FORECASTING THE SHORT END OF THE TERM STRUCTURE OF INTEREST RATES

by

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Abstract

This thesis examines the properties of two short-term interest rates: the federal funds rate and the rate of return on 90-day Treasury securities (T-Bills). Findings indicate strong evidence of cointegration among the two series. This result leads us to consider whether future movements in T-bill returns are predictable using the same methods used to predict the target federal funds rate. The "Taylor Rule," introduced by Taylor (1993), assumes the Federal Reserve considers inflation and the output gap in their deliberation of how to adjust the federal funds target rate. We do an in-sample analysis followed by an out-of-sample forecasting comparison. Findings show that, in addition to inflation and the output gap, the unemployment rate and stock market contain valuable information for forecasting future T-bill rates.

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CHAPTER 1 - Introduction

The ability to explain and predict the seemingly chaotic behavior of short-term government securities affects both primary and secondary market participants as well as policy makers. The impact of constantly changing security yields on these individuals and institutions are enormous and should be assessed closely. Expanding knowledge of how to predict changes in interest rates can, and often does, serve as a competitive advantage in the money markets. The specific asset of interest in this thesis is the 90-day United States Treasury Security (T-bill).

The ultimate riskless security is considered to be the U.S. Treasury bill. Thus the rate of return on this security is often referred to as the "risk-free rate" (Pratt, Reilly and Schweihs p. 161, 2000). T-bills are liquid; there is an active secondary market where they may be traded. They are important financial instruments to individuals, financial institutions, corporations, governments and the Federal Reserve System, all of which hold sizeable amounts of U.S. Treasury debt, including T-bills, in their portfolios (Rose p. 369, 1994).

The Taylor Rule is an important concept in the analysis of monetary policy decisions. Developed by John Taylor (1993), it seeks to explain how macroeconomic variables should help predict the federal funds rate. The rule will be heavily cited in the analysis to come because the federal funds rate tends to influence most interest rates in the United States. This tendency will be further explained in the sections to come.

In this thesis, independent variables are tested for correlation with movements in T-bill rates. Significant variables will then go through an additional out-of-sample test. The purpose of out-of-sample testing in this thesis is to get a better handle on the predictive power of the explanatory variables.

The most important concept of this thesis is not the estimated regression model, but rather an intuitive understanding of what economic forces consistently forecast T-bill rates and how firms and individuals can turn this knowledge into a profit generating tool. Our results are also useful to those interested in understanding Federal Reserve behavior.

CHAPTER 2 - The Literature

We have motivated explaining the T-bill rate using macroeconomic factors. The literature review portion of this thesis will focus on comparing and contrasting the variety of methods proposed to model the target federal funds rate.

One of the first and most influential “critiques” of policy modeling was that of Lucas (1976). Lucas’s work explains the downfalls of using technical analysis methods for predicting policy actions. Many important lessons were learned. First, any econometric finding should be supported by a microeconomic theory based upon rational agents. In this thesis, we assume the Federal Reserve is a rational agent acting to maximize the welfare of the economy in the long-run. Second, the structure of an econometric model varies greatly with changes in the structure of the series pertinent to the policy maker; from this we can infer that any change in policy will possibly change the structure of the econometric model at hand. In most cases, a backward-looking model is not known to be subject to this critique because of time-frame. To illustrate, in this thesis we are actually trying to predict policy changes using historical aggregates. In this case the Lucas critique is not relevant (see Diebold (1998)).

The first step in modeling the decisions of any organization or institution is to understand their motivation. In the case of most firms, decisions are made in order to maximize profit. However, government entities usually operate under a framework that encourages the maximization of welfare. The following passage was retrieved from section 2a of the Federal Reserve Act. The passage concerning the explicit monetary policy objectives of the Federal Reserve reads as follows:

- ❖ *The Board of Governors of the Federal Reserve System and the Federal Open Market Committee shall maintain long run growth of the monetary and credit aggregates commensurate with the economy's long run potential to increase production, so as to promote effectively the goals of maximum employment, stable prices, and moderate long-term interest rates.*

Frederic Mishkin (Federal Reserve Governer, 2006-2008) proposes the following seven guidelines as a model for central bank effectiveness. (Mishkin p. 37, 2007)

- Price stability provides substantial benefits;
- Fiscal policy should be aligned with monetary policy;
- Time inconsistency is a serious problem to be avoided;
- Monetary policy should be forward-looking;
- Accountability is a basic principle of democracy;
- Monetary policy should be concerned about output as well as price fluctuations; and
- The most serious economic downturns are associated with financial instability

The aforementioned guidelines are not set forth by any sort of legislation, but are instead the opinion of many monetary economists. Furthermore, they are a subjective outline of what a central bank considers while crafting a monetary policy strategy. Given its subjectivity, economists are met with many challenges in forecasting monetary decisions of the Federal Reserve.

