# The GDP, the US treasury yield and the federal funds rate: Who follows whom, when and why?

Note: The published version of this article has figures that are not well reproduced. The present version shows the figures better, and is also slightly modified to better describe the figures and hypotheses.


## Abstract

### Purpose

This study addresses the fundamental question on how the major players in the economy dynamically interact with each other: among the central bank, the investors in the bond market, and the firms and consumers that contribute to the economic growth, who gets information from whom, when and why?

### Design/methodology/approach

To answer, "who follow whom", we apply a novel technique to examine the lead-lag relations between three time series, the federal funds rate, the treasury yield curve, and the gross domestic product. To investigate "when and why", we apply principal component method to cluster economic states that are similar with respect to the eight descriptor variables.

### Findings

We show that the bond market potentially obtained information from the federal funds rate 61% of the time during the period 1977-2019, and at about the same percentage as the federal funds rate was a leading variable to GDP. Our analysis also suggests that the bond market obtained information directly from GDP when unemployment and inflation was high (34% of the time). In addition, we find that the federal fund rate was leading GDP when GDP deviated from the target value, consistent with the Federal Reserve's policy of boosting and damping the economy when GDP growth is low or high respectively.

### Originality/value

This article provides insights in fundamental questions that have important implications for empirical work on the monetary policy, financial stability, and economic activities.


*JEL Classification:* C53, E43, E47
*Keywords:* Term structure; Interest rates; GDP; Forecasts

# 1. INTRODUCTION

The treasury yield curve and the federal funds rate in US are among the most closely watched economic indicators. The shape of the yield curve is typically upward sloping, but it becomes flat or slopes down-ward (also known as "inverted") before an upcoming recession (Fama 1986, Estrella and Mishkin 1998, Rudebusch 2009).

In our study, we address the question on how the major players in the economy interact with each other: the Federal Reserve's Federal Open Market Committee, the investors in the bond market, and the firms and consumers that contribute to the economic growth; who gets information from whom, when and why? Several studies have addressed similar questions, e.g., Diebold, Rudebusch et al. (2006) and Bauer and Swanson (2020), but here we apply a new technique that allows us see actual leading relations between players. Besides, although a large literature has studied relations among the treasury yield curve, economy growth, and the federal funds rate, we provide another angel by connecting these financial metrics with their major players to understand those players' role, and the dynamic information flow in the economy.

First, we investigate the question "who follows whom" by examining the lead-lag relations between three time series: the federal funds rate (FF), the treasury yield curve (T), and the gross domestic product (GDP). We apply a relatively novel technique proposed by Seip and McNown (2007) that allows us to identify lead - lag relations between time series over short periods. One advantage of our technique is that it does not require the time series to be stationary, and it identifies very short time windows that show lead-lag relation. During the period 1977-2019, we find that the bond market potentially obtained information from the federal funds rate (61%) of the time and less often (34% of time) from the changes in gross domestic product (GDP). Meanwhile, the funds rate decision by Federal Reserve seems to lead the economic growth about 63% of the time.

Second, to answer the question "when and why", we combine the lead-lag relations with principal component analysis to cluster economic states that are similar with respect to the eight macroeconomics variables. We find that the bond market obtained information directly from GDP when unemployment (UE) and inflation INF) was high. Our analysis also suggests that the federal fund rate was leading GDP when GDP deviated from its target value, consistent with the aim of Federal Reserve's policy in managing economic growth.

The answers to these questions have important implications for empirical work on the monetary policy, financial stability, and economic activities. Knowing the interaction and dynamics of major players in the economy helps policymakers to make better predictions and to improve the effectiveness of the monetary policy. It also helps market participants to make better investment decisions and to adjust investment strategies. Our analysis help researchers understand the information flows between the major players in the economy and the potential feedback effect for a reverse influence.

In the rest of the manuscript, we first give a survey of the literature and develop three hypotheses, section 2. In section 3 we present the data with references to their sources. In section 4 we give an outline of the methods used, in particular the relatively novel method for identifying lead-lag relations and cycle times for cyclic series. In section 5 we present the results. First, in section 5, we show the patterns for lead-lag relations between the three macroeconomic variables, the yield curve, the Federal funds rate and the GDP. Thereafter, we show the economic conditions when lead-lag relations occur. In section 6 we discuss the results and in section 7 we conclude and offer some policy implications.

## 2. Literature review and hypotheses

There exists a substantial body of literature on the Fed's of interest rate, the factors that determine economic growth, and the predictive power of treasury yield curve on future economic activity. In this section, we provide a review of literature and develop our hypotheses on the relationships among the federal funds rate, the treasury yield curve, and the real economic activity. We use the cited author's terms for the yield curve and the federal fund's rate.

### 2.1 Yield curve and gross domestic product, GDP

A broad literature studies the predictive power of financial and macroeconomic leading indicators for real economic growth. Among these are the slope of the treasury yield curve that has been established as a leading indicator of future economic activity. For example, in the theoretical model of coincident and leading indicators of Stock and Watson (1988), the slope of the yield curve is found to be particularly useful predictors of future economic growth. Chen (1991) studied the relationship from financial investors' point of view and showed that the yield curve can forecast the changes in the future growth rates of gross national product. Estrella and Hardouvelis (1991), Estrella and Mishkin (1996) and Estrella and Mishkin (1998) have showed empirically that the slope of the treasury yields curve has strong predictive power for U.S. future real economic growth. Duarte, Venetis et al. (2005) confirm the ability of the yield curve as a leading indicator to predict output growth in the European Monetary Union. Nyberg (2010) showed that the yield curve is an important predictor for recessions in Germany.

While most of the research in this field studies the yield curve as a predictor of future economic activity, there could be a relation going in the opposite direction, from the changes in economic activity to the future yield curve. Evans and Marshall (2007) ask how macroeconomic impulses affect the nominal yield curve and identify different types of macro shocks. In particular, their measure of marginal-rate-of-substitution shock is shown to move output, real interest rates, and inflation in the same direction, shifting the nominal yield curve level. However, their measure of expansionary technology shock moves output and the real rate up, but drives expected inflation down, so its effect on nominal interest rates is ambiguous. Estrella (2005) develops a dynamic theoretical model with rational expectations and shows that the relation could go in both directions. The yield curve contains expectations of future activity, which in turn may depend on explicit monetary policy objects that is influenced by current economic activity. The author concludes that the yield curve should have predictive power for future economic output under most circumstances.

