0.96      0.96       140
```

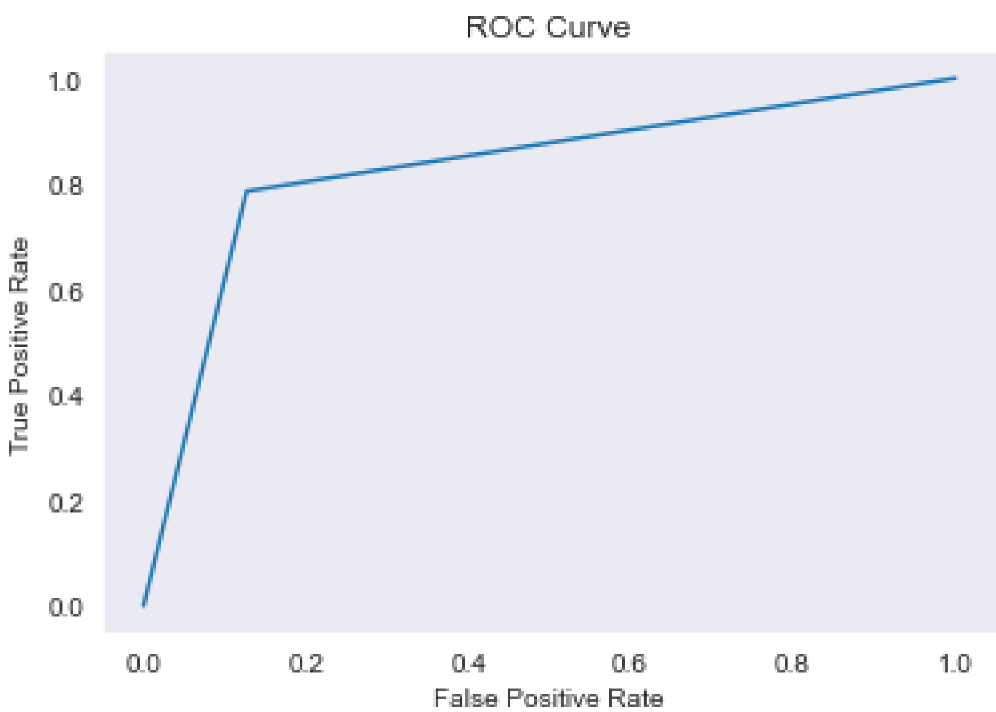
XGBoost Evaluation

```
print(" XgBoost   Evaluation")

ypred_xg= xg_reg.predict(Xtest_sc)

for i,val in enumerate(ypred_xg):
    if val>=0.5:
        ypred_xg[i]=1
    else:
        ypred_xg[i]=0
plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_xg,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_xg)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_xg, target_names=target_names))
```

```
 XgBoost   Evaluation
```



<Figure size 432x288 with 0 Axes>




```
 Classificatin Report
               precision    recall  f1-score   support

no recessions       0.97      0.87      0.92       126
```

```
  recessions       0.41      0.79      0.54        14

    accuracy                           0.86       140
   macro avg       0.69      0.83      0.73       140
weighted avg       0.92      0.86      0.88       140
```

Conclusion

Based on the metrics above the best performed models are:

- Random Forest with 0.96 accuracy
- Logistic Regressoin with 0.87 accuracy

Feature Extraction

Principle Components Analysis (PCA)

```
from sklearn.decomposition import PCA

pca = PCA(n_components=6)
xtrain_pca = pca.fit_transform(X_train_res)
PCA_xtrain = pd.DataFrame(data = xtrain_pca, columns = ['PC1', 'PC2','PC3','PC4','PC5
','PC6'])
PCA_xtrain.head()

        PC1       PC2       PC3       PC4       PC5       PC6
0  0.360594 -0.320608 -0.450603 -0.102697 -0.003927 -0.010318
1  0.424302 -1.144543 -0.522061 -0.225270  0.001244 -0.009947
2  0.425332 -0.174389  2.248403  0.017930  0.039620 -0.005283
3 -2.047636 -0.126508 -1.244694 -0.217519  0.027370  0.009374
4 -2.553951 -0.560759 -0.469191  0.227790 -0.023148  0.008034

xtest_pca = pca.fit_transform(Xtest)
PCA_xtest = pd.DataFrame(data = xtest_pca, columns = ['PC1', 'PC2','PC3','PC4','PC5',
'PC6'])
PCA_xtest.head()

        PC1       PC2       PC3       PC4       PC5       PC6
0 -0.029733  1.268054 -0.280329 -0.061026  0.035141  0.010688
1 -6.319451  0.243930 -0.233057 -0.014818 -0.033249  0.052236
2  2.391954 -1.508272 -0.592537  0.089570 -0.085850  0.001568
3  5.470421  1.180470  0.117734  0.018384 -0.120562 -0.007768
4 -1.327145 -2.248464  0.219334  0.097495 -0.041449 -0.083818

from sklearn.preprocessing import StandardScaler
sc2 = StandardScaler()
xtrain_sc2 = sc.fit_transform(PCA_xtrain)
Xtest_sc2 = sc.transform(PCA_xtest)
```

Building Models

Logistic Regression

```
#logistic regression
from sklearn import linear_model
logr = linear_model.LogisticRegression()
logr.fit(xtrain_sc2,y_train_res)

LogisticRegression()
```

Random Forest

```
rf = RandomForestClassifier(n_estimators=400,criterion="entropy")
rf = rf.fit(xtrain_sc2, y_train_res)
```

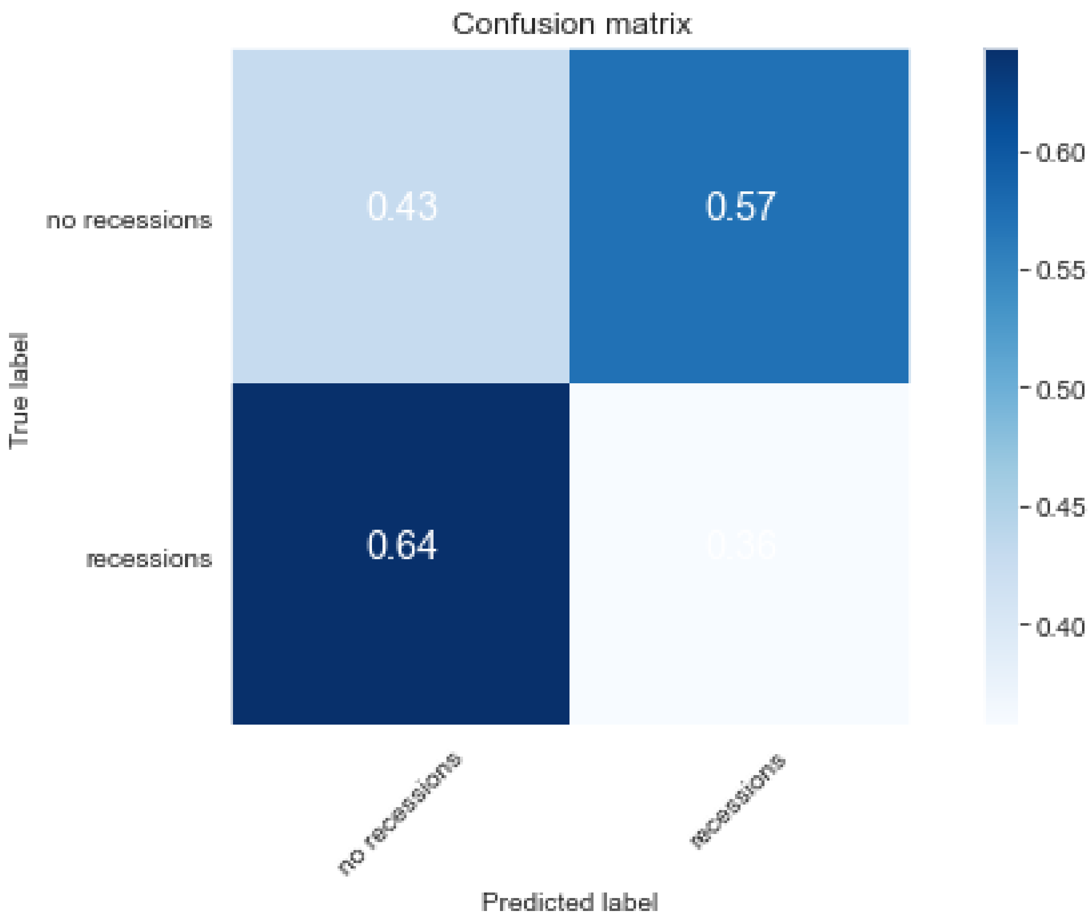
XGBoost

```
xg_reg = xgb.XGBRegressor(objective ='binary:logistic', colsample_bytree = 0.2, learn
ing_rate = 0.1,
                max_depth = 5, alpha = 10, n_estimators = 50)

xg_reg.fit(xtrain_sc2,y_train_res)

XGBRegressor(alpha=10, base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=0.2,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.1, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=5, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=50, n_jobs=0,
             num_parallel_tree=1, objective='binary:logistic', predictor='auto',
             random_state=0, ...)
```

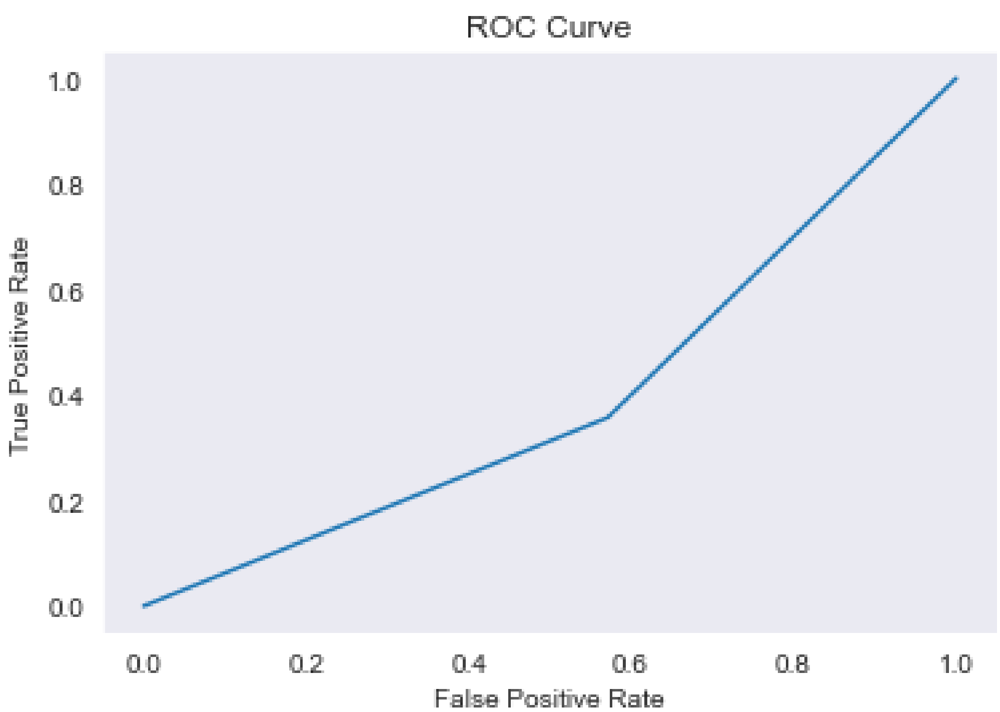
Models Evaluation

Logistic Regresion Evaluation

```
print(" Logisitc Regresion Evaluation")

ypred_logr = logr.predict(Xtest_sc2)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_logr,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_logr)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_logr, target_names=target_names))

 Logisitc Regresion Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```

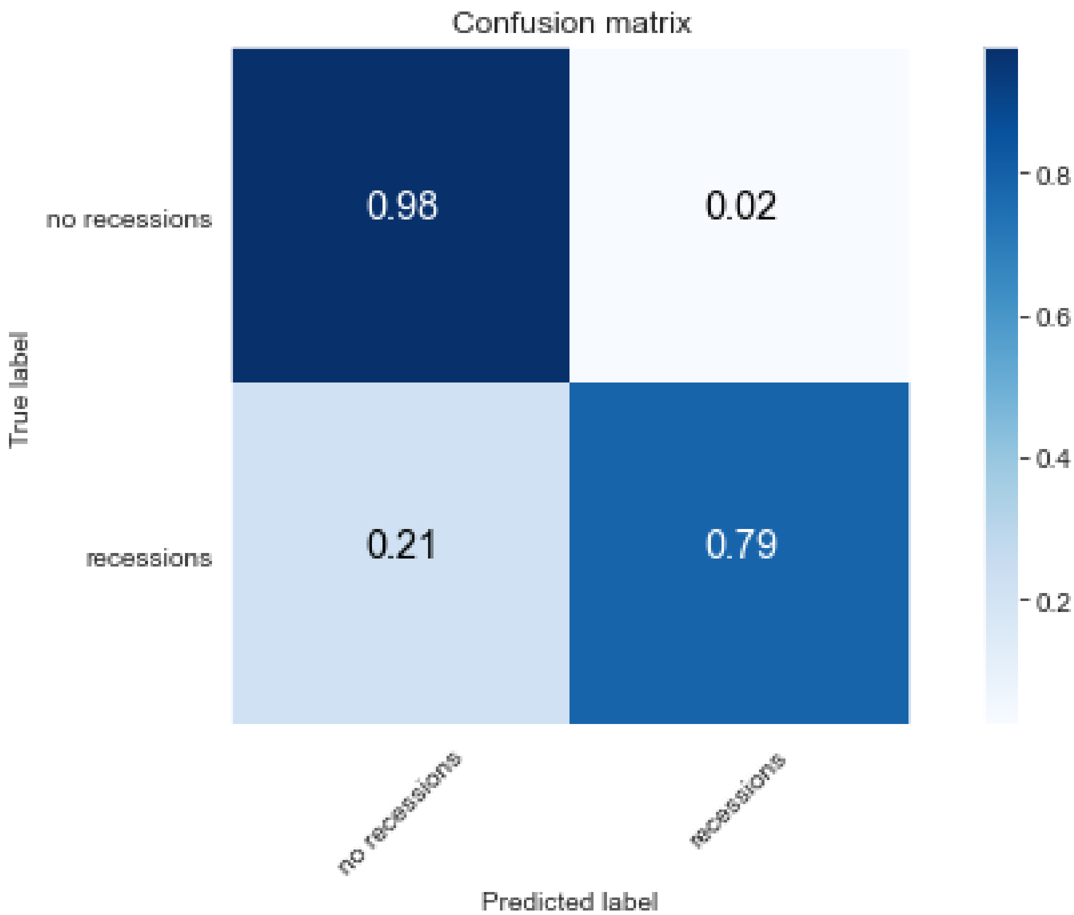



```
 Classificatin Report
                precision    recall  f1-score   support

no recessions       0.86      0.43      0.57       126
```

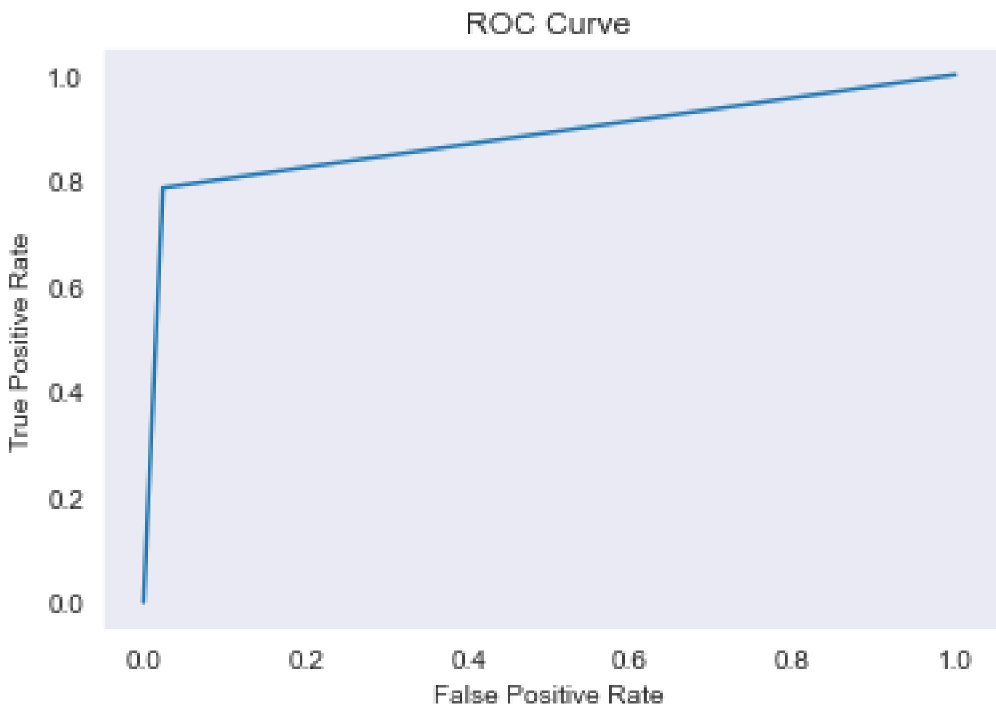
```
   recessions       0.06      0.36      0.11        14

     accuracy                           0.42       140
    macro avg       0.46      0.39      0.34       140
 weighted avg       0.78      0.42      0.53       140
```

```
print(" Random Forest Evaluation")

rf = RandomForestClassifier(n_estimators=300)
rf = rf.fit(X_train_res, y_train_res)
ypred_rf = rf.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_rf,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_rf)

#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest,ypred_rf, target_names=target_names))
```

```
 Random Forest Evaluation
```