As one can visualize, many difficulties arise in crafting a monetary strategy that satisfies the aforementioned goals. However, most of the popular literature indicates that the stable growth of a nation relies upon stabilizing inflation and output fluctuations. e.g. Taylor (1993) and Clarida, Gali, and Gertler (2000).

Setting a Target

Numerous attempts at modeling the tactical moves of the Federal Reserve have been made. Some papers estimate a reaction function that predicts the federal funds target rate. Khoury (1990) uses a number of empirical surveys to arrive at a reaction function. Bernanke and Blinder (1992), along with others, have used vector autoregressions to estimate prediction models as well. Although the aforementioned papers have found a great deal of success, Taylor (1993) proposed a more straightforward theoretical approach to predicting Federal Reserve decisions. Most literature on the issue, including Rudd and Rudebusch (1998), find the Taylor rule theoretically sound (especially during Greenspan's tenure) and offer a good amount of empirical evidence. The Taylor rule relates the federal funds rate target to inflation and the GDP according to

$$i_t = \pi_t + a_\pi \langle \pi_t - \pi_t^* \rangle + a_y \langle y_t \rangle + 2, \tag{1}$$

where, i = federal funds rate, π_t = Inflation, π_t^* = target inflation rate (Taylor calls for 2 percent), y_t = Output gap (100(real GDP - potential GDP) / potential GDP)

Based on Taylor's original specifications, a_π and a_y are set equal to .5. In the case of inflation being 50 basis points above target, the Federal Reserve would set the federal funds rate 25 basis points above the 2 percent steady-state equilibrium federal funds target, ceteris paribus. The 2 percent steady-state equilibrium rate was simply a rounded figure derived from the actual 2.2 percent average discovered by Taylor (1993) using the sample 1984:1-1992:3. Also, Taylor assumed π^* is equal to 2 percent, simply because if both the inflation rate and real GDP are on target, then the federal funds rate would be 4 percent, or 2 percent in real terms. Another implication to consider is that Taylor suggested the Federal Reserve would only raise or lower the federal funds rate if inflation and/or the output gap were off target by at least 1 percent.

Similar to most macroeconomic models which seek to predict an economic variable, the accuracy of the Taylor model is difficult to test because it includes independent variables that are difficult to quantify.

Bernanke (2010) reveals how the Federal Reserve interprets the usefulness of the Taylor rule. "Simple rules necessarily leave out many factors that may be relevant to the making of effective policy in a given episode, such as the risk of the policy rate hitting the zero lower bound, which is why we do not make monetary policy on the basis of such rules alone." Taking this type of approach to setting the target rate gives the FOMC the option to use discretionary policy. This might be accommodated by adding a random error term to the Taylor model.

Clarida, Gali, Gertler (2000) Approach

Clarida, Gali, and Gertler (2000) propose an extension to the Taylor model by way of using the same components proposed by Taylor in a forward-looking manner. Whether the Federal Reserve uses current data or forecasts of future data to make its decisions concerning the federal funds rate is still debated among economists. Despite the controversy, Clarida, Gali, and Gertler (2000) make a convincing argument. In their paper they explain how their expectations model collapses to the Taylor model in the event that the Federal Reserve is not forward-looking.

$$i_t = i^* + \beta_1 \left[E\left\langle \pi_{t,k} \middle| \delta_t \right\rangle - \pi^* \right] + \beta_2 \, E\left\langle y_{t,q} \middle| \delta_t \right\rangle \tag{2}$$

where $\pi_{t,k}$ denotes inflation between periods t and $(t+k)$. π^* is target inflation. $y_{t,q}$ is a measure of the output gap between periods t and $(t+q)$. δ_t is the information set the FOMC has access to when the rate is set. In both cases, E is the expectation operator.

The expectations model is, as you can see, a duplicate of the Taylor rule with the exception that it is forward-looking and uses expectations rather than historical and current data. The problem in modeling this equation empirically lies in the fact that $\pi_{t,k}$ and $y_{t,q}$ must be assessed using an ambiguous information set δ_t.