Based on these findings in the literature, we develop the following hypothesis with respect to our research question "who follows whom":

> ***H1**: The slope of Treasure yield curve, which is the difference between the long-term and short-term treasury bond interest rate, is a leading variable for the change in the real economic growth, measured by GDP. (T → GDP)*

## 2.2 Federal funds rate and yield curve

Federal funds rate is the interest rate charged for overnight interbank loans. When Federal Open Market Committee raises the federal funds rate, one could expect an increase in other short-term interest rate since short-term interest rates are largely benchmarked to the federal funds rate. However, it is less clear how monetary policy should affect the long-term interest rate, such as five-, ten-, and 15-year treasury bonds. Cook and Hahn (1989) estimates of the effects on interest rates of a publicly announced change in the federal funds rate. They find that in response to a 100-basis-point increase, short rates rise about 50 basis points, while long rates rise about 10 basis points. Similarly, Edelberg and Marshall (1996) examine at the relationship between monetary policy and long rates during the postwar period and find large effect for short rates and insignificant effect at longer maturities such as ten and 15 years maturities. In other words, increases in the Fed' interest rate flattens the yield slope, and decreases the curvature of the yield curve. Christensen (2018, Figure 1) shows the daily overnight federal funds rate targeted by the Fed and the yield difference between the ten-year and two-year treasury yields. The figure shows a clear negative relation between the federal funds rate and the slope of treasury yield curve.

In sum, the above literature suggests that the changes in the federal fund rate may affect the future yield curve. Thus, we develop our second hypothesis regarding "who follows whom" as the following:

> ***H2**: The change in the federal funds rate is a leading variable to a change in the slope of treasure yield curve. (FF →T).*

## 2.3 Gross domestic product, GDP, and Federal funds rate

Historically, the Federal Reserve's Federal Open Market Committee has set monetary policy by raising or lowering its target for the federal funds rate. The conventional wisdom is that the Federal Reserve examines the GDP and other financial and macroeconomic variables to determine the federal funds rate (Greenspan 2007). Specifically, Taylor (1993) argues that the Federal Reserve has a "target" for real GDP and inflation. The Fed raises federal funds rate and thereby tighten monetary policy when there is a positive output gap, that is, an excess of actual GDP over the target GDP. Taylor (1999) focuses on interest-rate rules in which the policy rate is adjusted in response to the state of the economy. With data back to 1879, the author shows that macroeconomic performance, in particular the volatility of inflation and real output, was quite different with the different policy rules. Other researchers also confirm that for given inflation rate and output gap, the Federal Reserve chose a much lower real interest rate in the 1960s and the 1970s than it did in the 1980s and 1990s (for example, Clarida, Gertler et al. (2000) and Orphanides (2003)

Even though the studies above show that the Federal Reserve adjusted policy rate differently in different periods, they also seem to agree that the policy rate has been adjusted in response to the output gap. Therefore, our third hypothesis regarding "who follows who" states as follows:

> **H3**: The real economic growth, measured by change in GDP, is most often a leading variable for a change in the federal funds rate. (GDP → FF).

Thus, our overall relations will be the circular GDP → FF →T → GDP. In addition, we examine "when" and "why" we obtain the lead-lag relations we propose.

# 3. DATA

Our sample period is from 1977 to 2019. We collect economic data at monthly frequency, from 1977M to 2019M5, that is, 512 entries. We use two sets of data. The first set is used to identify lead-lag relations between GDP, the treasury yield curve (denoted as T hereafter) and the federal funds rate (denoted as FF hereafter). The second is used to characterize the US economy and embed the lead-lag relations between the T, the FF and the GDP in a "map" of the economy.

## 3.1 GDP, the Yield curve T, and the federal fund rate FF

We use real gross domestic product (GDP), obtained from Federal Reserve Bank of St. Louis, as a proxy for economic growth. The real GDP is inflation adjusted. Since the GDP data are quarterly, we interpolated the GDP data to monthly to match the frequency of the other variables. We measured the yield curve as the difference between the 10-year and 2-years treasury bond yields [1]. We obtained the data for the difference between the 10 years constant maturity minus 2-year treasury constant maturity from the Federal Reserve Bank of St. Louis. We use the monthly effective federal funds rate (FEDFUNDS), retrieved from Federal Reserve Bank of St. Louis.

The GDP and the T data were linearly detrended to avoid long-term effects and thereafter centered and normalized to unit standard deviation. This can be done without loss of information since the two series are measured in different units. Last, the data were LOESS smoothed with parameters (f) = 0.1- 0.2 and (p) = 2 to avoid high frequency [2]. However, the Covid-19 pandemic in 2020 has caused an exceptionally rapid decrease in the GDP, which should not have been smoothed out. The data are summarized in Table 1.

[1] We use the difference between the 10-year and 2-year bond yields for two reasons. First, it is the most commonly used by financial commentators. Bauer and Mertens (2018) summarize that "financial commentators typically focus on the difference between the ten-year and two-year Treasury yield (10y–2y), because the former summarizes long-term perceptions and sentiment of bond market investors, while the latter is viewed as a reasonable indicator of the stance of monetary policy." Second, data coverage for the 2-year treasury constant maturity rate is long, available from June 1976. For our analysis, the long data coverage is an important factor to take into account.

[2] We use the LOESS smoothing algorithm as implemented in SigmaPlot. It has two parameters, (f) that gives the fraction of the time series that acts as a moving window and (p) that is the degree of the polynomial function used for interpolation. The parameters for LOSS soothing are shown in the variable list in Appendix 1

**Table 1 Data used in the study**

. All data is from https://fred.stlouisfed.org/series/. All data is from 1977 to 2019. The parameter,f, for the LOESS is a smoothing algorithm, see text

| Variable | Acro-nym | Unit | Average | Min | Max | Preliminary treatment |
|---|---|---|---|---|---|---|
| Real Gross domestic product | GDP | Billions of Dollar quarterly | 12184 | 6080 | 19254 | f = 0.1 |
| Effective Federal Funds Rate, Not SA | FF | % | 4.95 | 0.05 | 17.1 | f = 0.1 |
| 10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity , Not SA | T | % | 0.94 | -2.13 | 2.83 | f = 0.2 |
| Industrial Production: Total Index (INDPRO) | IP | Index 2012 = 100 | 80 | 46.83 | 110.55 | Linerarly detrended |
| Money Stock, SA | M2 | Billions of Dollar | 5627 | 1165 | 14872 | with GDP |
| Consumer Price Index, SA | CPI | Index 1982-1984 = 100, | 163.1 | 58,7 | 256,2 | - |
| Unemployment Rate, SA | UE | % | 6.32 | 3,68 | 11,0 | |
| Federal Debt: Total Public Debt Quarterly, SA | PDGDP | % of GDP | 62.9 | 30.6 | 105.2 | |

## 3.2 The US economy

Characterizing the economy by using data-rich data sets has been made in several studies. Moench (2008) suggests categories such as industrial production variables, employment variables and price indexes for such embedding measures.