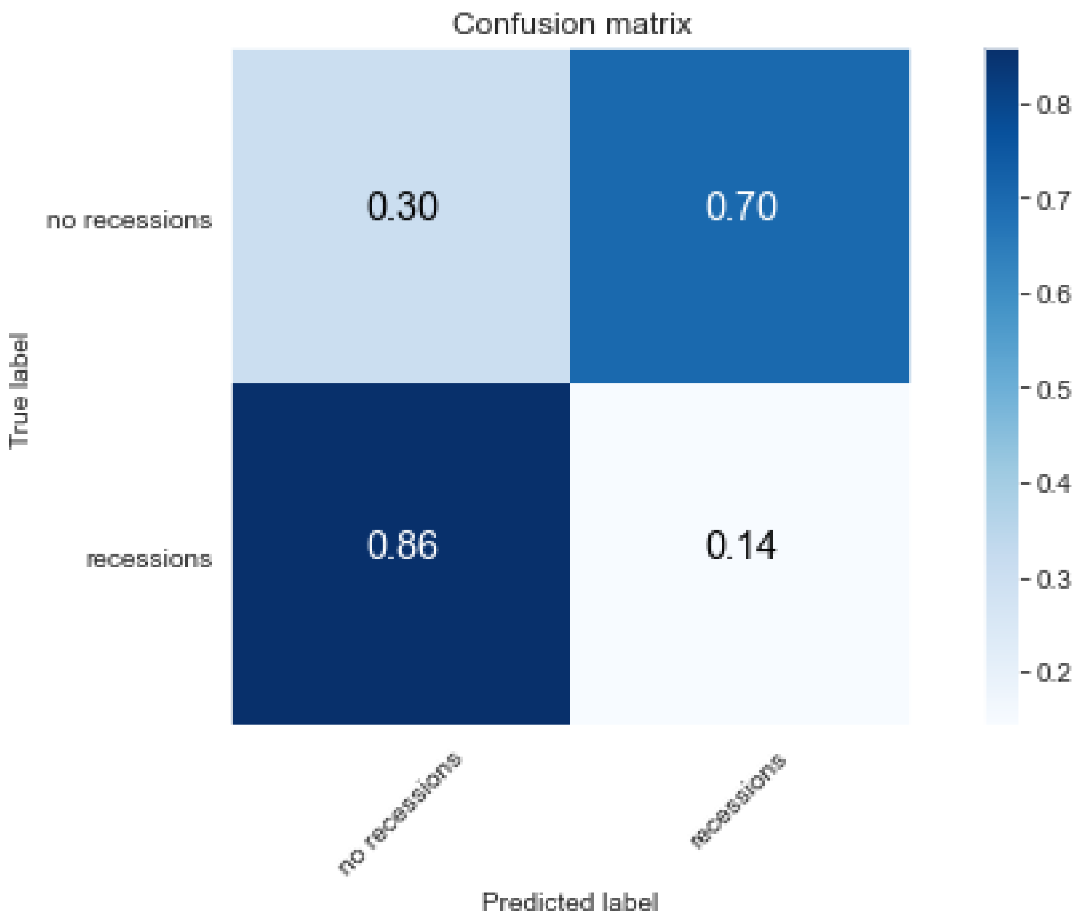

```
<Figure size 432x288 with 0 Axes>
```



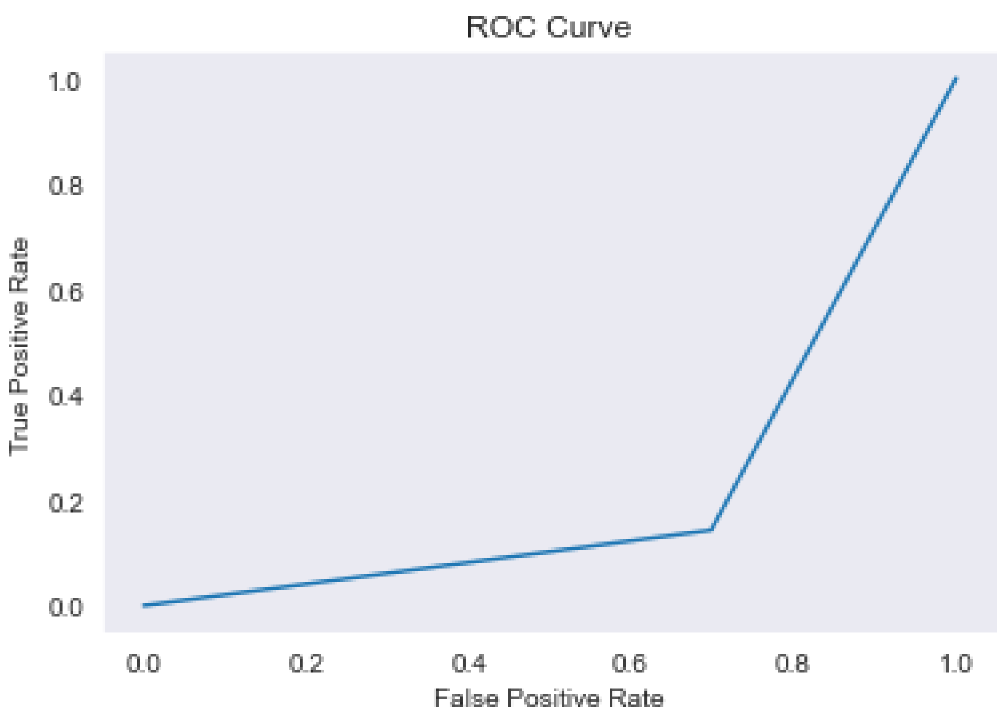

```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       0.98      0.98      0.98       126
   recessions       0.79      0.79      0.79        14

     accuracy                           0.96       140
    macro avg       0.88      0.88      0.88       140
 weighted avg       0.96      0.96      0.96       140
```

```
print(" XgBoost   Evaluation")

ypred_xg= xg_reg.predict(Xtest_sc2)

for i,val in enumerate(ypred_xg):
    if val>=0.5:
        ypred_xg[i]=1
    else:
        ypred_xg[i]=0
plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_xg,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_xg)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_xg, target_names=target_names))
```

```
 XgBoost   Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```




```
 Classificatin Report
               precision    recall  f1-score   support

no recessions       0.76      0.30      0.43       126
```

```
  recessions       0.02      0.14      0.04        14

    accuracy                           0.29       140
   macro avg       0.39      0.22      0.24       140
weighted avg       0.69      0.29      0.39       140
```

Conclusion (By using Feature Extraction)

Based on the metrics above the best performed models are:

- Random Forest with 0.95 accuracy
- Logistic Regression 0.42 accuracy

Appendix 2 Jupiter Notebook B

This section shows the Jupiter notebook B. The data is not from an Excel spreadsheet provided separately.

Binary classification

Split the data

```
from sklearn.model_selection import train_test_split
train,test = train_test_split(df,test_size=0.25,random_state=1,shuffle=True)

xtrain= train.drop(labels=["NBER_Rec"],axis=1)
ytrain = train["NBER_Rec"]

Xtest= test.drop(labels=["NBER_Rec"],axis=1)
ytest = test["NBER_Rec"]

print(" counts of label '1' in Train Set: {}".format(sum(ytrain == 1)))
print(" counts of label '0'in Train Set : {} \n".format(sum(ytrain == 0)))
```

```
 counts of label '1' in Train Set: 44
 counts of label '0'in Train Set : 373
```

```
373/44 #### The proportion
```

```
8.477272727272727
```

```
print(" counts of label '1' in Test Set: {}".format(sum(ytest == 1)))
print(" counts of label '0' in Test Set: {} \n".format(sum(ytest == 0)))
```

```
 counts of label '1' in Test Set: 14
 counts of label '0' in Test Set: 126
```

```
126/14   #### The proportion
```

```
9.0
```

Scale the data

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
xtrain_sc = sc.fit_transform(xtrain)
Xtest_sc = sc.transform(Xtest)
```

Build models

Logistic Regression

```
#logistic regression
from sklearn import linear_model
logr = linear_model.LogisticRegression()
logr.fit(xtrain_sc,ytrain)
```

```
LogisticRegression()
```

Random Decision Forest

```
rf = RandomForestClassifier(n_estimators=400,criterion="entropy")
rf = rf.fit(xtrain_sc, ytrain)
```

XGBoost

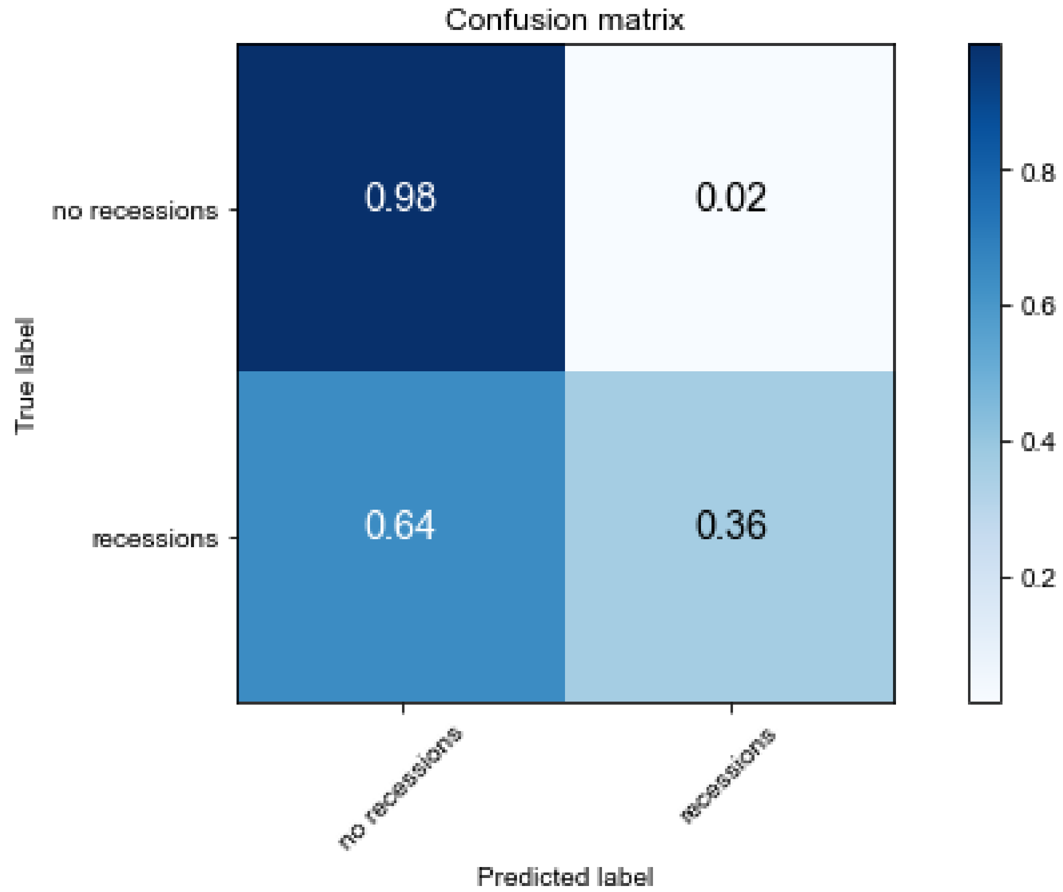
```
xg_reg = xgb.XGBRegressor(objective ='binary:logistic', colsample_bytree = 0.2, learn
ing_rate = 0.1,
                max_depth = 5, alpha = 10, n_estimators = 50)

xg_reg.fit(xtrain_sc,ytrain)

XGBRegressor(alpha=10, base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=0.2,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.1, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=5, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=50, n_jobs=0,
             num_parallel_tree=1, objective='binary:logistic', predictor='auto',
             random_state=0, ...)
```

Evaluation of the models

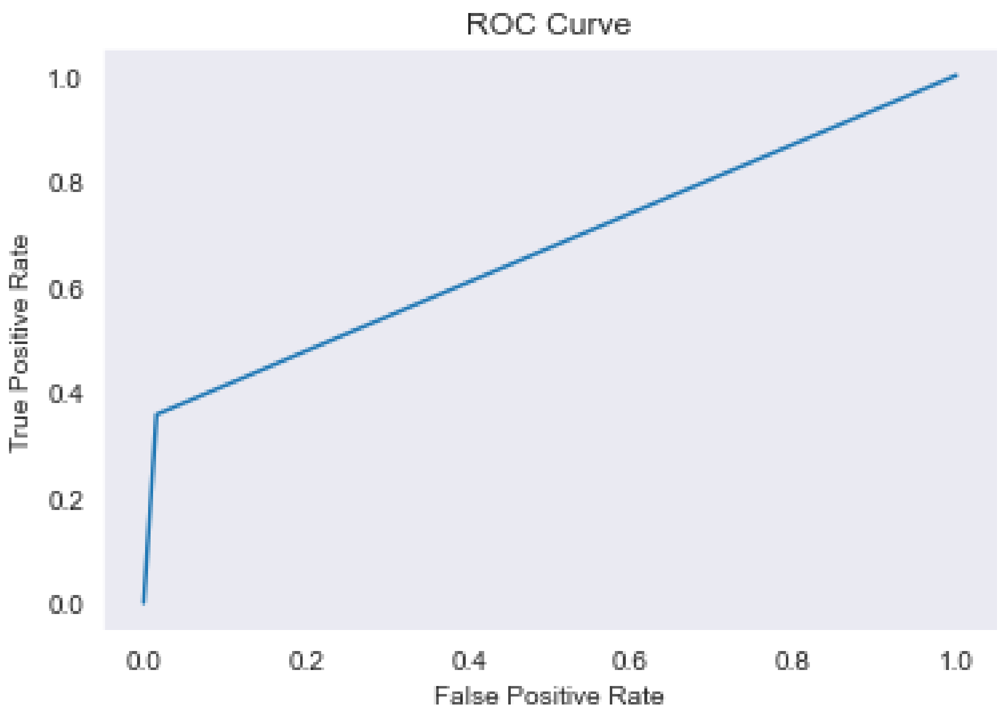
Logistic Regression Evaluation

```
print(" Logisitc Regresion Evaluation")

ypred_logr = logr.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_logr,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_logr)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_logr, target_names=target_names))
```

```
 Logisitc Regresion Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```



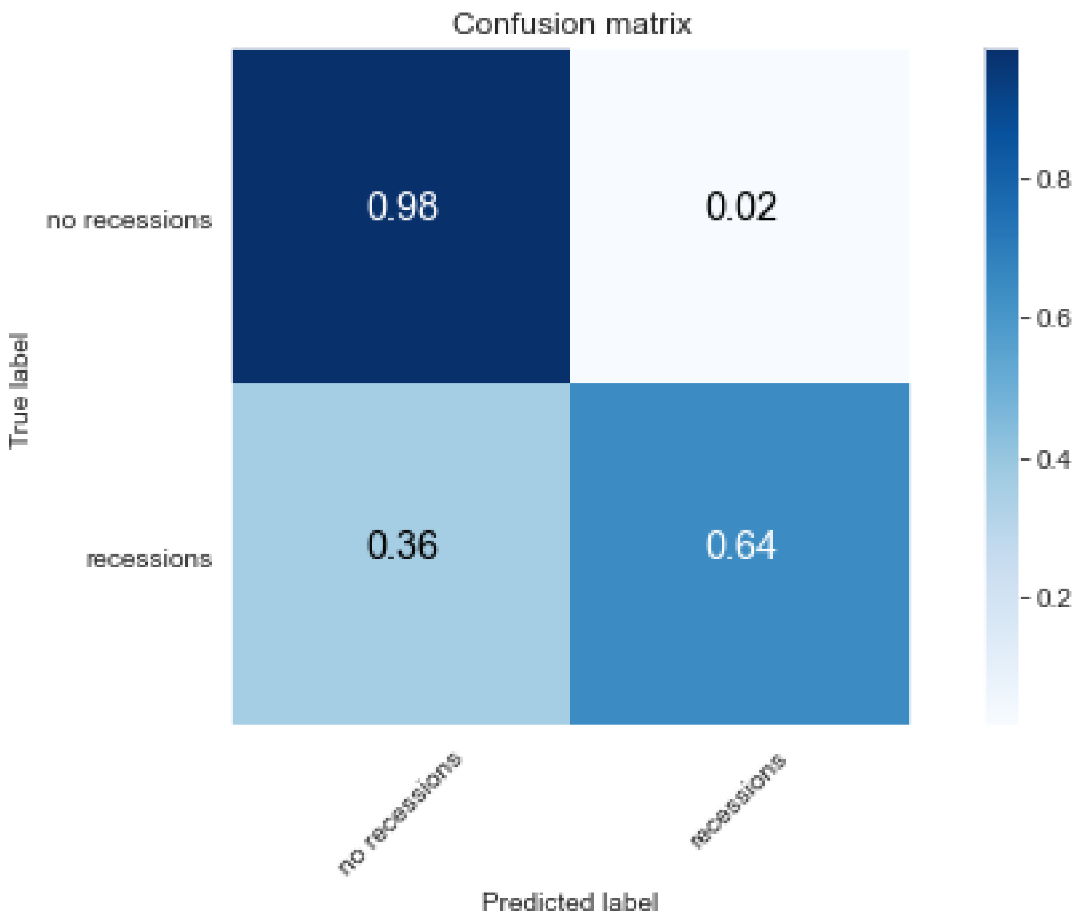

```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       0.93      0.98      0.96       126
```

```
  recessions       0.71      0.36      0.48        14

    accuracy                           0.92       140
   macro avg       0.82      0.67      0.72       140
weighted avg       0.91      0.92      0.91       140
```

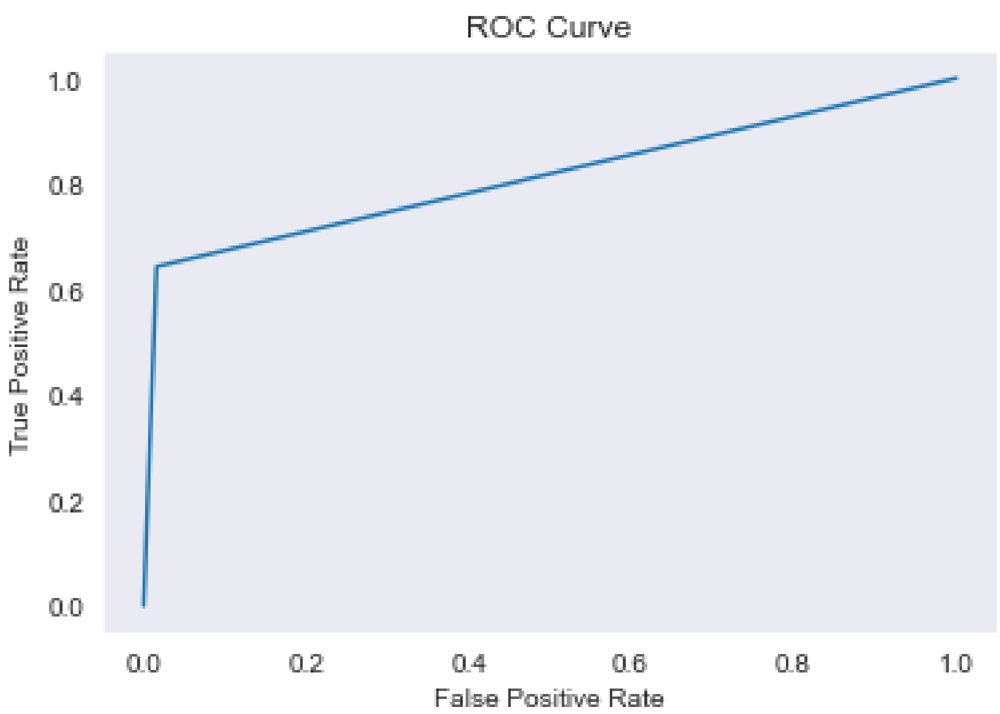
Random Forest Evaluation