The expectations model is consistent with the assumption that central banks should be forward-looking; whereas the Taylor rule, as introduced in Taylor (1993), leaves no room for this notion. However, Barro and Gordon (1983) outline one possible downfall to using a forward-looking model. Among others, they outline a problem concerning inflationary bias when discretionary policy rules are used and there exist the wrong incentives. Strict policy rules act to amend such inefficiencies; however they may not allow policy makers to act in the face of predictable shocks to inflation or the output gap. If the goal is to model Federal Reserve behavior, as opposed to saying what is optimal, we need to model what the Federal Reserve actually does.

A few problems arise in using purely theoretical models to judge the decisions of the Federal Reserve. First, there is a problem with the dependent variables of these models. In practice, the federal funds rate is a discrete variable that is very limited in sudden movement (recall the 1 percent threshold discussed earlier). Both the Taylor Rule and the Expectations Model assume the Federal Reserve will behave in a manner that allows them to make extreme changes to the interest rate until alignment with equilibrium is accomplished. However we know this is not the case because history has taught us that large changes are made over time in a smooth manner. As an example, consider the recession of 2008. The federal funds target rate was just below 5 percent at the beginning of the recession (December 2007); it was almost an entire year later (November 2008) that the federal funds target rate was down to 1 percent, later followed by the zero bound.

Other Approaches

Although the Taylor Rule and Expectations Model are among the most heavily cited models in monetary economics to date, some believe they still have problems. Surprisingly enough, most criticism of these models comes at the pen of policy makers themselves. King (1996) argues “the overriding objective of monetary policy should be price stability.” referring to such behavior as “inflation nutting.” Mishkin (p. 74-85, 2007) reveals from his experience working with the Federal Reserve that putting too great an emphasis on output fluctuations will produce undesirable results for a couple of reasons. First, accurate measures of the output gap are extremely difficult to obtain. This causes an overall difficulty in communication among policy makers. Second, even if output gap data is easy to obtain, inflation measures may already capture excess output (a simulation of this phenomenon will be modeled later in this thesis). With regard to these observations, Svensson (1997) suggests setting the federal funds rate so that the following rule is satisfied.

$$E\langle \pi_{t+2} \rangle = \pi^* \tag{3}$$

The goal would be to target an inflation forecast rather than an interest rate. The general premise is to set the rate so future inflation (two quarters ahead in this case) is expected to be equal to target inflation. Such a policy rule would allow the central bank to care about the output gap in the short run. There again, difficulty arises in using a method as implicit as this. However, you can see how the approach contrasts with the others.

Hitting the Target

The Federal Reserve has only announced an explicit target for the federal funds rate since 1995 ("Open Market Operations" 2010). Although in earlier years a target was set, there was less effort made to publicize it. According to Taylor (2001), messages about federal funds rate target changes were sent through specific types of purchases or sales of securities under certain circumstances. This method of message transmission led to poor information exchange among the Federal Reserve and the nation at large. The method of announcing the target rate is more effective at maintaining a small spread between the target and effective rate. According to Meulendyke (1998, 142), "The rate has tended to move to the new, preferred level as soon as the banks know the intended rate." This intuition will be useful for our analysis to come.

CHAPTER 3 - The Experiment

Interest Rate Behavior

The T-bill is an interesting security considering its relationship with the target (and effective) federal funds rate. These two rates have moved closely for years. Figure 1 illustrates the relationship between T-bills and the target federal funds rate from roughly 2004 to 2009. Figure 2 shows the T-bill rate and the effective federal funds rate. Theoretically, the relationship exists because the federal funds rate is controlled via the FOMC in primary markets (with dealers who have created relationships with the Federal Reserve), in order to attain a desirable federal funds effective rate. Considering the federal funds effective rate is the weighted average of all lending between Federal Reserve member institutions (banks mostly), we can infer that the Federal Reserve has no direct influence over this rate. However, if the Federal Reserve buys and sells T-bills in a way such that their prevailing rate of return is just below that of the federal funds rate target, the federal funds effective rate will naturally prevail slightly above the T-bill rate (as long as there exists a liquidity preference), and thus close to the federal funds target rate. Since 1995 ("Open Market Operations" 2010) the Federal Reserve has set an explicit target however and this process has been almost automatic ever since. Federal funds lending now tends to adjust contemporaneously with the explicit target. We infer this is due to expectations.