We characterize the US economy with eight financial and macroeconomic variables that are shown in the literature to affect economic growth. These are industrial production, GDP, monetary supply, treasury yield curve, inflation, unemployment rate, federal funds rate (FF), and public debt. These variables are also shown in Table 1.

We obtain industrial production total index (denoted as IP) from Federal Reserve Bank of St. Louis and linearly detrend the data to avoid the long-term effect. We measure monetary supply as M2 money stock divided with GDP (denoted as M2GDP), where the weekly data on M2 money stock is retrieved from Federal Reserve Bank of St. Louis and is transformed to monthly data. We use consumer price index for all urban consumers (labelled as CPI) from Federal Reserve Bank of St. Louis as a measure for inflation. From the same data source, we also obtain the unemployment rate for all population in United States aged 15-64 (denoted as UE) and the total public debt as percent of GDP (denoted as PDGDP).

To capture the different economic states, we identify recession periods using the National Bureau of Economic Research

(NBER) definitions. The US recessions during the period 1977 to 2019 are shown in Table 2. The right column in the table shows our calculation of the number of months that a negative T- value leads the first month of a NBER recession.

**Table 2 Recessions in the USA 1970 to 2019.**

| Recession | Key factors | Period | Number of months that -T leads the recession |
|---|---|---|---|
| The 1980 recession | The Volcker inflation targeting | Jan 1980–July 1980 | 19 |
| The 1981–1982 recession | The 1979 energy crisis | July 1981–Nov 1982 | - |
| Early 1990s recession | 1990 oil price shock | July 1990–Mar 1991 | 14 |
| Early 2000s recession | The dotcom bubble, the 9/11 attacks and accounting scandals at major U.S. corporations | Mar 2001–Nov 2001 | 16 |
| The 2008 recession | The subprime mortgage crisis in US and global financial crisis | Dec 2007–June 2009 | 21 |
| Average | | | 17.5 ± 3.1 |

Note: Data from NBER, National bureau of economic research.

For the last five recessions during 1977-2019, the time between the first month that the treasure yield curve became negative and the first month of NBER recessions were on average 17.5 ± 3.1 months.

# 4. METHOD

To investigate "who follows whom", we first examine the lead-lag (denoted as LL hereafter) relations between three time series, the federal funds rate (FF), the treasury yield curve (T) and the gross domestic product (GDP): LL (-FF, GDP), LL (FF, T) and LL (GDP, T). Roughly speaking, the first relation, LL (-FF, GDP), shows a management situation where the Fed is managing GDP by changing FF; the next two relations, LL (FF, T) and LL (GDP, T), show the information that investors and management in the market use to make decisions. This helps us under-stand the information flows between the major players in the economy and the potential feedback effect for a reverse influence.

Second, to find out "when and why", we apply the principal component analysis that cluster economic states that are similar with respect to the eight key macroeconomic variables.

## 4.1 The Leading –lagging method

Since the lead-lag relations may change with time, it is important to examine the relations over several time windows, e.g., Schrimpf and Wang (2010) and Diebold, Rudebusch et al. (2006). One advantage of the LL- technique used here is that it does not require the time series to be stationary, and it identifies very short time windows that show lead-lag relation. To our know-ledge, other techniques to establish lead-lag relations require the time series to be stationary, e.g., Mosedale, Stephenson et al.

(2006) on Granger causality tests, and therefore preferably much longer.

The lead-lag method calculates running average lead-lag relations, cycle times and lead and lag times (Phase shifts between cyclic series). The description closely follows that of Seip, Grøn et al. (2018). To illustrate this method, we provide an example in Figure 1 using a simple sine function, sin (0.5t + $\phi$ ×RAND()) where $\phi$ = + 0.785 for t = 1-10 and $\phi$ = -0.785 for t = 11-20, and RAND() is the Excel random generator. The lead-lag method is based on the dual representation of a pair of leading and lagging time series, first, as time (x-axis) and the series (y-axis), Figure 1a, and second, as phase plot with one series on the x-axis and the other series on the y-axis, Figure 1b. Two perfect sine functions would show an ellipse with the major axis in the 1:1 or the 1: -1 direction. The two series that shift in being leading and lagging and the direction of the rotation of the trajectories, clock-wise or counter clock-wise, determines which series is leading and which is lagging. A visual illustration of the relation between paired cyclic series and their phase portrait can be found in Seip and Gron (2017) or for a rapid glance in https://en.wikipedia.org/wiki/Lissajous-_curve#/media/File:Lissajous_phase.svg.

The rotational patterns are quantified in phase plot by the angle, (V)[3].

$$(1)\quad V = sign(\bar{v}_1 \times \bar{v}_2) \cdot A\cos\left(\frac{\bar{v}_1 \cdot \bar{v}_2}{|\bar{v}_1| \cdot |\bar{v}_2|}\right)$$

Where $v_1$ and $v_2$ are two vectors formed by two sequential trajectories between three sequential points in the phase plot. The sizes of the angels V are depicted as the light grey bars in Figure 1c. This helps us understand the information flows between the major players in the economy and the potential feedback effect for a reverse influence.

### 4.1.1 Lead-lag strength

From the angels we identify a lead-lag strength as:

$$(2)\qquad LL = (N_{pos}-N_{neg})/\,(N_{pos} + N_{neg})$$

Where $N_{pos}$ and $N_{neg}$ are the relative numbers of positive and negative rotations in a sample of N total = $N_{pos}$ + $N_{neg}$ rotations. In this example, we use $N_{total}$ = 9. The variable LL range between -1 (the y-variable leads the x -variable) and +1 (the y-variable lags the x- variable). For LL to obtain a value of 1.0, with $N_+$ = 9 and $N_-$ = 0 so that LL = (9-0)/(9+0) = 1.0. In terms of rotations in a phase plot, it would mean that two stochastic series would result in a persistent counter clock- wise rotation for nine consecutive time steps. We calculate a 95% confidence interval using Monte Carlo simulations with two uniformly stochastic series 9 steps long. The 95% confidence interval was found as the limit for 1000 runs. The numbers LL are depicted as the black bars in Figure 1c.