```
print(" Random Forest Evaluation")

rf = RandomForestClassifier(n_estimators=300)
rf = rf.fit(xtrain_sc, ytrain)
ypred_rf = rf.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_rf,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_rf)

#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest,ypred_rf, target_names=target_names))
```

```
 Random Forest Evaluation
```



<Figure size 432x288 with 0 Axes>



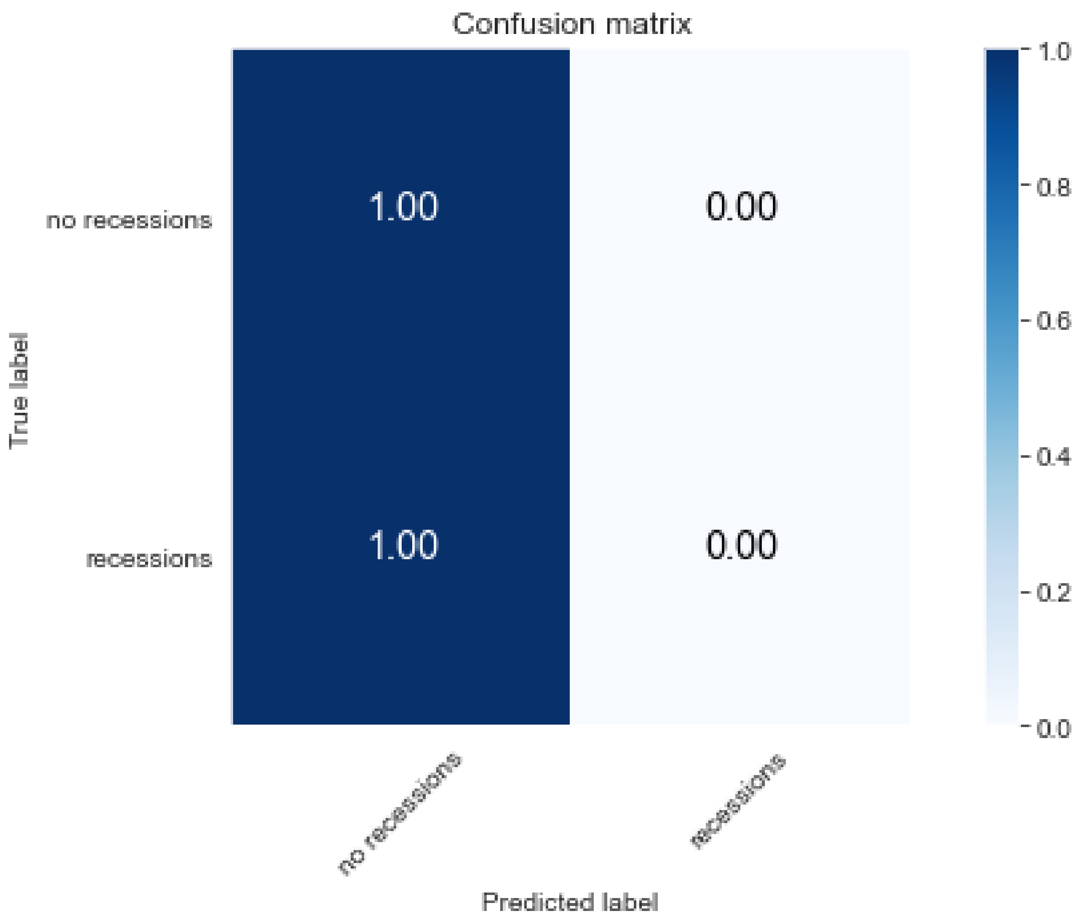

```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       0.96      0.98      0.97       126
```

```
   recessions       0.82      0.64      0.72        14

     accuracy                           0.95       140
    macro avg       0.89      0.81      0.85       140
 weighted avg       0.95      0.95      0.95       140
```

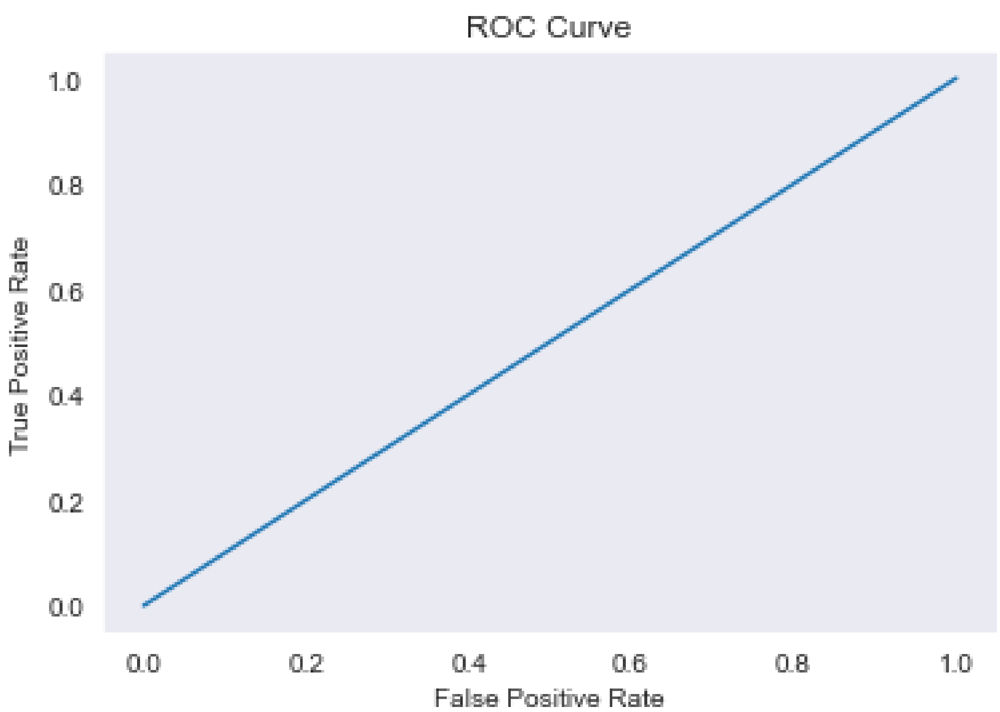
XGBoost Evaluation

```
print(" XgBoost   Evaluation")

ypred_xg= xg_reg.predict(Xtest_sc)

for i,val in enumerate(ypred_xg):
    if val>=0.5:
        ypred_xg[i]=1
    else:
        ypred_xg[i]=0
plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_xg,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_xg)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_xg, target_names=target_names))
```

```
 XgBoost   Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```




```
 Classificatin Report
               precision    recall  f1-score   support

no recessions       0.90      1.00      0.95       126
```

```
   recessions       0.00      0.00      0.00        14

     accuracy                           0.90       140
    macro avg       0.45      0.50      0.47       140
 weighted avg       0.81      0.90      0.85       140
```

```
C:\Users\doren\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control this behav
ior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\doren\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control this behav
ior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\doren\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control this behav
ior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Conclusion

Based on the metrics above the best performed models are:

- Random Forest with 0.95 accuracy
- Logistic Regressoin with 0.92 accuracy

Models using Balanced Data (SMOTE)

```
print("Before OverSampling, counts of label '1': {}".format(sum(ytrain == 1)))
print("Before OverSampling, counts of label '0': {} \n".format(sum(ytrain == 0)))

from imblearn.over_sampling import SMOTE

sm = SMOTE(k_neighbors=5,random_state = 100)
X_train_res, y_train_res = sm.fit_resample(xtrain_sc, ytrain.ravel())

print('After OverSampling, the shape of train_X: {}'.format(X_train_res.shape))
print('After OverSampling, the shape of train_y: {} \n'.format(y_train_res.shape))

print("After OverSampling, counts of label '1': {}".format(sum(y_train_res == 1)))
print("After OverSampling, counts of label '0': {}".format(sum(y_train_res == 0)))
```

```
Before OverSampling, counts of label '1': 44
Before OverSampling, counts of label '0': 373

After OverSampling, the shape of train_X: (746, 6)
After OverSampling, the shape of train_y: (746,)

After OverSampling, counts of label '1': 373
After OverSampling, counts of label '0': 373
```

Logistic Regression

```
#logistic regression
from sklearn import linear_model
logr = linear_model.LogisticRegression()
logr.fit(X_train_res, y_train_res)
```

```
LogisticRegression()
```

Random Decision Forest

```
rf = RandomForestClassifier(n_estimators=400,criterion="entropy")
rf = rf.fit(X_train_res, y_train_res)
```

XGBoost

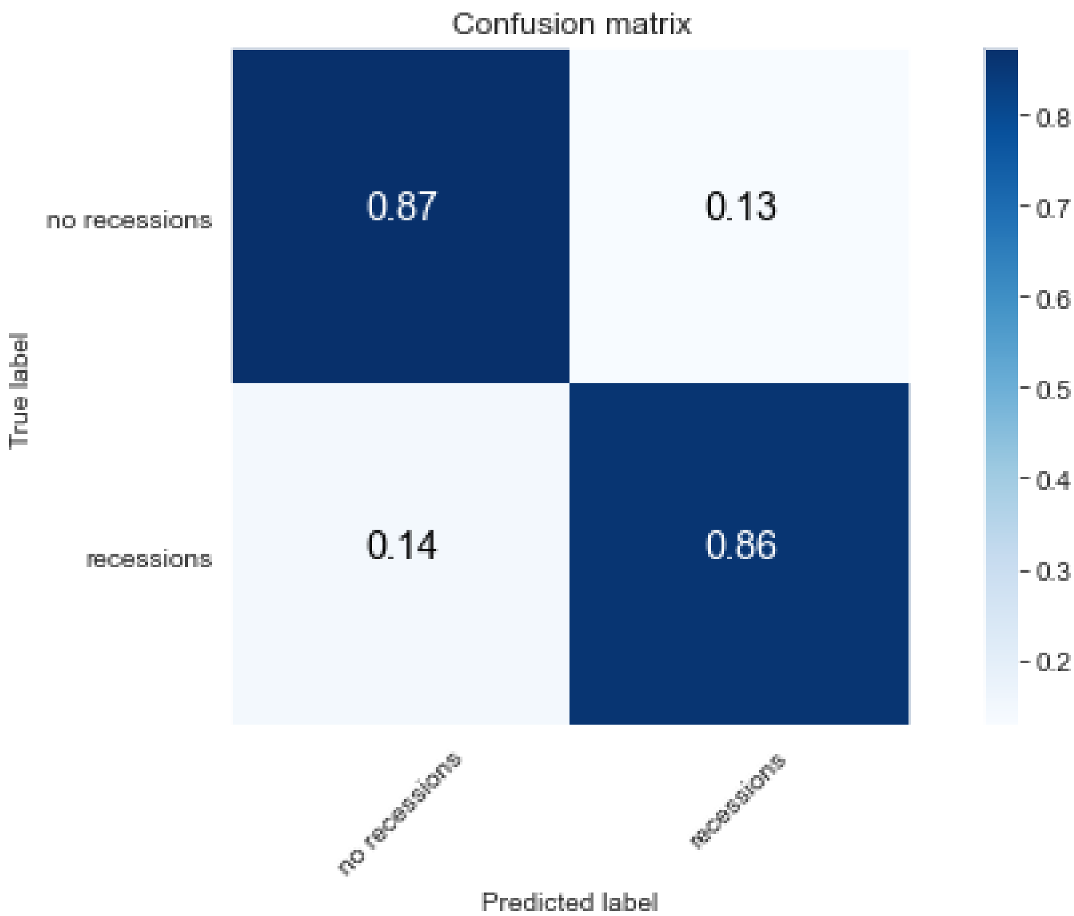
```
xg_reg = xgb.XGBRegressor(objective ='binary:logistic', colsample_bytree = 0.2, learn
ing_rate = 0.1,
                max_depth = 5, alpha = 10, n_estimators = 50)

xg_reg.fit(X_train_res, y_train_res)

XGBRegressor(alpha=10, base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=0.2,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.1, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=5, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=50, n_jobs=0,
             num_parallel_tree=1, objective='binary:logistic', predictor='auto',
             random_state=0, ...)
```

Evaluation of the models

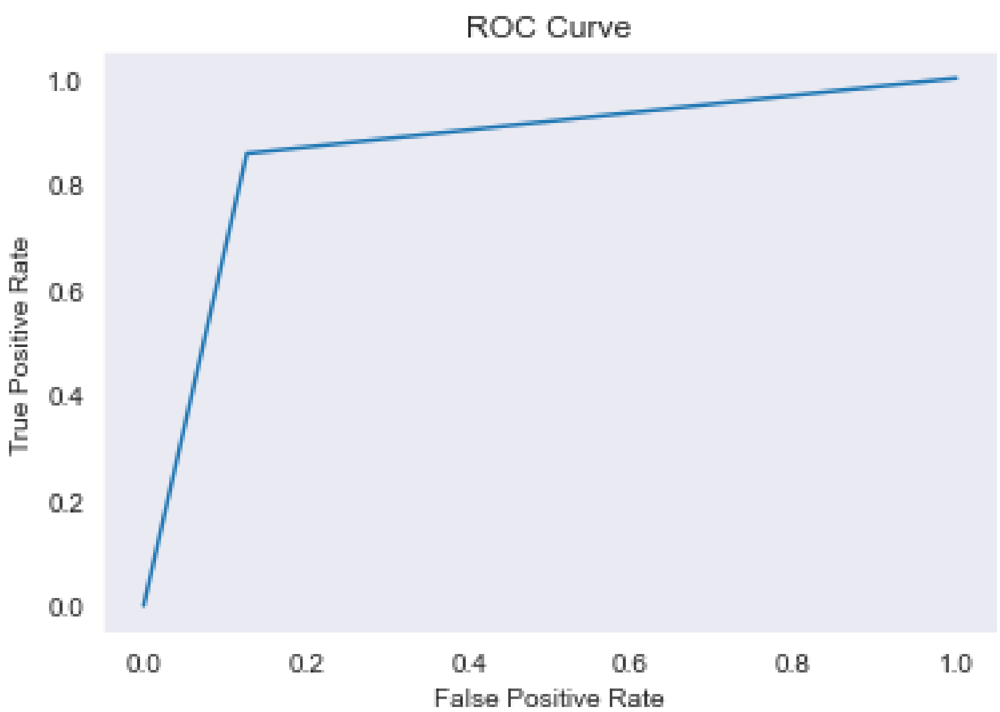
Logistic Regression Evaluation

```
print(" Logisitc Regresion Evaluation")

ypred_logr = logr.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_logr,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_logr)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_logr, target_names=target_names))
```

```
 Logisitc Regresion Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```



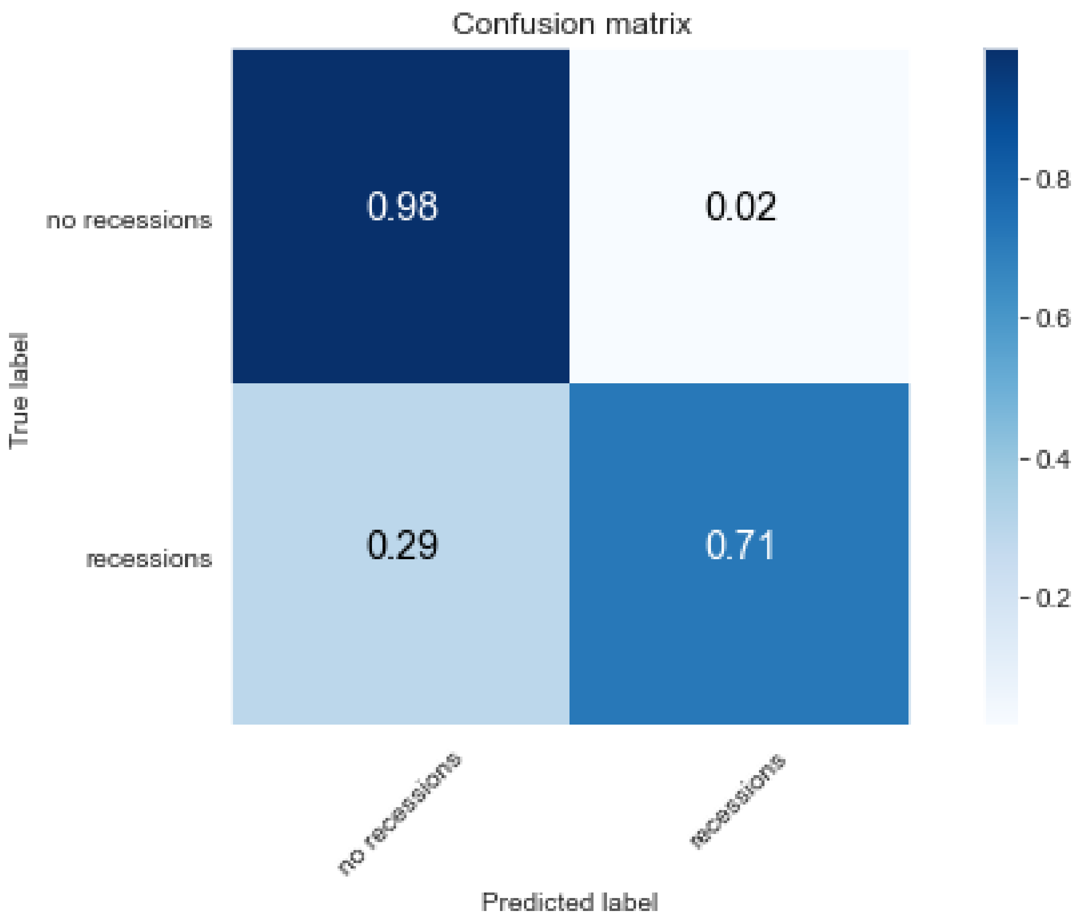

```
 Classificatin Report
               precision    recall  f1-score   support

no recessions       0.98      0.87      0.92       126
```

```
   recessions       0.43      0.86      0.57        14

     accuracy                           0.87       140
    macro avg       0.71      0.87      0.75       140
 weighted avg       0.93      0.87      0.89       140
```