Figure 1: Daily Federal Funds Target Rate and 3-Month Treasury Bill Yields

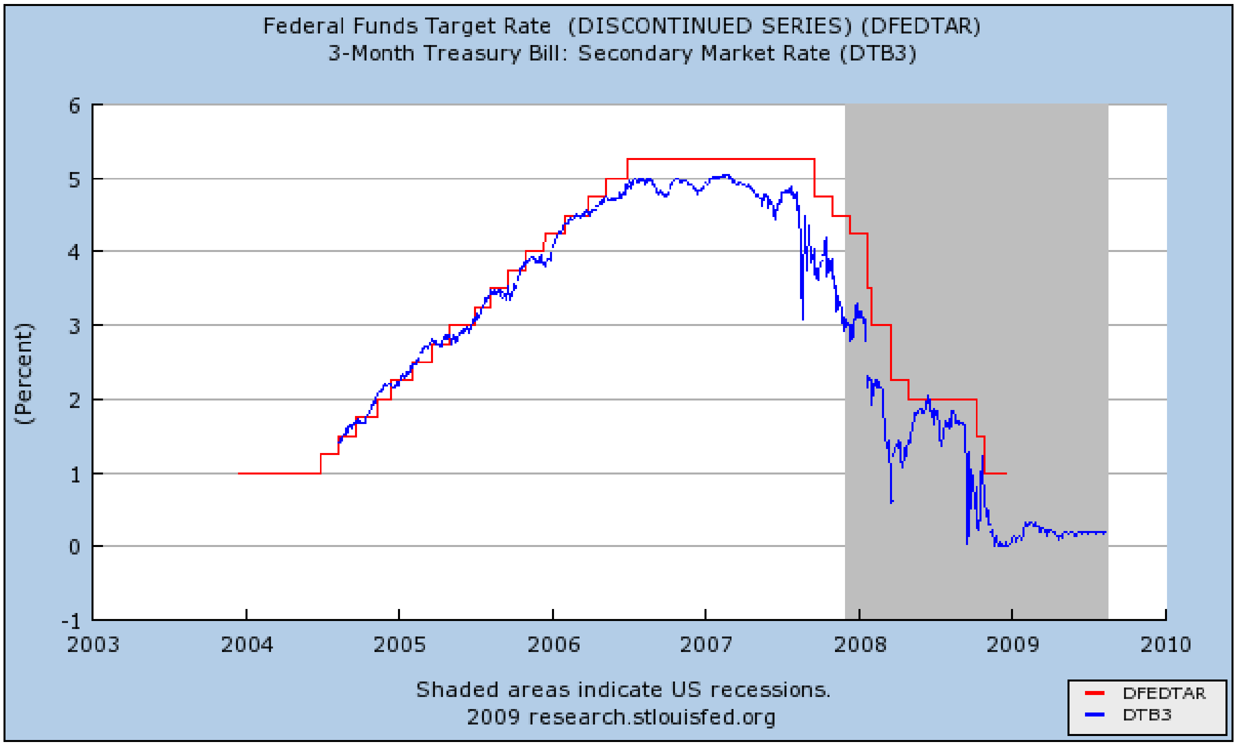
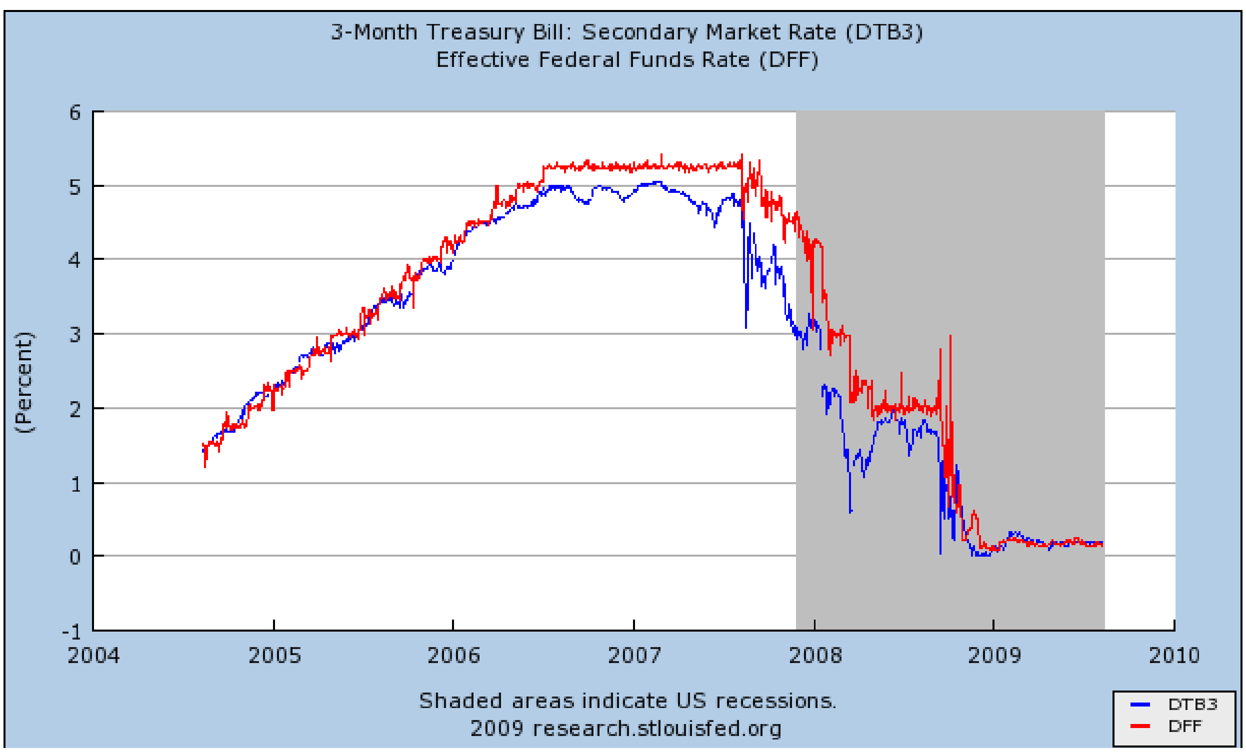