[3]With x- coordinates in A1 to A3 and y-coordinates in B1 to B3 the angle is calculated by pasting the following Excel expression into C2: =SIGN((A2-A1)*(B3-B2)-(B2-B1)*(A3-A2))*ACOS(((A2-A1)*(A3-A2) + (B2-B1)*(B3-B2))/(SQRT((A2-A1)^2+(B2-B1)^2)*SQRT((A3-A2)^2+(B3-B2)^2))).

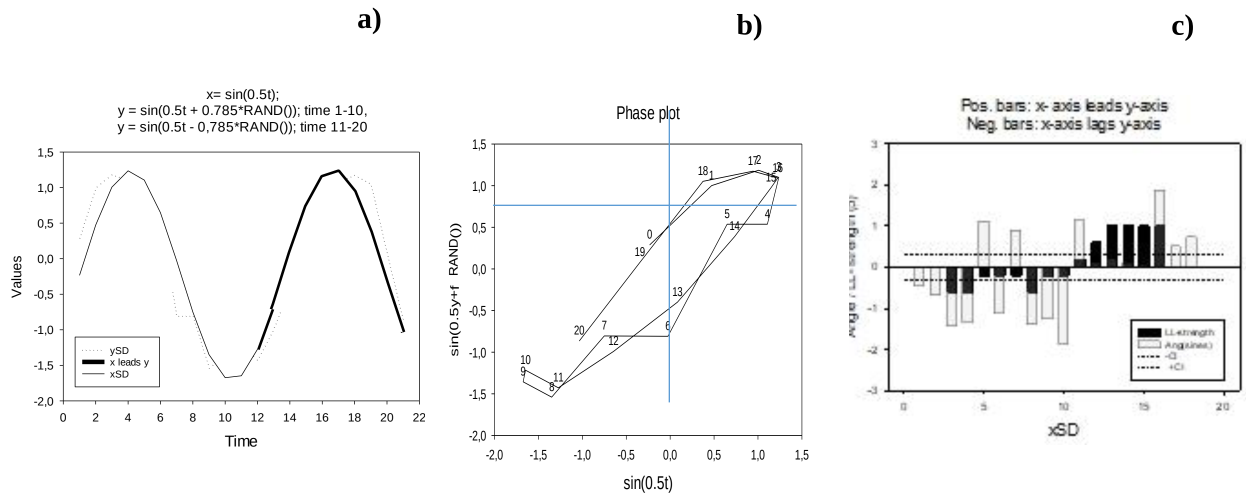



**Figure 1 Example: Calculating leading-lagging (LL) relations and LL-strength.**
a) Two sine functions: the smooth curve is a simple sine function, sin (0.5t), the dashed curve has the form sin (0.5t + $\phi$ ×RAND()) where $\phi$ = + 0.785 for t = 1-10 and $\phi$ = -0.785 for t = 11-20. RAND() is the Excel random generator. Bold part of the simple sine function, xSD, shows that it leads ySD. b) In a phase plot with sin (0.5.t) on the x- axis and the sin(0.5t+$\phi$ RAND()) on the y-axis, the time series rotates first counterclockwise (1 to 10, negative by definition) then counterclockwise 11 to 20; $\theta$ is the angle between two consecutive trajectories. The wedge suggests the angle between the origin and lines to observations 1 and 2. See text for details. c) Angles between successive trajectories (grey bars) and LL-strength (black bars). Dashed lines suggest confidence limits for persistent rotation in the phase plot and persistent leading or lagging relations in the time series plot. Figure redrawn after (Seip, Grøn et al. 2018)**.**

The dashed lines show the 95% confidence interval for significantly persistent rotations in the phase plot, and significant cycles in the time series plot. Note that if the series are smoothed, the confidence interval will be larger because some noise should be removed.

### 4.1.2 Cycle times

When the trajectory of the two series closes in the phase plot, the common cycle time for the two series is the time corresponding to the number of observations that is required for the closure. For example, it requires about six time steps to close the elliptic form in Figure 1b, corresponding the cycle length, CL ≈ 6.28 ≈ 2π for the sine functions in Figure 1a. Thus, the lead-lag relations between two time series are characterized by three time series: the angels $V_i$ (n = 3), the lead-lag strength, LL - strength (n = 9) and the cycle times, CL.

## 4.2 Principal component analysis (PCA)

To investigate “when and why”, we apply the principal component analysis (PCA) to cluster economic states that described by eight macroeconomic variables. Our analyses generate two sets of graphs. The first type of graph, a “map” of US economic states, is based on the score plot of PCA that clusters similar economic characteristics. The second type of graph, the loading graph, tells us which variable determines the position of the states in the first graph. In the loading graph, samples that are at a right angle to each other relative to the origin in the loading plot will either be unrelated or be ¼ of a cycle length out of phase with each other. (Two perfect sine functions with a common cycle length that are ¼-cycle length out of phase will be at a right angle to each other.)

We first depict the recession periods as defined by the NBER in the "map". We then examine which economic variables that distinguish the recessions. The economies may be similar or quite different; the latter suggest that recessions can occur under different conditions and ultimately be caused by geopolitical events or non-rational behavior, e.g. Akerlof and Shiller (2009). Thereafter, we compare the trajectories for the lead-lag relations for all three pairs of variables to the states of the economy. If these trajectories are identified in restricted areas in the "map", the economic states that are represented in the areas will characterize the economies outlined by the trajectories.

### 4.3. LOESS smoothing.

We use the LOESS smoothing algorithm as implemented in SigmaPlot. It has two parameters, (f) that gives the fraction of the time series that acts as a moving window and (p) that is the degree of the polynomial function used for interpolation.

### 4.4 Software

The data processing and analyses are made in Excel and with the software package SigmaPlot. All Figures in the paper are made in SigmaPlot, but Excel versions and the data behind each Figure are included in an Excel book.

## 5. RESULTS

We first present the results for the lead-lag relations. Thereafter, we present the "map" of US economy 1977 to 2019M5 that shows the economic context for the lead-lag relations we have identified.