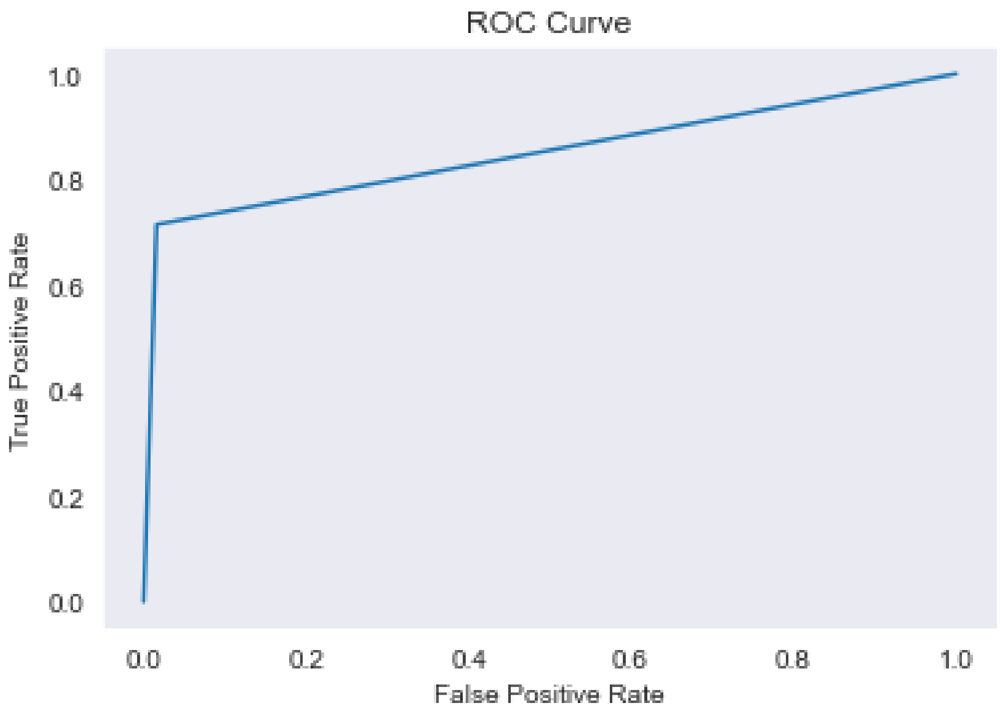
Random Forest Evaluation

```
print(" Random Forest Evaluation")

rf = RandomForestClassifier(n_estimators=300)
rf = rf.fit(xtrain_sc, ytrain)
ypred_rf = rf.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_rf,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_rf)

#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest,ypred_rf, target_names=target_names))
```

```
 Random Forest Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```



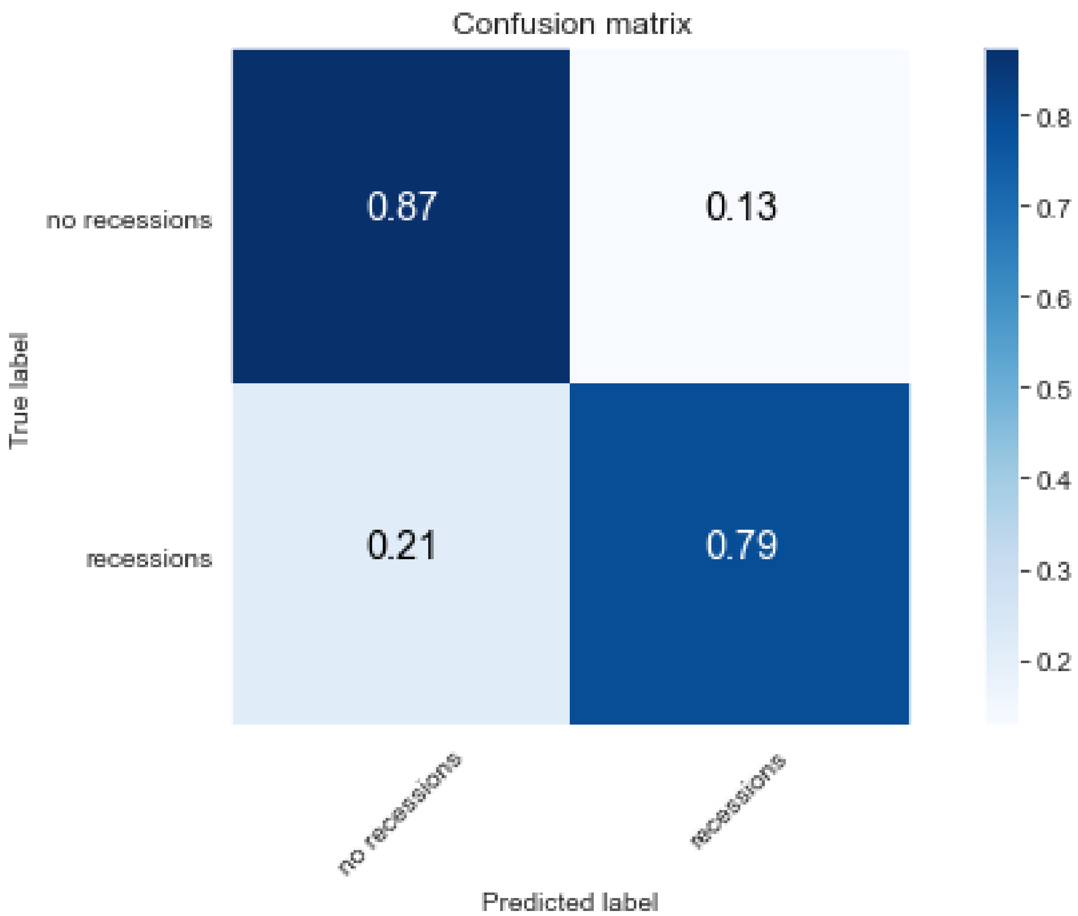

```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       0.97      0.98      0.98       126
```

```
   recessions       0.83      0.71      0.77        14

     accuracy                           0.96       140
    macro avg       0.90      0.85      0.87       140
 weighted avg       0.96      0.96      0.96       140
```

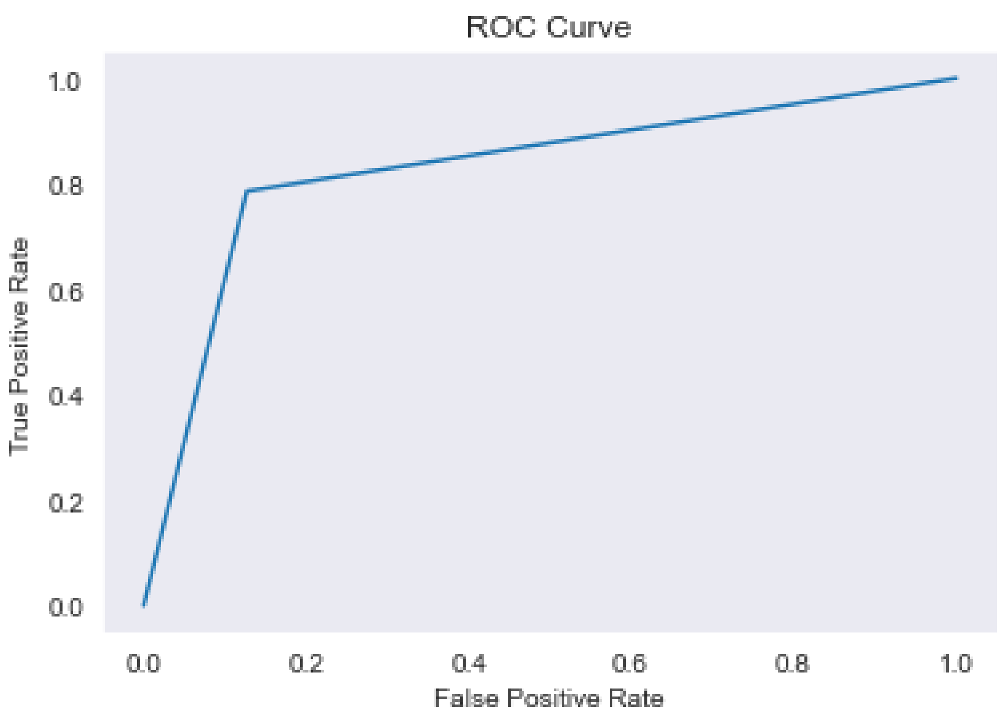
XGBoost Evaluation

```
print(" XgBoost   Evaluation")

ypred_xg= xg_reg.predict(Xtest_sc)

for i,val in enumerate(ypred_xg):
    if val>=0.5:
        ypred_xg[i]=1
    else:
        ypred_xg[i]=0
plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_xg,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_xg)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_xg, target_names=target_names))
```

```
 XgBoost   Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```




```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       0.97      0.87      0.92       126
```

```
   recessions       0.41      0.79      0.54        14

     accuracy                           0.86       140
    macro avg       0.69      0.83      0.73       140
 weighted avg       0.92      0.86      0.88       140
```

Conclusion

Based on the metrics above the best performed models are:

- Random Forest with 0.96 accuracy
- Logistic Regressoin with 0.87 accuracy

Feature Extraction

Principle Components Analysis (PCA)

```
from sklearn.decomposition import PCA

pca = PCA(n_components=6)
xtrain_pca = pca.fit_transform(X_train_res)
PCA_xtrain = pd.DataFrame(data = xtrain_pca, columns = ['PC1', 'PC2','PC3','PC4','PC5
','PC6'])
PCA_xtrain.head()
```

	PC1	PC2	PC3	PC4	PC5	PC6
0	0.360594	-0.320608	-0.450603	-0.102697	-0.003927	-0.010318
1	0.424302	-1.144543	-0.522061	-0.225270	0.001244	-0.009947
2	0.425332	-0.174389	2.248403	0.017930	0.039620	-0.005283
3	-2.047636	-0.126508	-1.244694	-0.217519	0.027370	0.009374
4	-2.553951	-0.560759	-0.469191	0.227790	-0.023148	0.008034

```
xtest_pca = pca.fit_transform(Xtest)
PCA_xtest = pd.DataFrame(data = xtest_pca, columns = ['PC1', 'PC2','PC3','PC4','PC5',
'PC6'])
PCA_xtest.head()
```

	PC1	PC2	PC3	PC4	PC5	PC6
0	-0.029733	1.268054	-0.280329	-0.061026	0.035141	0.010688
1	-6.319451	0.243930	-0.233057	-0.014818	-0.033249	0.052236
2	2.391954	-1.508272	-0.592537	0.089570	-0.085850	0.001568
3	5.470421	1.180470	0.117734	0.018384	-0.120562	-0.007768
4	-1.327145	-2.248464	0.219334	0.097495	-0.041449	-0.083818

```
from sklearn.preprocessing import StandardScaler
sc2 = StandardScaler()
xtrain_sc2 = sc.fit_transform(PCA_xtrain)
Xtest_sc2 = sc.transform(PCA_xtest)
```

Building Models

Logistic Regression

```
#logistic regression
from sklearn import linear_model
logr = linear_model.LogisticRegression()
logr.fit(xtrain_sc2,y_train_res)

LogisticRegression()
```

Random Forest

```
rf = RandomForestClassifier(n_estimators=400,criterion="entropy")
rf = rf.fit(xtrain_sc2, y_train_res)
```

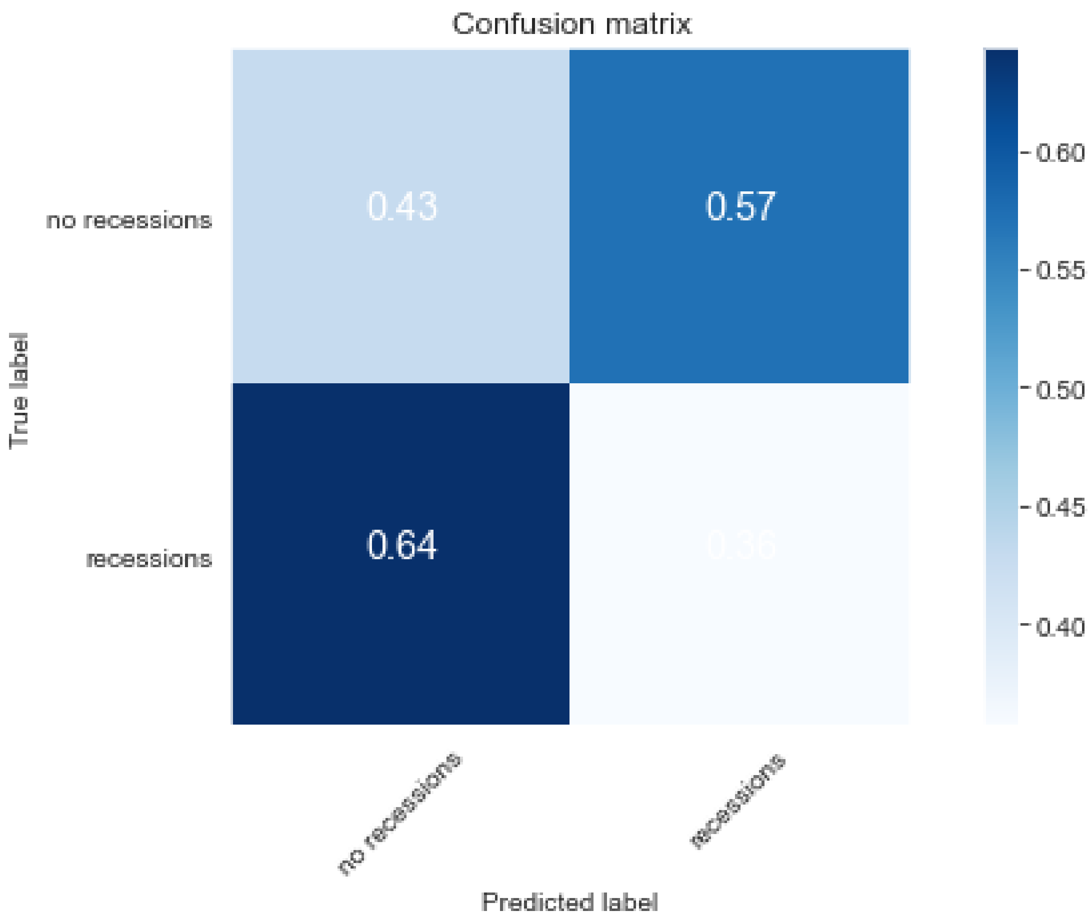
XGBoost

```
xg_reg = xgb.XGBRegressor(objective ='binary:logistic', colsample_bytree = 0.2, learn
ing_rate = 0.1,
                max_depth = 5, alpha = 10, n_estimators = 50)

xg_reg.fit(xtrain_sc2,y_train_res)

XGBRegressor(alpha=10, base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=0.2,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.1, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=5, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=50, n_jobs=0,
             num_parallel_tree=1, objective='binary:logistic', predictor='auto',
             random_state=0, ...)
```

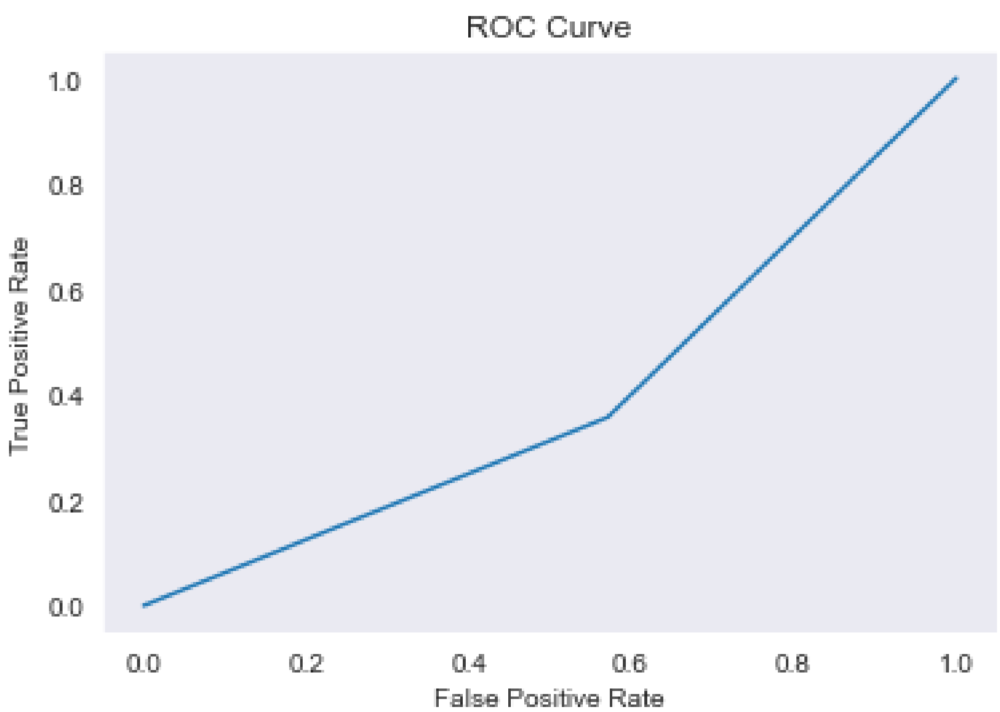
Models Evaluation

Logistic Regresion Evaluation

```
print(" Logisitc Regresion Evaluation")

ypred_logr = logr.predict(Xtest_sc2)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_logr,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_logr)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_logr, target_names=target_names))

 Logisitc Regresion Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```

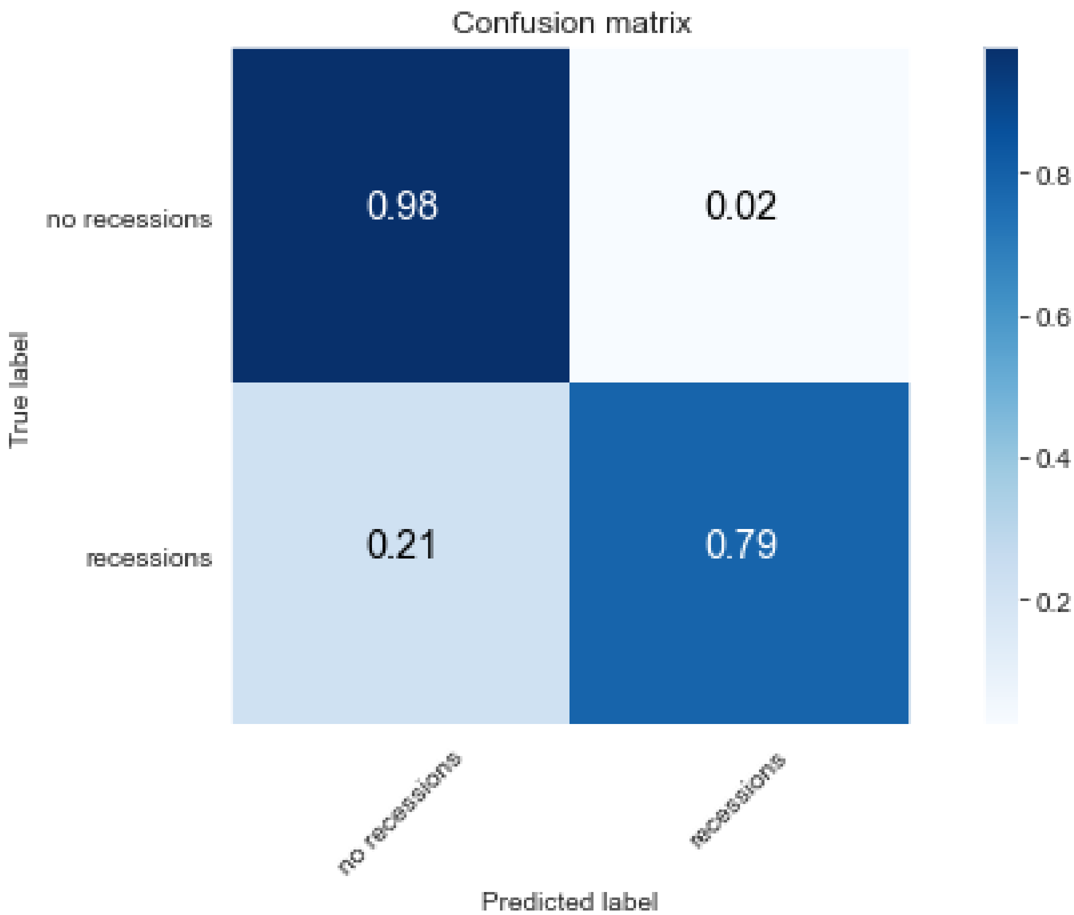