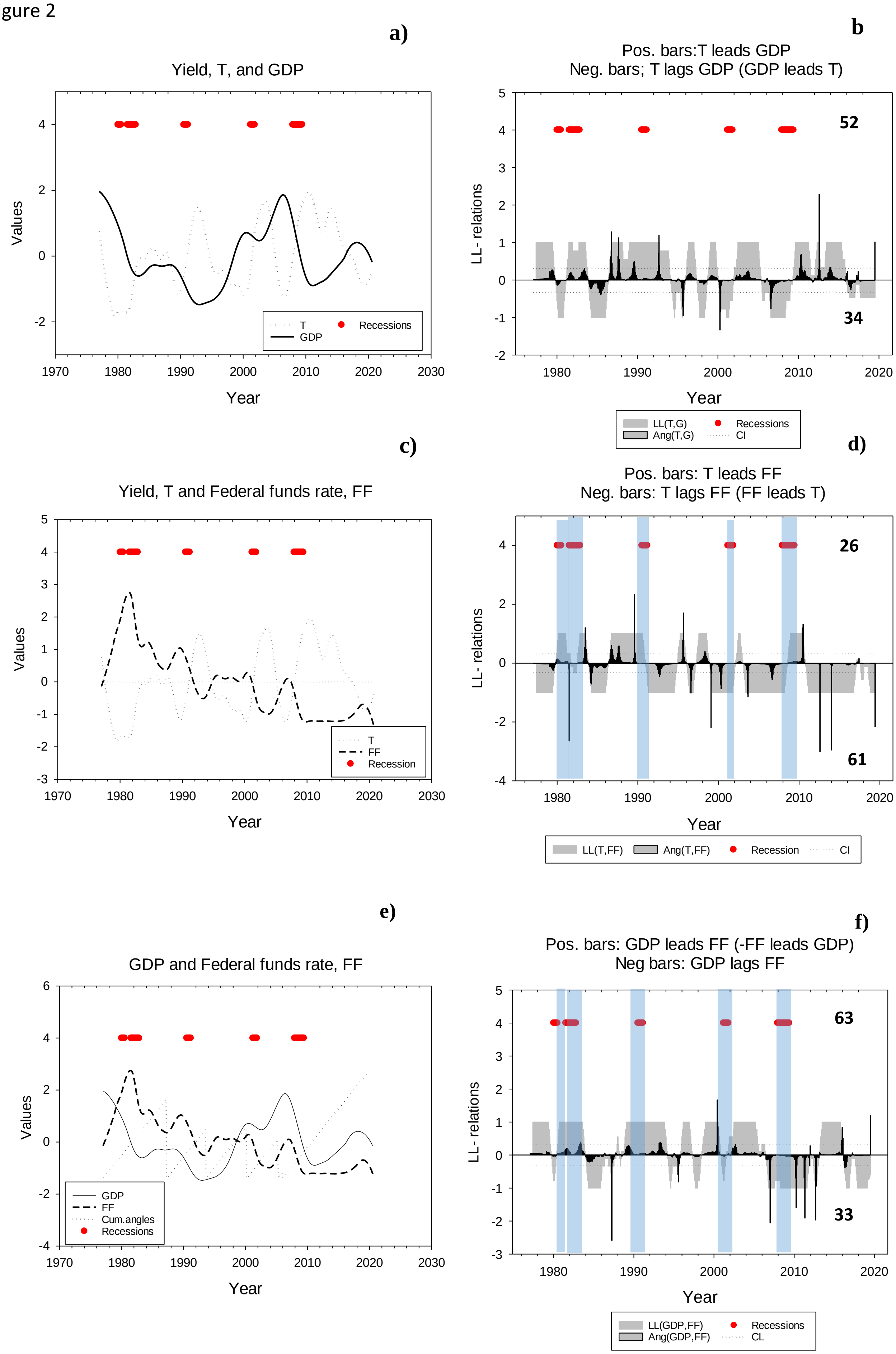
### 5.1 Leading- lagging relations.

. The LOESS smoothed time series are shown in Figure 2a (T and GDP), Figure 2c (T and FF), and Figure 2e (GDP and FF). The lead-lag relations are presented in in Figure 2b (T and GDP), Figure 2d (T and FF) and Figure 2f (GDP and FF). Positive light shaded bars show that the first variable leads the second variable whereas negative light shaded bars show that the first variable lags the second variable. The black bars show lead-lag relations over three consecutive observations.

The dashed horizontal lines designate the 95% confidence intervals for the LL relation, but refer to the unsmoothed time series. The number in bold show the percentage of time that the positive and negative bars suggest significant leading relations. Note that leading times do not sum to 100 % since there are portions where lead-lag relations are not significant. The time windows for the NBER recessions are drawn as red horizontal lines and marked with light shaded rectangles in the right column panels.

The lead-lag relation of the yield curve T and GDP is shown in Figure 2a and 2b. For our sample period of 1977-2019, T is a significant leading variable for GDP for 52% of time, (T → GDP) whereas GDP leads T for 34% of times. This finding is consistent with Hypothesis, **H1**, that the slope of Treasure yield curve is often a leading variable for the change in the real economic growth, measured by GDP.

Figure 2



a)
Yield, T, and GDP
Values
Year
T
GDP
Recessions
b
Pos. bars:T leads GDP
Neg. bars; T lags GDP (GDP leads T)
LL- relations
52
34
Year
LL(T,G)
Ang(T,G)
Recessions
CI
c)
Yield, T and Federal funds rate, FF
Values
Year
T
FF
Recession
d)
Pos. bars: T leads FF
Neg. bars: T lags FF (FF leads T)
LL- relations
26
61
Year
LL(T,FF)
Ang(T,FF)
Recession
CI
e)
GDP and Federal funds rate, FF
Values
Year
GDP
FF
Cum.angles
Recessions
f)
Pos. bars: GDP leads FF (-FF leads GDP)
Neg bars: GDP lags FF
LL- relations
63
33
Year
LL(GDP,FF)
Ang(GDP,FF)
Recessions
CL

**Figure 2. The yield curve, T, the federal funds rate, FF, and GDP.**
**a**) The T and the GDP, detrended, centered and normalized to unit standard deviation. Horizontal dots: the recession periods between 1977 and 2019. **b**) Lead-lag (LL) - relations between the yield curve, T, and GDP. Grey bars: LL relations with n = 9 and black bars with n = 3. Horizontal dots: The NBER recession periods; dashed, horizontal lines, 95% confidence limits for LL-relations. Bold numbers: years with significant LL- relations. **c**) The yield curve, T, and the FF. The rest as in panel a. **d**) LL-relations between T and FF. The rest as in panel b. **e**) The GDP and the FF. Dashed zigzag line: common cycles for GDP and FF. The rest as in panel a. **f**) LL-relations between GDP and FF. The rest are as in panel b.

Next, we look at Figure 2c and 2d that depict the lead-lag relation between the yield curve T and the federal funds rate FF. For the period 1977-2019, FF is shown to be a significant leading variable for T for 61% of times (FF →T) while it lags T for only 26% of times, Figure 2d. This finding provides some support to our Hypothesis, **H2**, that the change in the federal funds rate is often a leading variable for a change in the slope of treasure yield curve.

The lead-lag relation of the pair FF and GDP is shown in Figure 2e and 2f. During period 1977-2019, GDP is a significant leading variable for FF for 63% of the time (GDP →FF; and – FF →GDP), supporting our Hypothesis, **H3**, that the real economic growth, measured by change in GDP, is often a leading variable for FF. In addition, the pair FF and GDP appears to show the most similar procyclic pattern. To better understand the lead-lag relation over the business cycle, we have added a dashed curve in Figure 2e that indicates a common cycle length for the FF and GDP based on the closure of trajectories for the two time series in a phase plot. The cycle lengths range between about 60 and 80 months. Plotting GDP against FF (both series normalized to unit standard deviation) gives a slope, s = 0.0962, $p > 0.1$ suggesting that the overall phase shift is less than ½ cycle length (the series are procyclic), but close to ¼ cycle length (the main pattern for the trajectories in the phase plot show almost a circle and gives $R \approx 0$, not shown in figure). Thus, the lead-time for FF to GDP should be in the range 15 to 20 months (≈ ¼ of 60 to 80 months).

## 5.2 A "map" of US economy 1977 to 2019

In Figure 3, we construct a "map" of the US economy 1977M1 to 2019M5 by defining the economy with eight economic variables. By comparing the score plot (Figure 3a) with the loading plot (Figure 3b), we see that recent recessions are occurring under increasingly lower FF and with increasingly higher monetary supply, M2GDP, and public debt, PDGDP.

Figure 3c to f show the lead-lag relations embedded in the US economy map. We choose to show the lead-lag relations that correspond to our three hypotheses, that is, the cases when (minus) FF leads GDP (63 %), when FF leads T (61%), and when GDP leads T (34%). (Note that the Fed lowers its interest rate when it wants to boost the economy). Figure 3c shows that the Federal Reserve is a leading "player" when IP and GDP are low and when they are high. This is for example the case from 1989 to 1994, and these dates correspond to the dates for light gray positive bars in Figure 2f that designate a leading role for -FF to GDP.

**Figure 3**

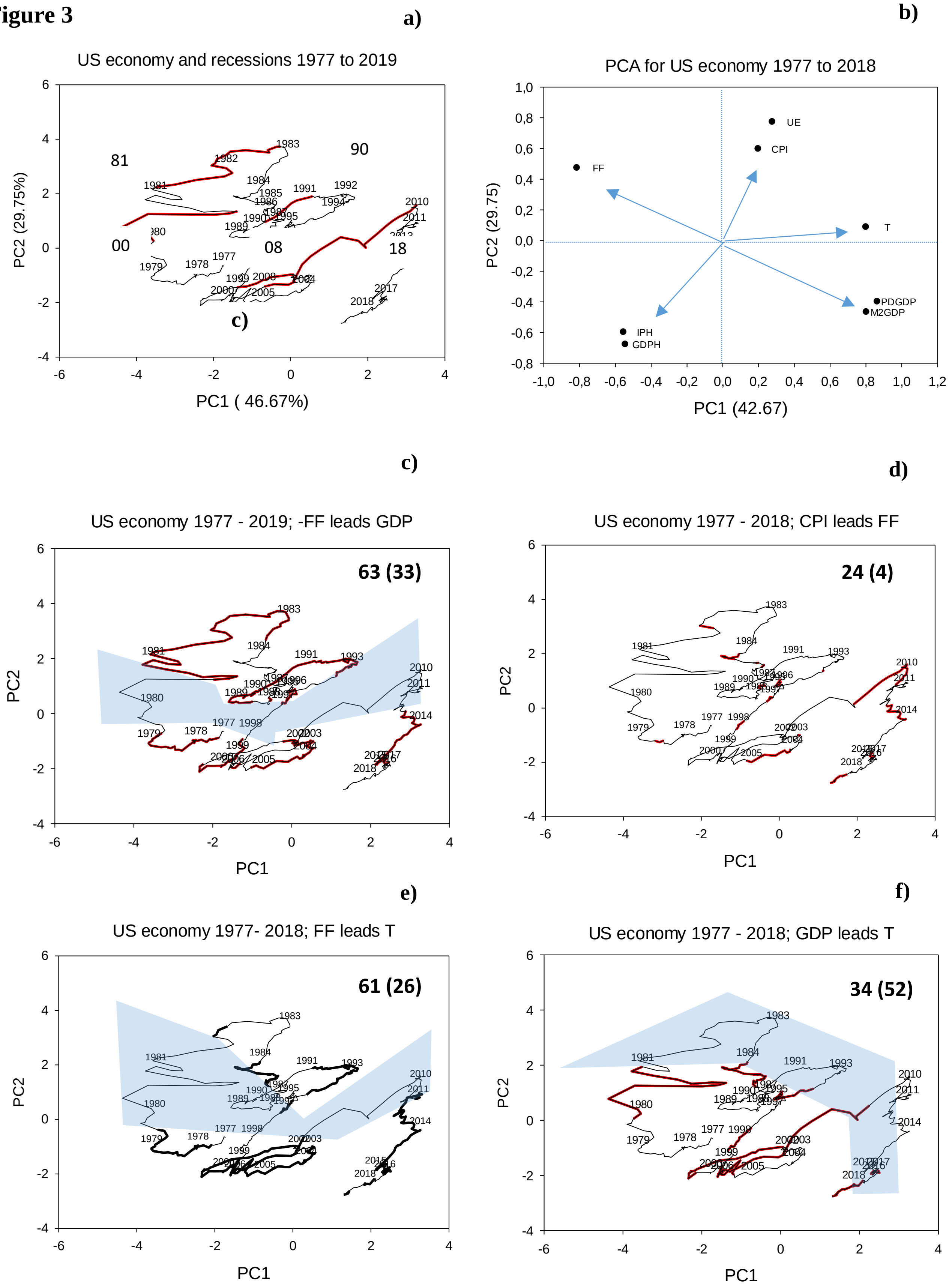



**Figure 3 The US economy 1977 to 2019 as defined by the 8 variables**

**a**) The thick red curves show the recession periods as defined by NBER. **b**) The loading plot show the variables that define the scores in panel a. **c)** The thick red curves show the observations where -FF leads GDP. **d**) CPI leads FF, **e**) -FF leads T. **f**) GDP leads T. The variables that define the US economy are the detrended industrial production (IPH), the detrended Gross domestic product (GDPH), monetary supply M2 divided by GDP (M2GDP), the treasury yield curve (T), the consumer price index (CPI), the unemployment (UE), the federal funds rate (FF), and public debt divided by GDP (PDGDP).