```
 Classificatin Report
                precision    recall  f1-score   support

no recessions       0.86      0.43      0.57       126
```

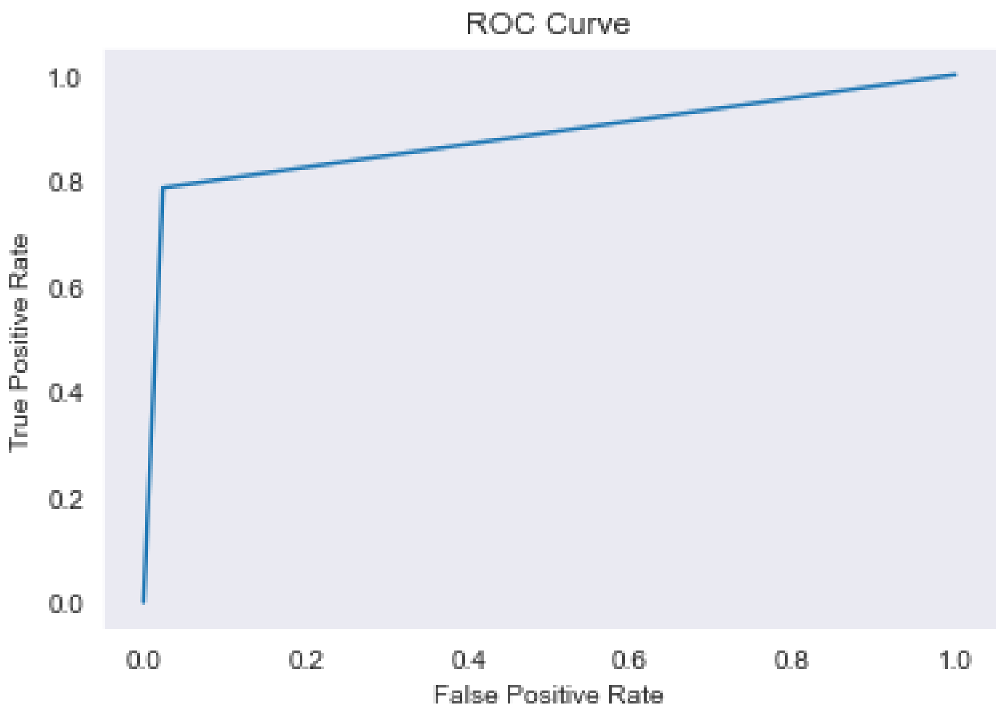
```
   recessions       0.06      0.36      0.11        14

     accuracy                           0.42       140
    macro avg       0.46      0.39      0.34       140
 weighted avg       0.78      0.42      0.53       140
```

```
print(" Random Forest Evaluation")

rf = RandomForestClassifier(n_estimators=300)
rf = rf.fit(X_train_res, y_train_res)
ypred_rf = rf.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_rf,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_rf)

#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest,ypred_rf, target_names=target_names))
```

```
 Random Forest Evaluation
```



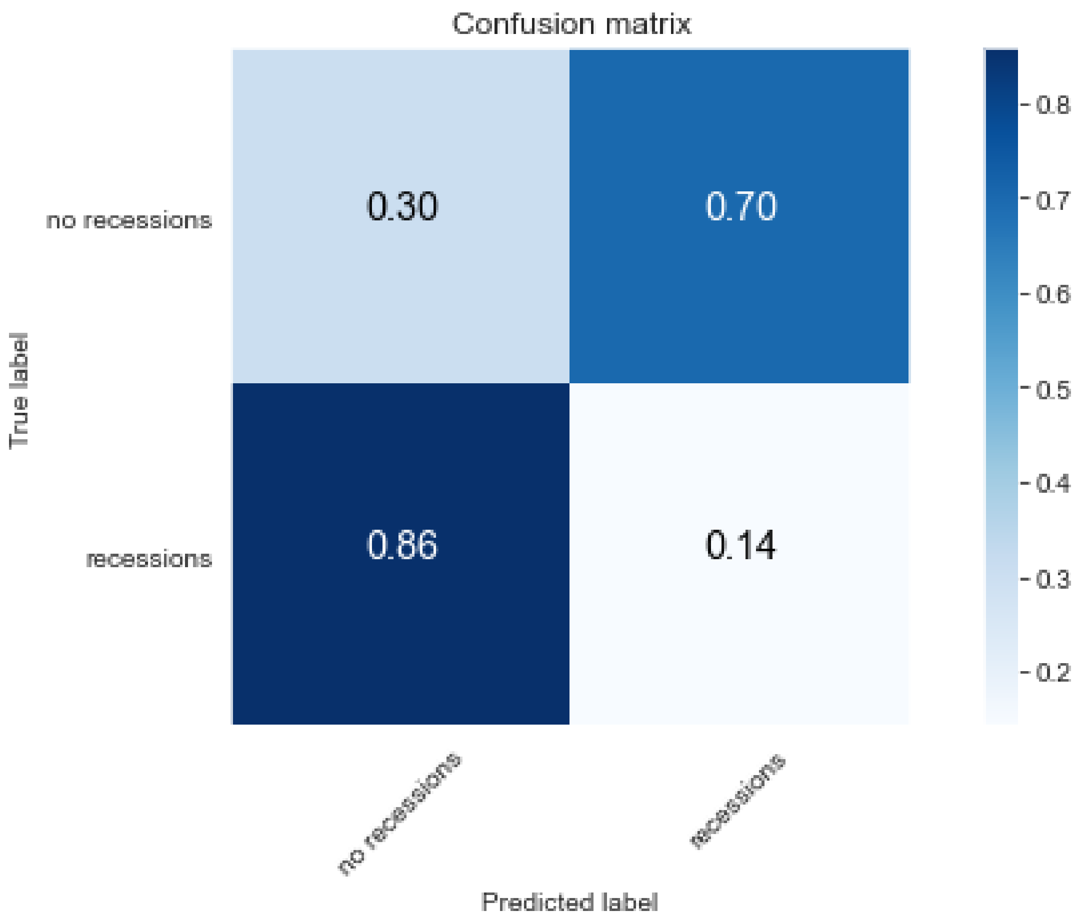

```
<Figure size 432x288 with 0 Axes>
```



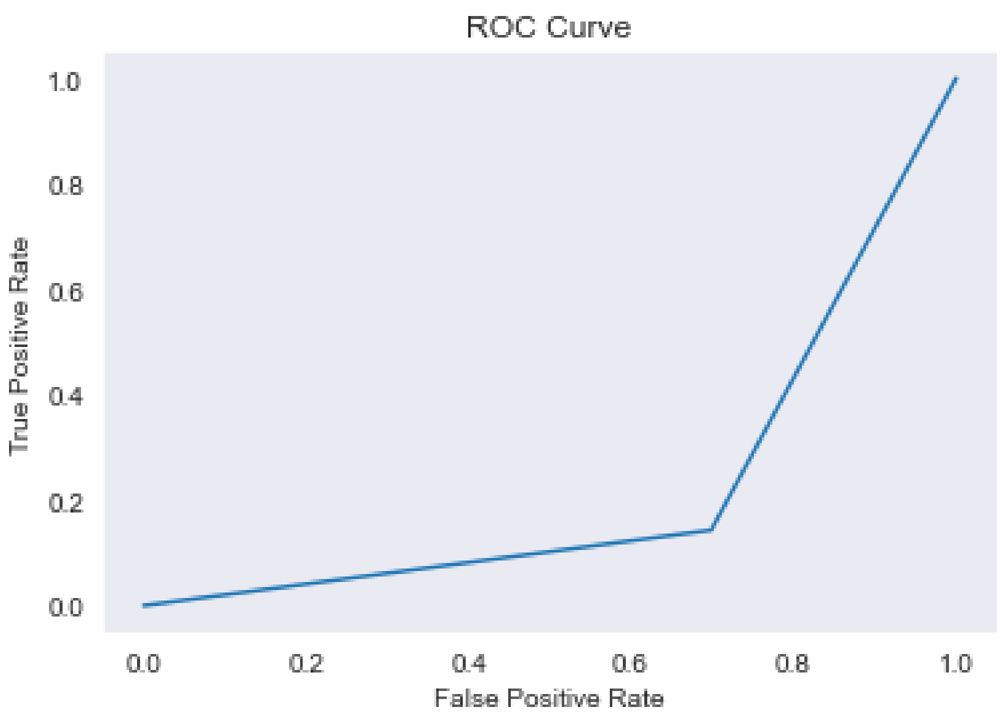

```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       0.98      0.98      0.98       126
   recessions       0.79      0.79      0.79        14

     accuracy                           0.96       140
    macro avg       0.88      0.88      0.88       140
 weighted avg       0.96      0.96      0.96       140
```

```
print(" XgBoost   Evaluation")

ypred_xg= xg_reg.predict(Xtest_sc2)

for i,val in enumerate(ypred_xg):
    if val>=0.5:
        ypred_xg[i]=1
    else:
        ypred_xg[i]=0
plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_xg,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_xg)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_xg, target_names=target_names))
```

```
 XgBoost   Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```




```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       0.76      0.30      0.43       126
```

```
  recessions       0.02      0.14      0.04        14

    accuracy                           0.29       140
   macro avg       0.39      0.22      0.24       140
weighted avg       0.69      0.29      0.39       140
```

Conclusion (By using Feature Extraction)

Based on the metrics above the best performed models are:

- Random Forest with 0.95 accuracy
- Logistic Regression 0.42 accuracy

Appendix 3 Jupiter Notebook C

This section shows the Jupiter notebook B. The data is not from an Excel spreadsheet provided separately.

Binary classification

Split the data

```
from sklearn.model_selection import train_test_split
train,test = train_test_split(df,test_size=0.25,random_state=1,shuffle=True)

xtrain= train.drop(labels=["NBER_Rec"],axis=1)
ytrain = train["NBER_Rec"]

Xtest= test.drop(labels=["NBER_Rec"],axis=1)
ytest = test["NBER_Rec"]

print(" counts of label '1' in Train Set: {}".format(sum(ytrain == 1)))
print(" counts of label '0'in Train Set : {} \n".format(sum(ytrain == 0)))
```

```
 counts of label '1' in Train Set: 39
 counts of label '0'in Train Set : 378
```

```
378/39 #### The proportion
```

```
9.692307692307692
```

```
print(" counts of label '1' in Test Set: {}".format(sum(ytest == 1)))
print(" counts of label '0' in Test Set: {} \n".format(sum(ytest == 0)))
```

```
 counts of label '1' in Test Set: 19
 counts of label '0' in Test Set: 120
```

```
120/19   #### The proportion
```

```
6.315789473684211
```

Scale the data

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
xtrain_sc = sc.fit_transform(xtrain)
Xtest_sc = sc.transform(Xtest)
```

Build models

Logistic Regression

```
#logistic regression
from sklearn import linear_model
logr = linear_model.LogisticRegression()
logr.fit(xtrain_sc,ytrain)
```

```
LogisticRegression()
```

Random Decision Forest

```
rf = RandomForestClassifier(n_estimators=400,criterion="entropy")
rf = rf.fit(xtrain_sc, ytrain)
```

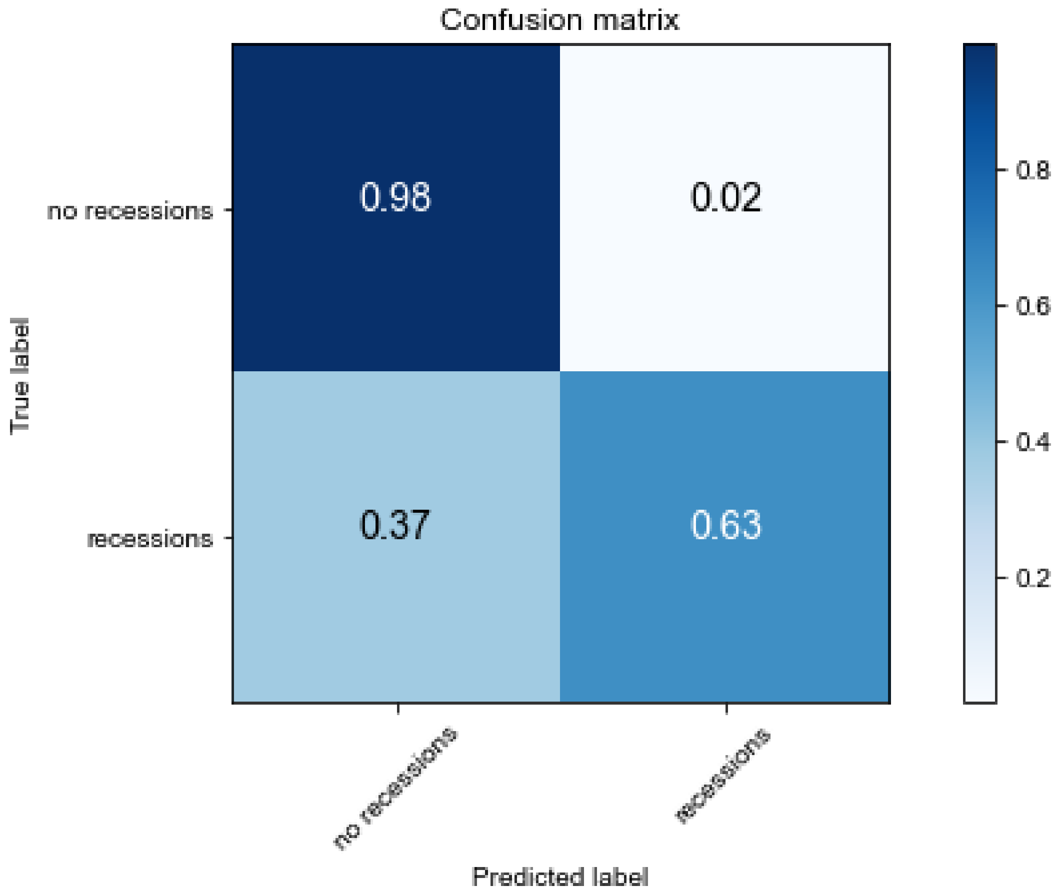
XGBoost

```
xg_reg = xgb.XGBRegressor(objective ='binary:logistic', colsample_bytree = 0.2, learn
ing_rate = 0.1,
                max_depth = 5, alpha = 10, n_estimators = 50)

xg_reg.fit(xtrain_sc,ytrain)

XGBRegressor(alpha=10, base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=0.2,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.1, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=5, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=50, n_jobs=0,
             num_parallel_tree=1, objective='binary:logistic', predictor='auto',
             random_state=0, ...)
```

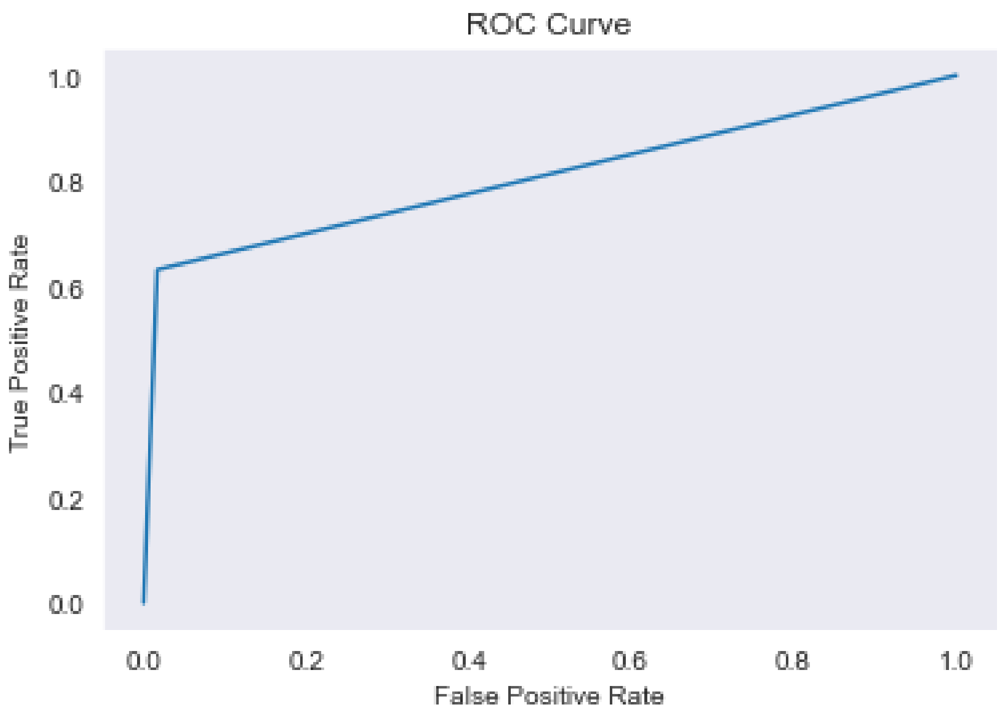
Evaluation of the models

Logistic Regression Evaluation