Figure 3d shows when the Fed also examines inflation as expressed by the CPI. It appears that the Fed only sporadically consider inflation. Inflation leads FF only 24 % of the time.

Figure 3e shows that the investors potentially also use information from the Fed at low and high values of GDP and IP (FF leads T), that is, consistent with the Federal Reserve managing the economy by increasing or decreasing FF.

Figure 3f shows the economy when the investors, T, potentially use information from GDP in their investment decisions. It appears that they do so, except when unemployment, UE, and inflation, CPI, are high.

# 6. DISCUSSION

We discuss what type of information that is available to the Fed, the investors in the bond market, and to the sectors in the economy that collectively determine the GDP.

## 6.1 Lead-lag relations: who, when and why

We assume that when a variable leads a target variable, the information contained in the time series that represent the first variable can potentially be used in decisions that determine the value of the target variable. Thus, a leading relation determines the "when". Our interpretation of the "why" is obtained by embedding the "when" trajectories in a richer economic context of eight macroeconomic time series.

### 6.1.1 The recessions

The distribution of the recessions on the US economy "map" was shown in Figure 3a. Three of these variables, IP, CPI and FF, represent the minimum set of fundamentals needed to capture basic macroeconomic dynamics Diebold, Rudebusch et al. (2006). Recent recessions are at lower FF, higher monetary supply, M2GDP and higher public debt, PDGDP, than the early recessions. Thus, recessions may not depend so much on the actual fiscal and monetary policy, as on third factors that are not described with common macroeconomic time series. Thus, recessions may occur under quite different economies. This may support the findings by Akerlof and Shiller (2009) that there are non-economic and non-rational motives that contributes to recessions. An explanation may be that the investors identify the triggering factors for a recession and incorporate that information into their decisions on buying and selling treasury bonds with different maturities, that is, they determine the T.

### 6.1.2 The Fed, inflation (the CPI) and GDP.

The Fed plays a leading role for the GDP during periods with slow and very high GDP growth (Figure 3c). The Fed's leading role is also associated with a high UE and a high CPI. (GDP is detrended, so we only see the decadal trends). Thus, the leading relation of the Fed's policy may support the role of the Fed as a causative player in the economy.

The Taylor (1993) rule describes how two of the objectives for the Fed's policy: inflation and GDP growth should be incorporated into the Fed's policy decisions. The time windows where CPI leads FF are short and scattered so we believe that inflation has not been a great issue for the Fed during the period 1977-2019M5. However, it might have been an issue around 2005 and on - off from 2008 onward.

### 6.1.3 The Investors (the T) and the Fed

The leading role of FF is most pronounced at high and low values of FF, and during the period just prior to the 2008 recession (Supplementary materials 1). The FF may also have been an issue for investors during the GDP increase following the 2008 recession. This period is characterized by high monetary supply, M2, and high public debt, PDGDP. During the period 1977 to 2019M5, investors have been increasingly dependent on the Fed for information, in the sense that over the time FF has become a more frequent leading variable to T, (Supplementary material 2). Thus, the investors, T, as well as the economy GDP, appear to follow the Fed, and this "double" following occur 50% of the time. However, Moench (2008), examining how the yield curve develop, did not include the FF, but included several versions of the IP indexes. Estrella (2005) found that the forecasting skill of the yield curve has a large relative weight if the policy follows the Taylor (1993) rule. Our result may contrast with findings by Guisinger, Owyang et al. (2019) and Bauer and Swanson (2020) that economic forecasting by the Fed and the private sector has obtained comparable skill with time so that Fed's forecast now should count less.

### 6.1.4 The investor, (the T), and GDP

We found that GDP was leading T 34 % of the time. (In 52% of the time, T leads GDP, Figure 3f, which is consistent with the predictive power of yield curve on GDP as shown in Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), Ang, Plazzesi et al. (2006), Bauer and Mertens (2018). Except for the time prior to and including the 2008 recession, it appears that GDP leads T at times where GDP has intermediate or high values. Investors seem to use GDP as complementary to FF as a source of information. The overlap between the two sources is 22%, but with 7 % of the overlap during the period 2005 and 2008.

In summary, the sequence of major information flow is GDP →FF →T →GDP. However, since it is the negative FF that in theory govern GDP, our results show that (minus) FF → GDP, that is, the Fed govern the economy most of the time.

## 6.2 Robustness of the results

Most of our variables are in monthly frequency while our key variable GDP was originally only available at quarterly and was interpolated to monthly data. So, there could be a potential concern that the way we interpolate the quarterly GDP data to monthly may affect our results. As a robustness check, we compare our GDP variable with the US Monthly GDP (MGDP) Index from IHS Markit. According to IHS Markis, they use calculation and aggregation methods comparable to the official GDP from the U.S. Bureau of Economic Analysis to derive a comprehensive measure of monthly changes in output. Ideally, we would like to run an additional test using the monthly GDP index from IHS Markit to see if the results hold. Unfortunately, the data series is only available from January 1992, which is too short for our study.

In addition to the long data history, we have another reason to favor our interpolated GDP measure. This data comes directly from the Federal Reserve which is closed followed by other market participants and the way we interpolate the quarterly data to monthly is simple and straightforward. To be able to answer, “who follows whom, when and why” and to identify the information flow, we need to make sure that the information is easily accessible to the market players. Therefore, we do not consider IHS Markit GDP index as a better measure.

Nevertheless, we did compare our interpolated monthly data with IHS monthly index for the period 1992-2020 by estimating a linear regression between the two series. The correlation between the two were 99.9% which suggests that our interpolated monthly GDP variable is virtually the same as IHS Markis GDP index. Thus, we do not expect our results to change if we use IHS Markis GDP index for the same sample period.

To our knowledge there is only the LL-method by Seip and McNown (2007) that can calculate LL- relations over very short time windows $\approx$ 3-10 although cross correlation techniques have been used over relatively short periods, $\approx$ 21 samples long (Kestin, Karoly et al. 1998). In our study, LL- relations change over $14.7 \pm 13.1$ time steps for T and GDP. To assess the robustness of our results, we examine if the results can be supported by reasonable economic arguments. The results that the FF leads GDP when the output gap is large is supported by current theories and current monetary policy of the Federal reserve, e.g., Asso, A. et al. (2010). The relation between T and GDP were studied by Estrella and Hardouvelis (1991) for the period 1955 to 1988 and showed a leading role for the yield curve four quarters ahead of real GDP growth ($R^2 = 0.35$). This would fit with our result that our choice of the T leads GDP 52 % of the time 1977 to 2019, whereas GDP leads T only 34 % of the time, ( 24 % of the time the LL- relation is inconclusive).

## 7. CONCLUSION AND POLICY IMPLICATIONS

In this study, we ask how the major players in the economy dynamically interact with each other: among the central bank, the investors in the bond market, and the firms and consumers that contribute to the economic growth; who gets information from whom, when and why? Using the lead-lag method by Seip and McNown (2007), we show that during the period 1977-2019 the bond market participants potentially obtained information from the federal funds rate (61% of the time) and less often (34% of time) from the changes in gross domestic product. Meanwhile, the funds rate decision by Federal Reserve seems to lead the economic growth about 63% of the time. Combining these results with principal component analysis, we find some evidence that the bond market obtained information directly from GDP when unemployment and inflation was high. In addition, our results also suggests that that the federal fund rate was leading GDP when the output gap was either small or large. Thus, the policy makers followed the Taylor rule with respect to rent setting, but only sporadically with respect to inflation. The lag time between the Federal Reserve's monetary policy move and the market's response is 15 to 20 months. The Federal Reserve obtains information from movements in GDP (33 % of the time), but also from the T (26 % of the time) and from CPI (24 % of the time).

Our study is similar to others in the following way. First, our finding that the Treasure yield curve is often a leading variable for the change in GDP is in line with studies such as Estrella and Hardouvelis (1991), Estrella and Mishkin (1996) Estrella and Mishkin (1996), Estrella and Mishkin (1998), Duarte, Venetis et al. (2005) and Nyberg (2010). However, our analysis also suggests that the relation can go in the opposite direction although less often, confirming the findings of Estrella (2005) and Evans and Marshall (2007). In addition, our finding that the change in GDP can lead the change in the federal funds rate support Taylor (1993) and Taylor (1999) rule.

Our research differs from others on three issues. First, we apply a relatively novel technique that allows us to identify lead-lag relations between time series over short periods and embed the LL- method in the principal component analysis to identify the common factors in the economic states. Second, although the relations between each pair of T, GDP and FF have been studies separately, we put all three factors together and allow directions to go all directions. Third, we connect the T, GDP, and the FF with their major players to understand those players' role and the dynamic information flow in the economy.

Our study provides insights in fundamental questions that have important implications for empirical work on the monetary policy, financial stability, and economic activities. Policymakers could make better predictions and improve the effectiveness of the monetary policy when knowing more about the dynamics of information flow and the potential feedback effect for a reverse influence. Investors in the financial can also make better investment decisions by understanding the role of each major player in the economy. Finally, we hope our analysis will inspire researchers on future research in macro-economics and financial markets.

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**Supplementary material 1: The Yield curve, T, leading before recessions**

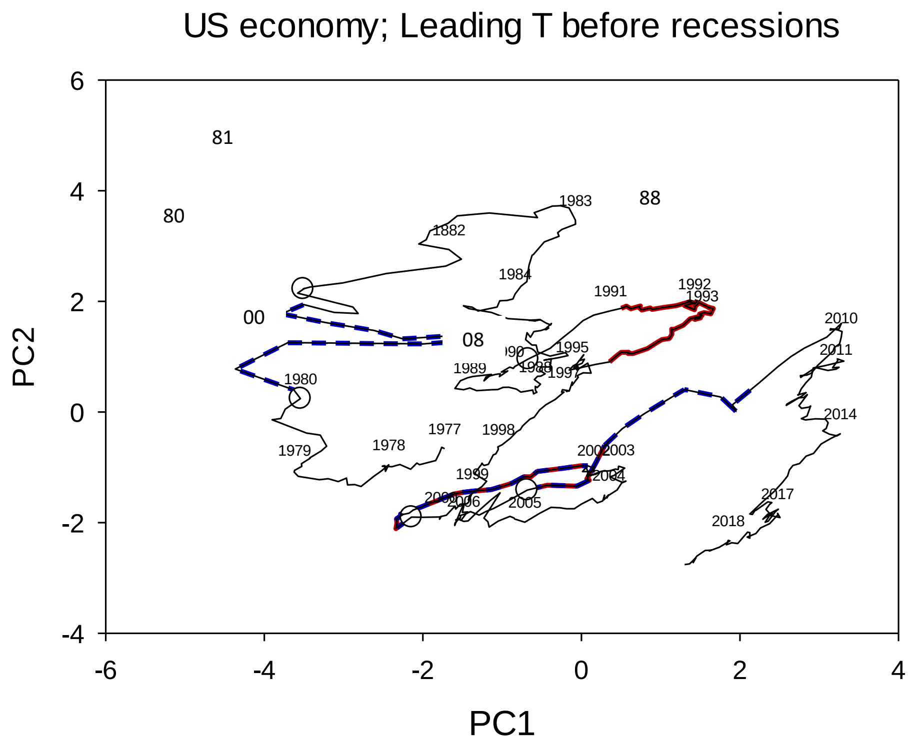


Figure S1. Thin lines are the  US Economy; Blue dashed lines show that GDP leads T; Bold lines shows that FF leads T; Circles designate recessions.

**Supplementary material 2. Fraction of months out of 120 months where FF is leading T**

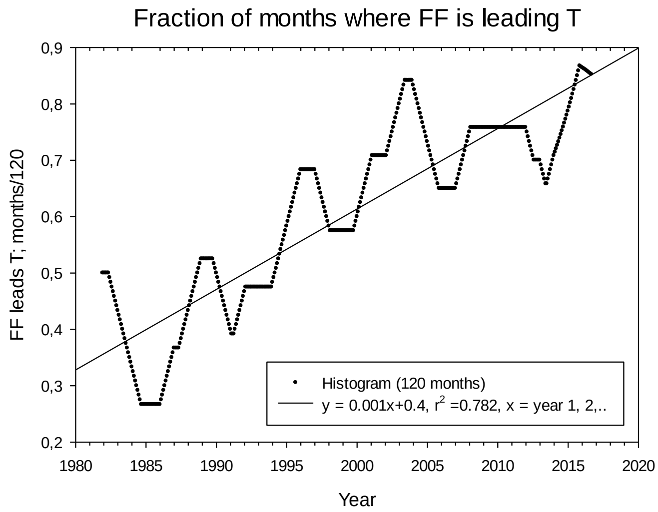


Figure S2. Federal funds rate leads the yield curve, T.