```
print(" Logisitc Regresion Evaluation")

ypred_logr = logr.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_logr,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_logr)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_logr, target_names=target_names))


 Logisitc Regresion Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```



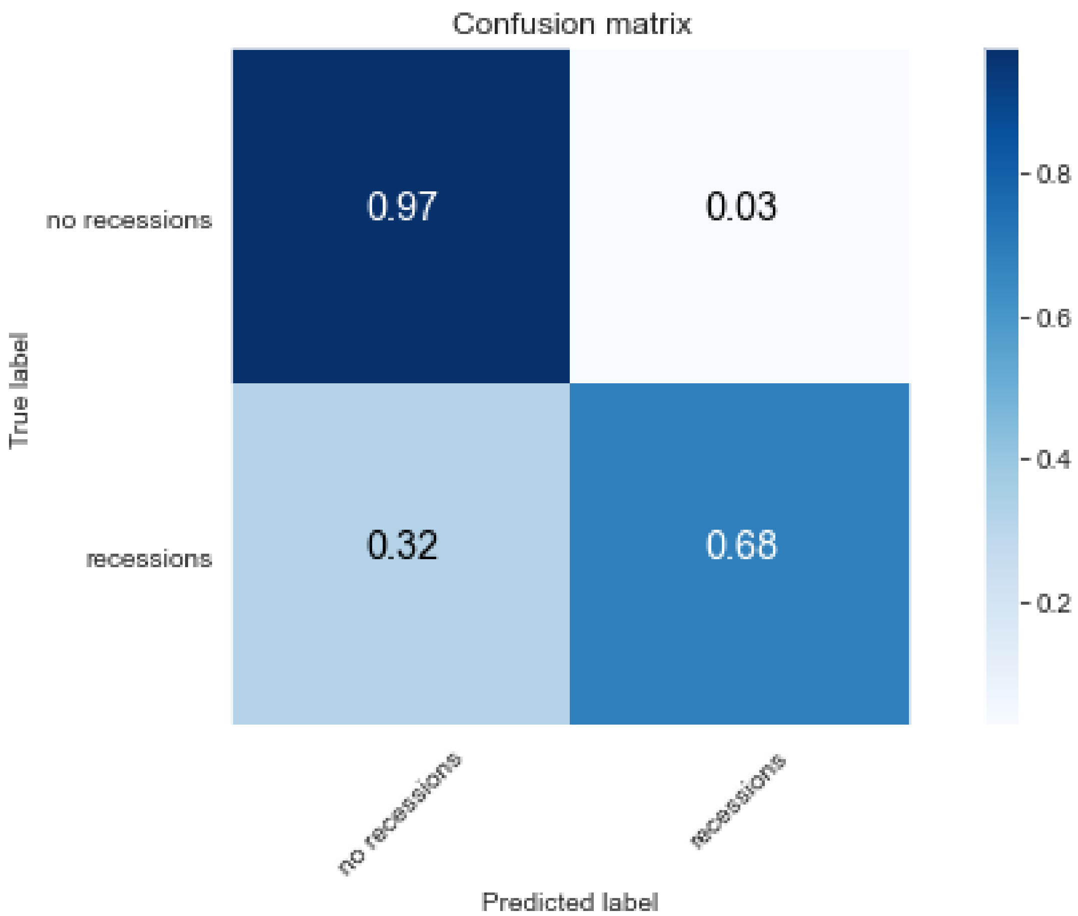

```
 Classificatin Report
               precision    recall  f1-score   support

no recessions       0.94      0.98      0.96       120
```

```
  recessions       0.86      0.63      0.73        19

    accuracy                           0.94       139
   macro avg       0.90      0.81      0.85       139
weighted avg       0.93      0.94      0.93       139
```

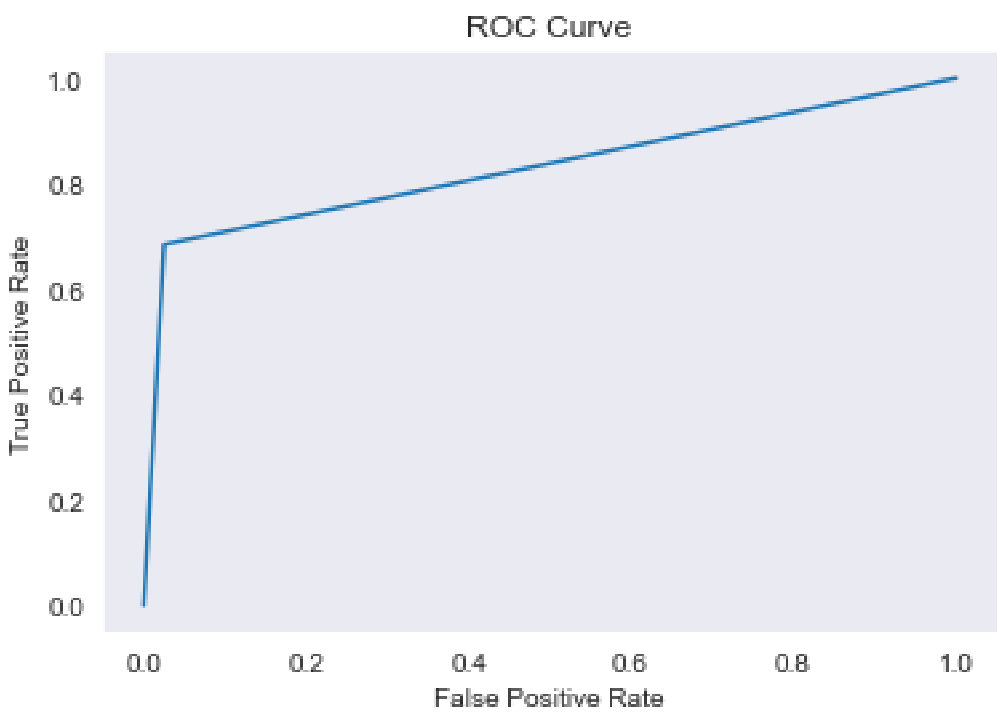
Random Forest Evaluation

```
print(" Random Forest Evaluation")

rf = RandomForestClassifier(n_estimators=300)
rf = rf.fit(xtrain_sc, ytrain)
ypred_rf = rf.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_rf,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_rf)

#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest,ypred_rf, target_names=target_names))
```

```
 Random Forest Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```



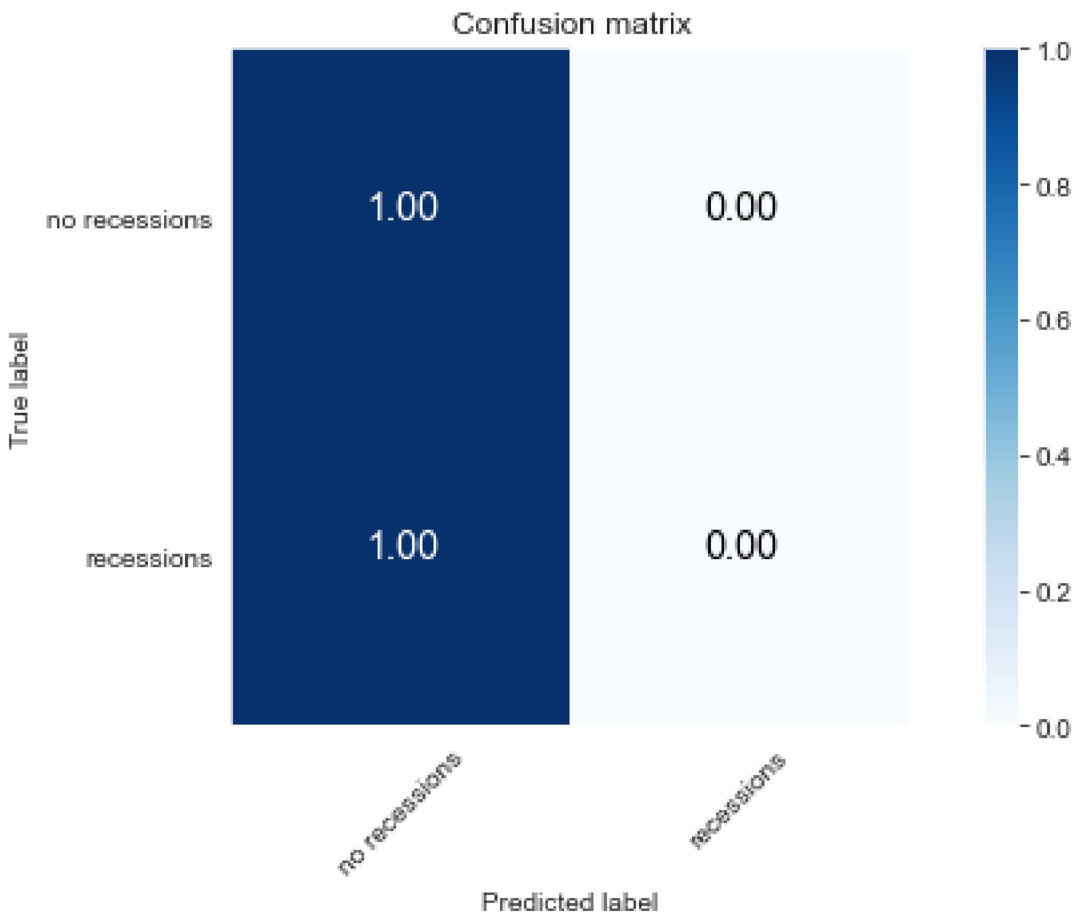

```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       0.95      0.97      0.96       120
```

```
   recessions       0.81      0.68      0.74        19

     accuracy                           0.94       139
    macro avg       0.88      0.83      0.85       139
 weighted avg       0.93      0.94      0.93       139
```

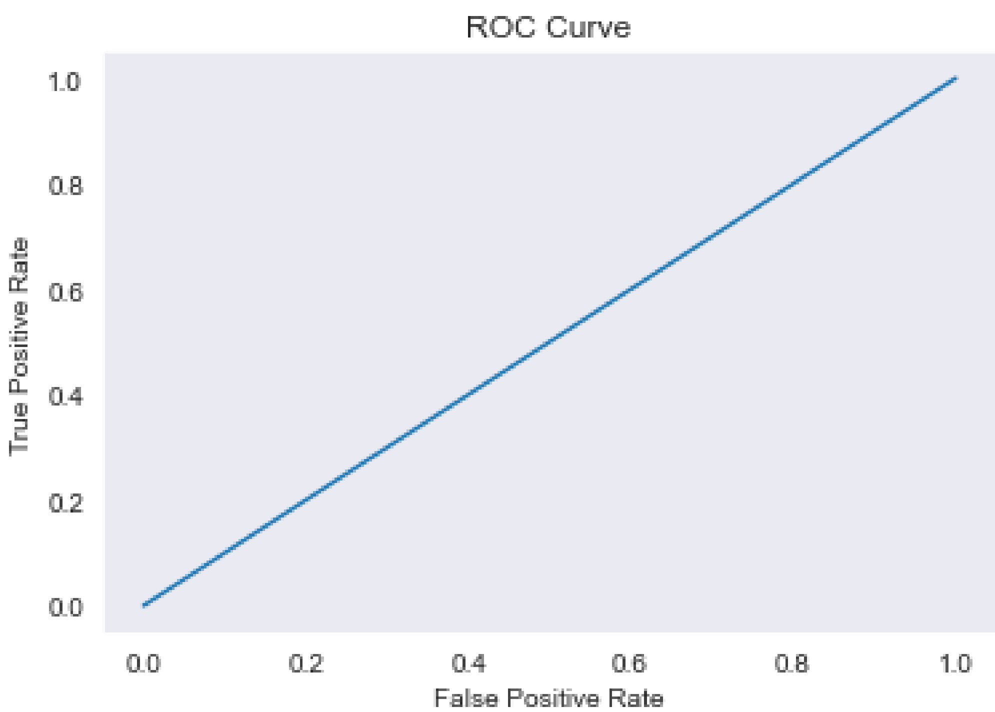
XGBoost Evaluation

```
print(" XgBoost   Evaluation")

ypred_xg= xg_reg.predict(Xtest_sc)

for i,val in enumerate(ypred_xg):
    if val>=0.5:
        ypred_xg[i]=1
    else:
        ypred_xg[i]=0
plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_xg,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_xg)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_xg, target_names=target_names))
```

```
 XgBoost   Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```




```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       0.86      1.00      0.93       120
```

```
  recessions       0.00      0.00      0.00        19

    accuracy                           0.86       139
   macro avg       0.43      0.50      0.46       139
weighted avg       0.75      0.86      0.80       139


C:\Users\doren\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control this behav
ior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\doren\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control this behav
ior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\doren\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control this behav
ior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Conclusion

Based on the metrics above the best performed models are:

- Random Forest with 0.94 accuracy
- Logistic Regressoin with 0.94 accuracy

Models using Balanced Data (SMOTE)

```
print("Before OverSampling, counts of label '1': {}".format(sum(ytrain == 1)))
print("Before OverSampling, counts of label '0': {} \n".format(sum(ytrain == 0)))

from imblearn.over_sampling import SMOTE

sm = SMOTE(k_neighbors=5,random_state = 100)
X_train_res, y_train_res = sm.fit_resample(xtrain_sc, ytrain.ravel())

print('After OverSampling, the shape of train_X: {}'.format(X_train_res.shape))
print('After OverSampling, the shape of train_y: {} \n'.format(y_train_res.shape))

print("After OverSampling, counts of label '1': {}".format(sum(y_train_res == 1)))
print("After OverSampling, counts of label '0': {}".format(sum(y_train_res == 0)))
```

```
Before OverSampling, counts of label '1': 39
Before OverSampling, counts of label '0': 378

After OverSampling, the shape of train_X: (756, 9)
After OverSampling, the shape of train_y: (756,)

After OverSampling, counts of label '1': 378
After OverSampling, counts of label '0': 378
```

Logistic Regression

```
#logistic regression
from sklearn import linear_model
logr = linear_model.LogisticRegression()
logr.fit(X_train_res, y_train_res)
```

```
LogisticRegression()
```

Random Decision Forest

```
rf = RandomForestClassifier(n_estimators=400,criterion="entropy")
rf = rf.fit(X_train_res, y_train_res)
```

XGBoost

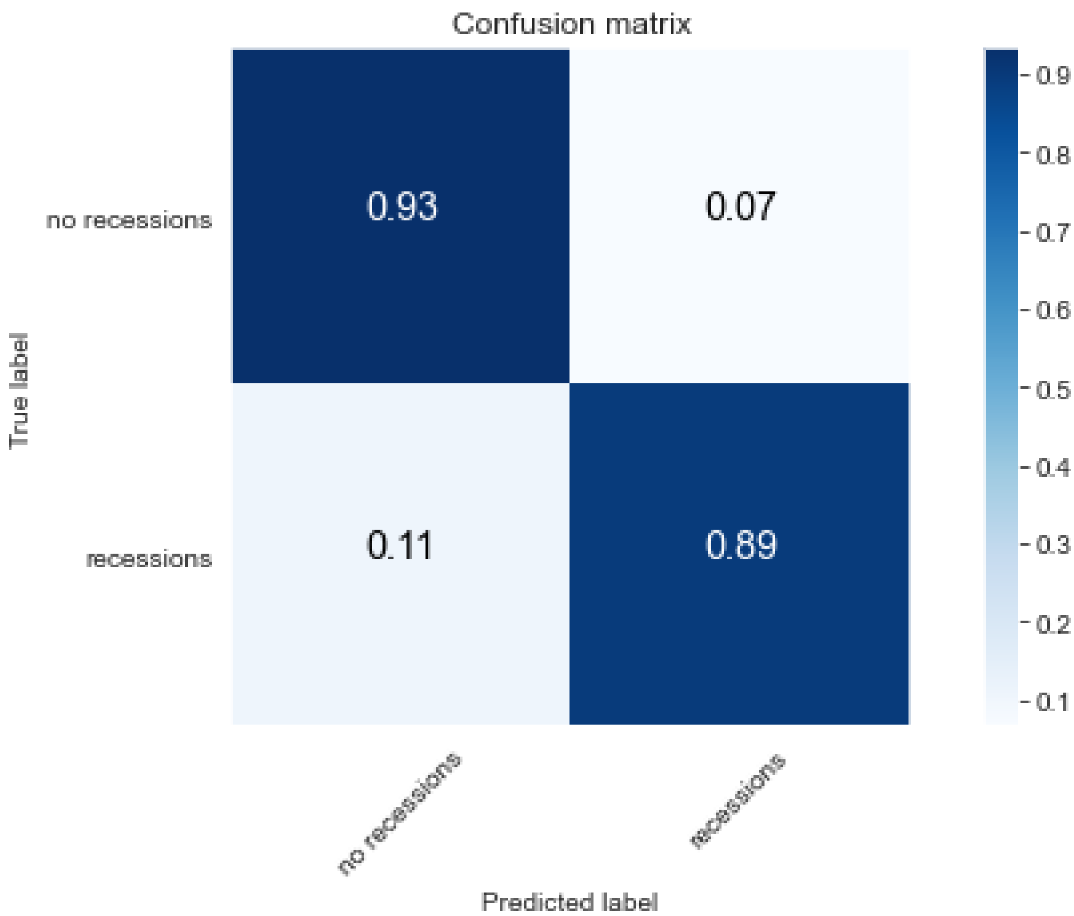
```
xg_reg = xgb.XGBRegressor(objective ='binary:logistic', colsample_bytree = 0.2, learn
ing_rate = 0.1,
                max_depth = 5, alpha = 10, n_estimators = 50)

xg_reg.fit(X_train_res, y_train_res)

XGBRegressor(alpha=10, base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=0.2,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.1, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=5, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=50, n_jobs=0,
             num_parallel_tree=1, objective='binary:logistic', predictor='auto',
             random_state=0, ...)
```

Evaluation of the models

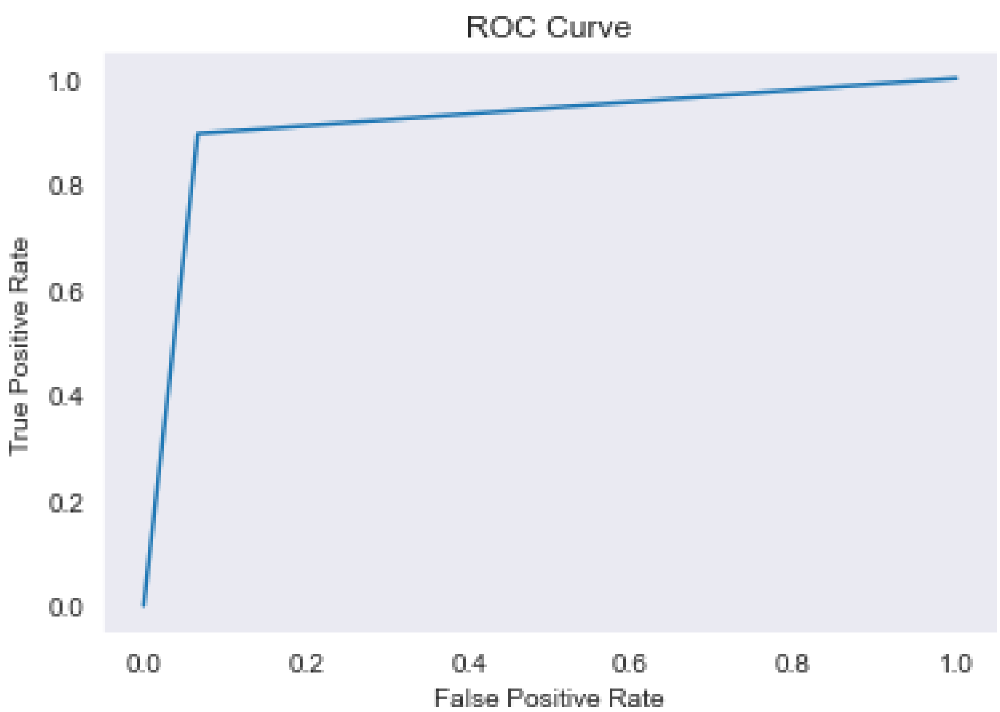
Logistic Regression Evaluation

```
print(" Logisitc Regresion Evaluation")

ypred_logr = logr.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_logr,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_logr)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_logr, target_names=target_names))
```

```
 Logisitc Regresion Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```



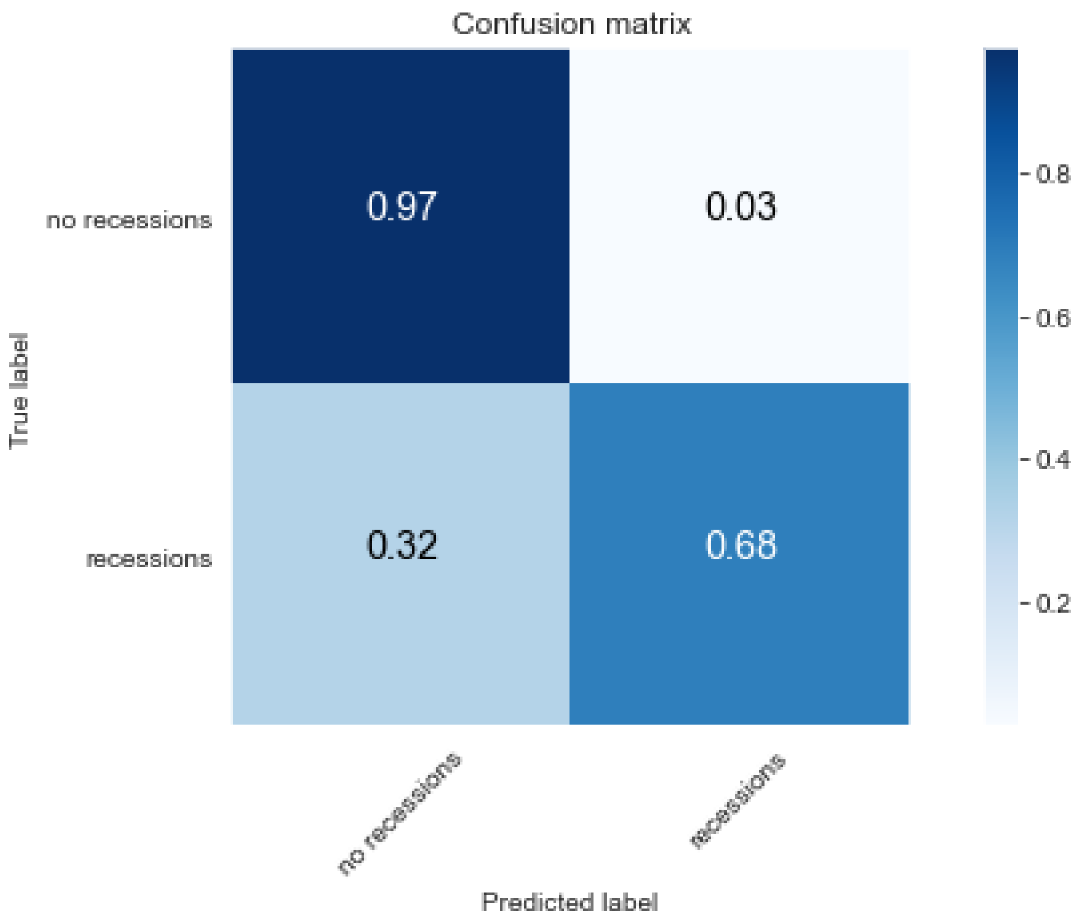

```
 Classificatin Report
               precision    recall  f1-score   support

no recessions       0.98      0.93      0.96       120
```

```
  recessions       0.68      0.89      0.77        19

    accuracy                           0.93       139
   macro avg       0.83      0.91      0.86       139
weighted avg       0.94      0.93      0.93       139
```

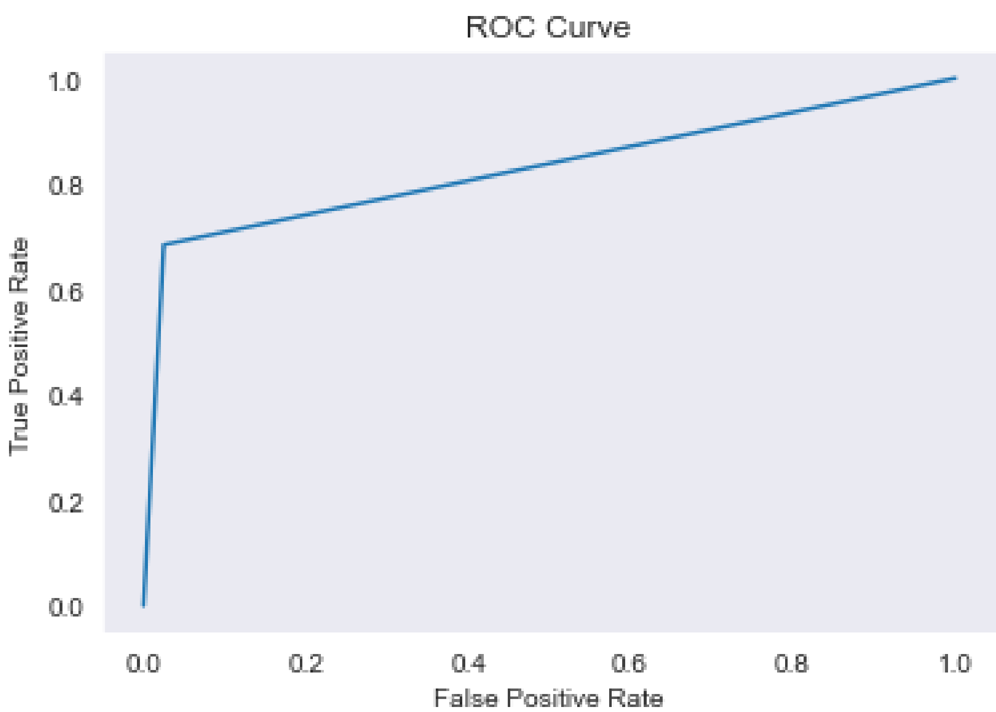
Random Forest Evaluation

```
print(" Random Forest Evaluation")

rf = RandomForestClassifier(n_estimators=300)
rf = rf.fit(xtrain_sc, ytrain)
ypred_rf = rf.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_rf,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_rf)

#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest,ypred_rf, target_names=target_names))
```

```
 Random Forest Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```



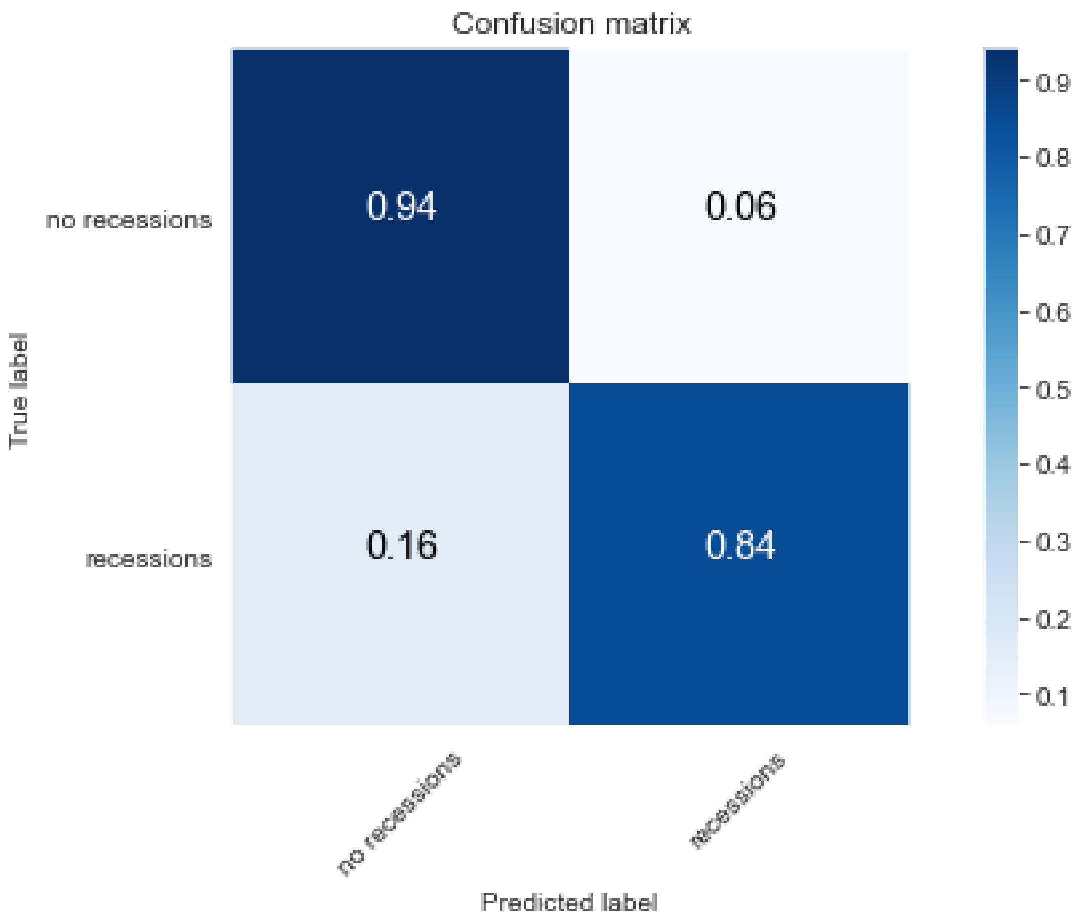

```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       0.95      0.97      0.96       120
```

```
  recessions       0.81      0.68      0.74        19

    accuracy                           0.94       139
   macro avg       0.88      0.83      0.85       139
weighted avg       0.93      0.94      0.93       139
```

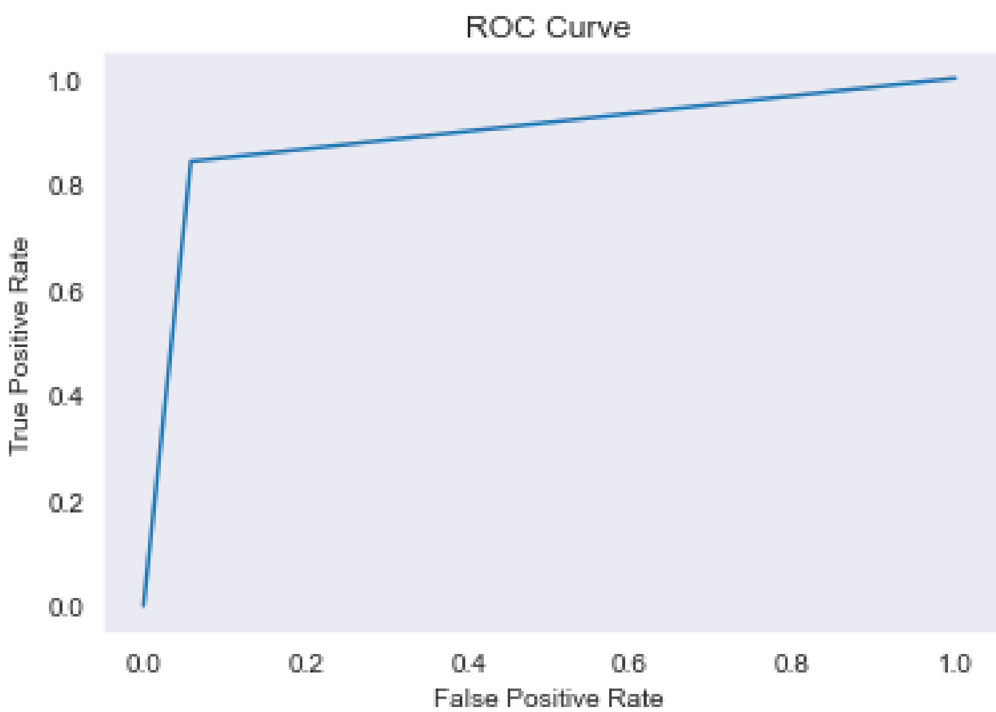
XGBoost Evaluation

```
print(" XgBoost   Evaluation")

ypred_xg= xg_reg.predict(Xtest_sc)

for i,val in enumerate(ypred_xg):
    if val>=0.5:
        ypred_xg[i]=1
    else:
        ypred_xg[i]=0
plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_xg,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_xg)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_xg, target_names=target_names))
```

```
 XgBoost   Evaluation
```



<Figure size 432x288 with 0 Axes>




```
 Classificatin Report
               precision    recall  f1-score   support

no recessions       0.97      0.94      0.96       120
```

```
   recessions       0.70      0.84      0.76        19

     accuracy                           0.76       139
    macro avg       0.83      0.89      0.86       139
 weighted avg       0.94      0.93      0.93       139
```

Conclusion

Based on the metrics above the best performed models are: All same accuracy of : 0.93

Feature Extraction

Principle Components Analysis (PCA)

```
from sklearn.decomposition import PCA

pca = PCA(n_components=9)
xtrain_pca = pca.fit_transform(X_train_res)
PCA_xtrain = pd.DataFrame(data = xtrain_pca, columns = ['PC1', 'PC2','PC3','PC4','PC5
','PC6','PC7','PC8','PC9'])
PCA_xtrain.head()

        PC1       PC2       PC3       PC4       PC5       PC6       PC7  \
0 -0.360659 -0.876865  0.749651 -0.562075 -0.612735  0.230313  0.101575
1  0.006831 -1.728549 -0.103952  0.540974 -0.690155  0.359255 -0.058321
2 -0.161850 -2.716711 -0.123973  0.144837 -1.269101  0.522676 -0.168591
3  0.259249  0.017613  1.955885 -0.546235 -0.346817 -0.913668  0.173424
4 -2.725554 -0.102672  2.906407  1.129097  0.866135  1.390252  0.283735

        PC8       PC9
0  0.022111 -0.008038
1  0.005255 -0.005832
2  0.019566 -0.003763
3  0.046853  0.000697
4  0.012331  0.002094

xtest_pca = pca.fit_transform(Xtest)
PCA_xtest = pd.DataFrame(data = xtest_pca, columns = ['PC1', 'PC2','PC3','PC4','PC5',
'PC6','PC7','PC8','PC9'])
PCA_xtest.head()

        PC1       PC2       PC3       PC4       PC5       PC6       PC7  \
0  0.247919 -2.912200 -1.878636 -1.732440  0.627026 -0.106630 -0.042557
1 -5.710951 -3.409826  3.922411  0.851880  0.381541  0.392459  0.028634
2  2.828691 -2.694209  1.037342 -2.141584 -0.393546 -0.441874  0.027557
3  5.259373  2.054305 -1.899996 -0.648189  0.210434  0.197108 -0.002075
4 -0.996691 -1.412183  2.237035 -0.645472 -0.829105  0.231915  0.066443

        PC8       PC9
0  0.111207  0.028385
1  0.035625 -0.079878
2 -0.078106  0.018613
3 -0.123686 -0.019872
4 -0.058031 -0.081813

from sklearn.preprocessing import StandardScaler
sc2 = StandardScaler()
xtrain_sc2 = sc.fit_transform(PCA_xtrain)
Xtest_sc2 = sc.transform(PCA_xtest)
```

Building Models

Logistic Regression

```
#logistic regression
from sklearn import linear_model
logr = linear_model.LogisticRegression()
logr.fit(xtrain_sc2,y_train_res)

LogisticRegression()
```

Random Forest

```
rf = RandomForestClassifier(n_estimators=400,criterion="entropy")
rf = rf.fit(xtrain_sc2, y_train_res)
```

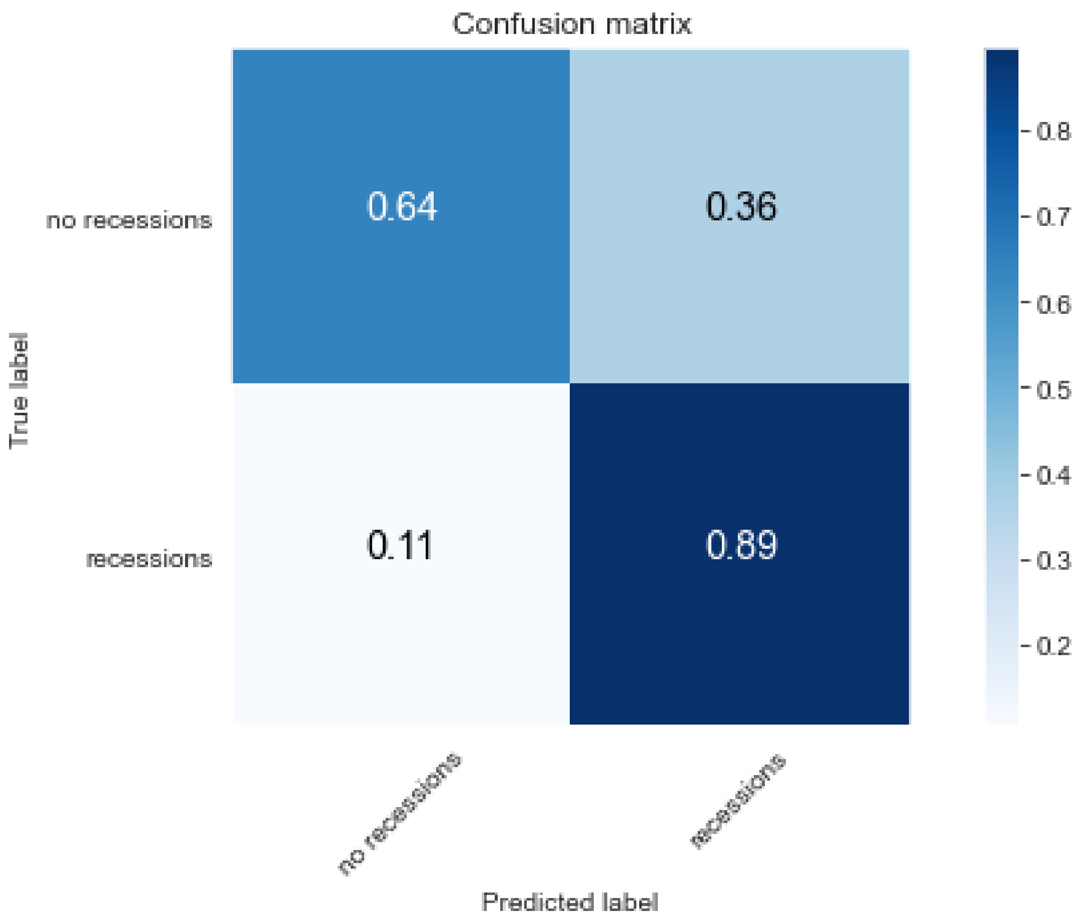
XGBoost

```
xg_reg = xgb.XGBRegressor(objective ='binary:logistic', colsample_bytree = 0.2, learn
ing_rate = 0.1,
                max_depth = 5, alpha = 10, n_estimators = 50)

xg_reg.fit(xtrain_sc2,y_train_res)

XGBRegressor(alpha=10, base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=0.2,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.1, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=5, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=50, n_jobs=0,
             num_parallel_tree=1, objective='binary:logistic', predictor='auto',
             random_state=0, ...)
```

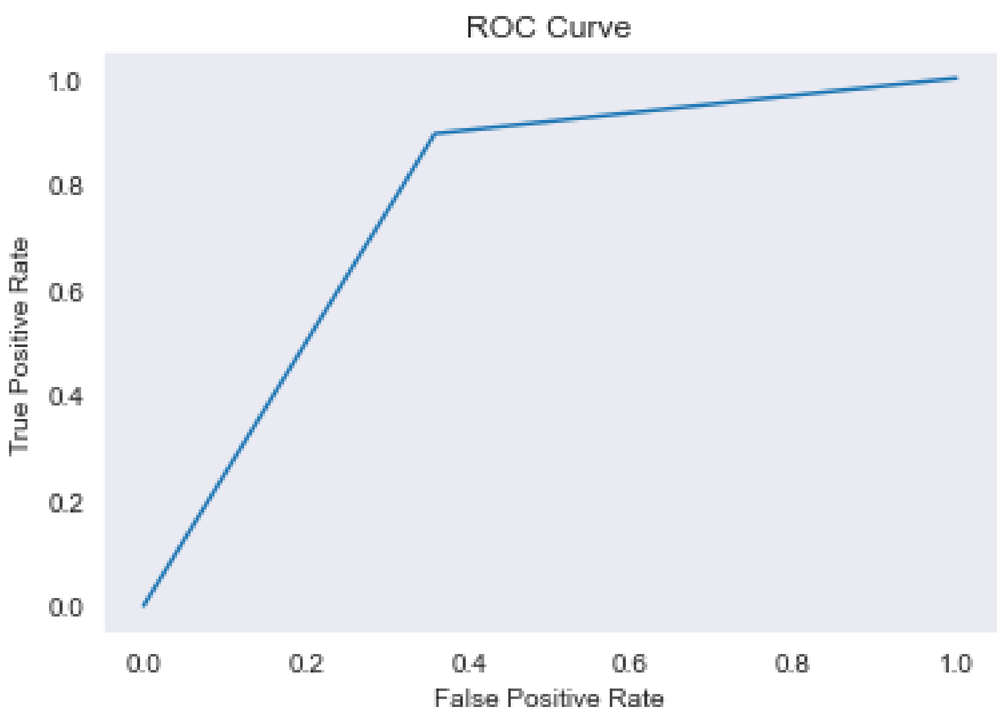
Models Evaluation

Logistic Regresion Evaluation

```
print(" Logisitc Regresion Evaluation")

ypred_logr = logr.predict(Xtest_sc2)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_logr,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_logr)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_logr, target_names=target_names))

 Logisitc Regresion Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```



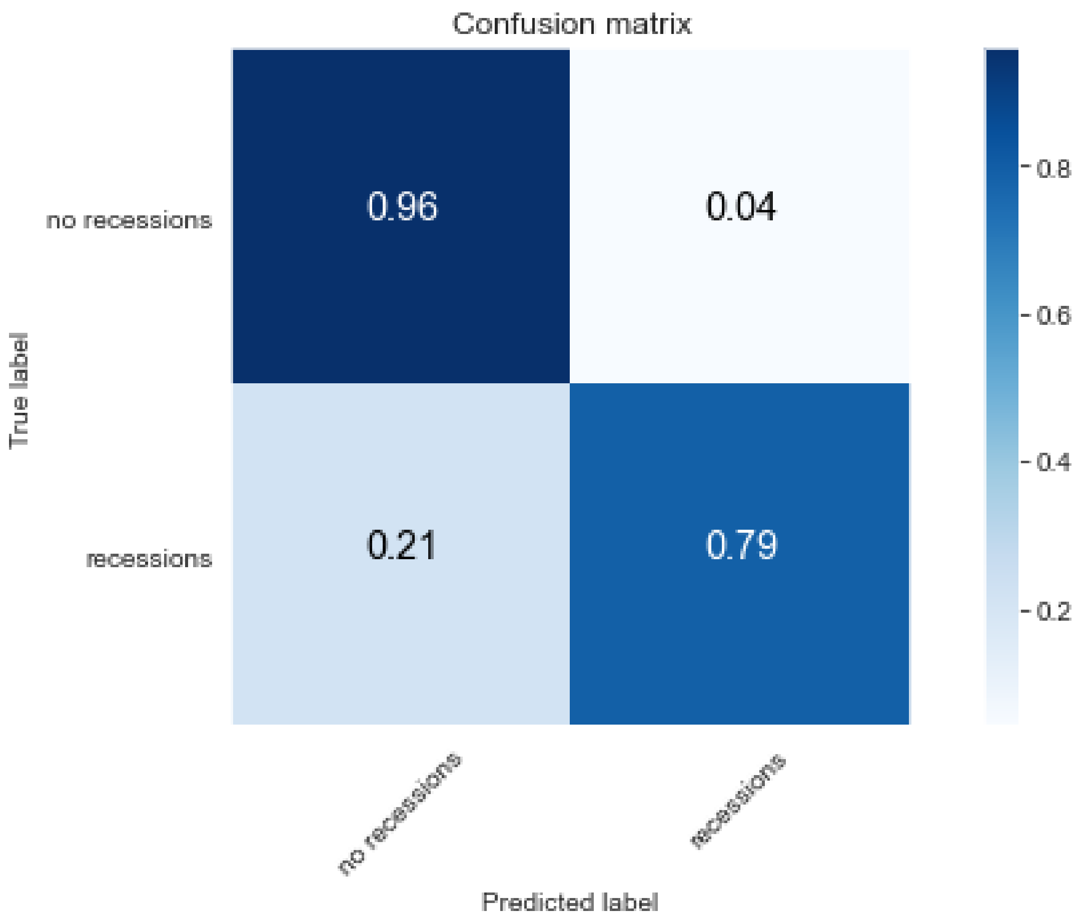

```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       0.97      0.64      0.77       120
```

```
  recessions       0.28      0.89      0.43        19

    accuracy                           0.68       139
   macro avg       0.63      0.77      0.60       139
weighted avg       0.88      0.68      0.73       139
```

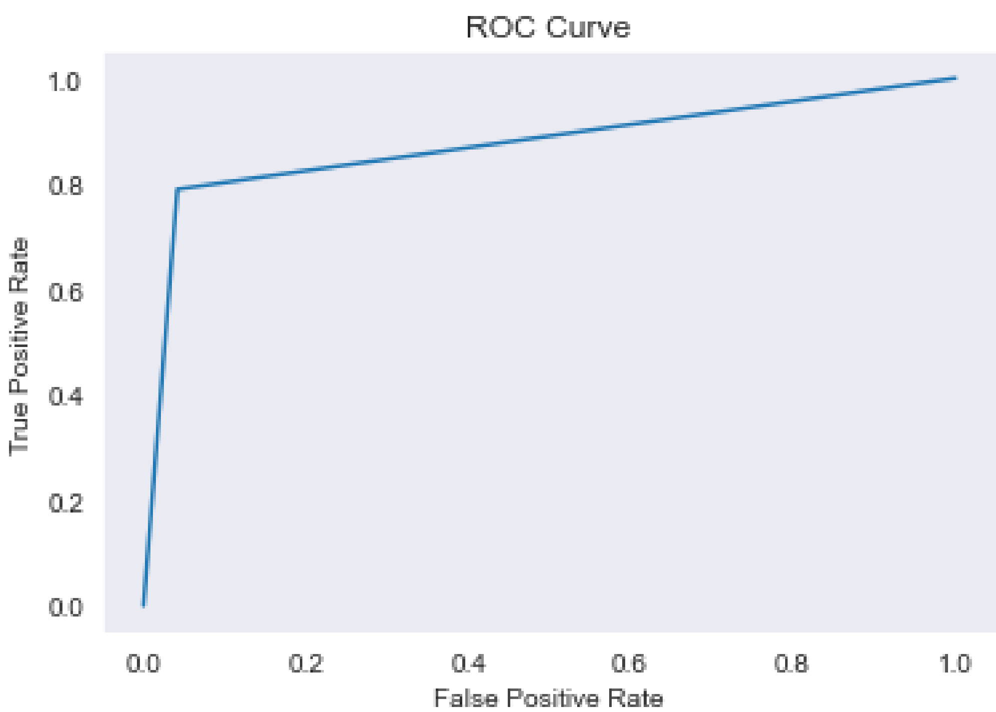
Random Forest Evaluation

```
print(" Random Forest Evaluation")

rf = RandomForestClassifier(n_estimators=300)
rf = rf.fit(X_train_res, y_train_res)
ypred_rf = rf.predict(Xtest_sc)

plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_rf,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_rf)

#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest,ypred_rf, target_names=target_names))
```

```
 Random Forest Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```



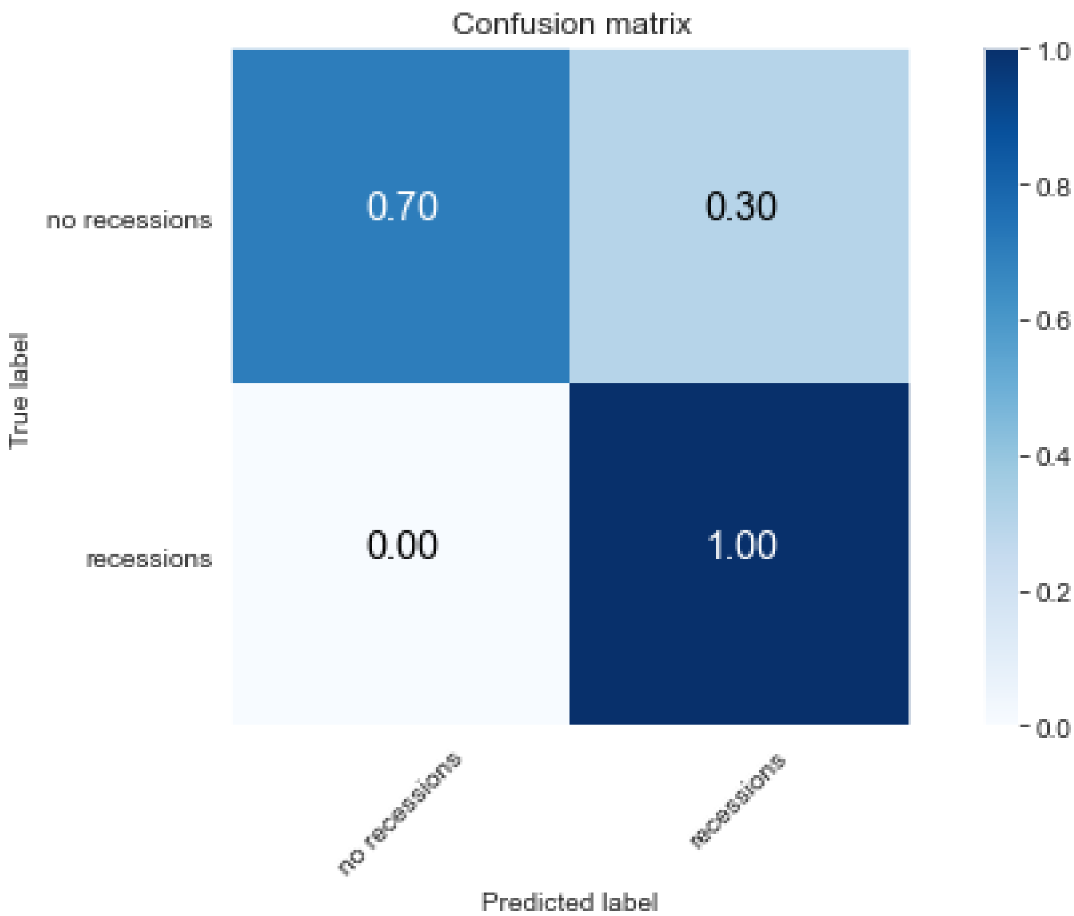

```
 Classificatin Report
               precision    recall  f1-score   support

no recessions       0.97      0.96      0.96       120
```

```
 recessions       0.75      0.79      0.77        19

   accuracy                           0.94       139
  macro avg       0.86      0.87      0.87       139
weighted avg      0.94      0.94      0.94       139
```

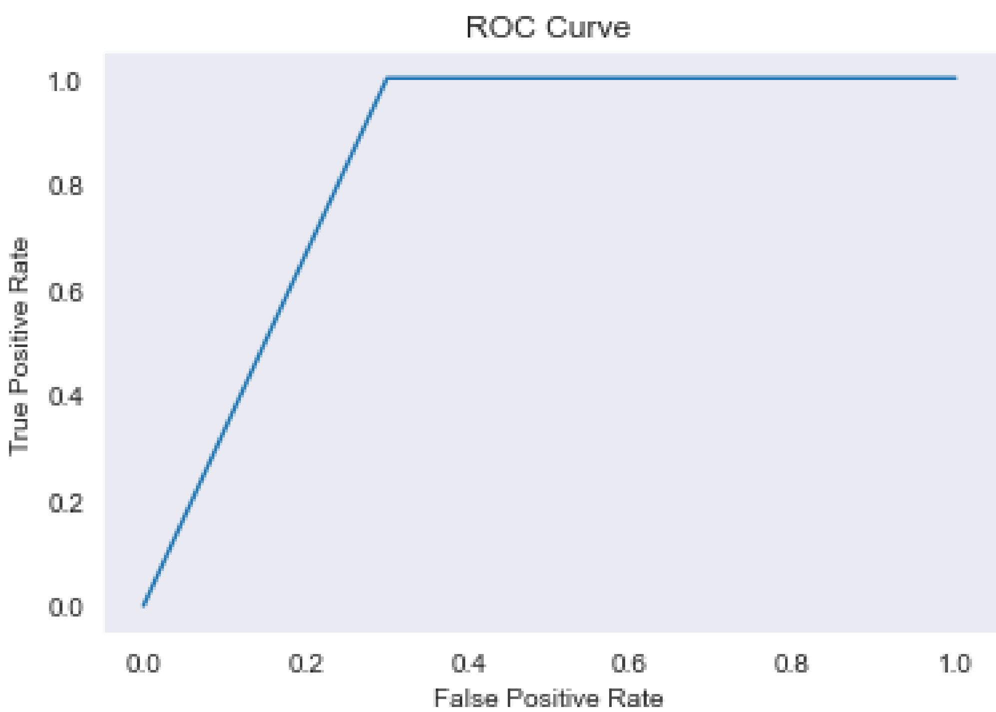
XGBoost Evaluation

```
print(" XgBoost   Evaluation")

ypred_xg= xg_reg.predict(Xtest_sc2)

for i,val in enumerate(ypred_xg):
    if val>=0.5:
        ypred_xg[i]=1
    else:
        ypred_xg[i]=0
plt.figure(figsize=(8,5))
plot_confusion_matrix(ytest,ypred_xg,target_names)

#metrics
fpr, tpr, _ = metrics.roc_curve(ytest,  ypred_xg)
#ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title("ROC Curve")
plt.show()

print(" Classificatin Report")
print(classification_report(ytest, ypred_xg, target_names=target_names))
```

```
 XgBoost   Evaluation
```




```
<Figure size 432x288 with 0 Axes>
```




```
 Classificatin Report
              precision    recall  f1-score   support

no recessions       1.00      0.70      0.82       120
```

```
  recessions       0.35      1.00      0.51        19

    accuracy                           0.74       139
   macro avg       0.67      0.85      0.67       139
weighted avg       0.91      0.74      0.78       139
```

Conclusion (By using Feature Extraction)

Based on the metrics above the best performed models are:

- Random Forest with 0.94 accuracy
- XGBoost with 0.74 accuracy