Figure 2: Effective Federal Funds Rate and 3-Month Treasury Bill Yields



Sarno and Thornton (2003) use the Johansen maximum likelihood cointegration procedure developed by Johansen (1991) to show strong evidence of cointegration among the federal funds rate and T-bill that is surprisingly stable over the time period of 1974-1999. Sarno and Thornton (2003) also found the federal funds rate tends to adjust more quickly to the equilibrium rate than T-bills (possibly an explanation for the non-linear behavior). They suggest this could be attributed to factors such as transaction costs and infrequent/frequent trading.

Test for a Unit-Root

The Augmented Dickey-Fuller technique is employed in this thesis to test for evidence of a unit-root process. The method was developed across the course of several papers, including Said and Dickey (1984), and is an extension of the original Dickey-Fuller test. This procedure begins by choosing an optimal lag length. In this thesis we use the lag length that minimizes the value of Bayesian Information Criteria (BIC). Once the optimal lag length is chosen, the following regression is run:

$$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \sum_{j=1}^{k} \beta_j \, \Delta y_{t-j} + \varepsilon_t, \tag{4}$$

where y is the observed variable. The null hypothesis of a unit root is H_0: $\beta_1 = 0$, the alternative hypothesis H_0: $\beta_1 < 1$. A t-test of that hypothesis does not have a standard distribution, so we use critical values provided by Stata.

It comes as no surprise we cannot reject the null hypothesis of a unit root in either case. Most studies find that interest rates are non-stationary (e.g., Stock and Watson, 1988, 1999a).

Table 1: Augmented Dickey-Fuller Procedure for Variables: Federal Funds Effective Rate and 3-Month Treasury Bill Yields.

3-Month T-bill Rate

Dickey-Fuller test for unit root Number of obs = 83

	Interpolated Dickey-Fuller		
Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-0.480	-3.534	-2.904	-2.587

Effective Federal Funds Rate

Dickey-Fuller test for unit root Number of obs = 83

	Interpolated Dickey-Fuller		
Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-0.369	-3.534	-2.904	-2.587

Test for Cointegration - Results for Johansen Test

Integration of all series tested for cointegration is required. We confirm this using the Augmented Dicky-Fuller test (above). Given that both the federal funds rate and T-bill rate are non-stationary, the Johansen test for cointegration. For this method, the order of integration does not matter (an advantage over the Engle-Granger method). Using a slightly more updated sample period than that of Sarno and Thornton (2003) (1983:1-2003:4), Table 2 summarizes a Johansen test for cointegration. We are able to reject the null hypothesis of zero cointegrating relations, with a test statistic of 109.9, compared with a critical value of 15.4. We cannot reject the null of one cointegrating relation against two relations. This is consistent with our expectations. There can be at most one relation with two variables. These results indicate a maximum of 1 cointegrating relationship between the T-bill rate and the federal funds rate.[1] Results were obtained from testing with an unrestricted constant term.

To illustrate this cointegrating relationship in a more concrete manner, consider the T-bill rate ($BILL_t$) and the federal funds rate ($FFER_t$). In this case, we will assume both $BILL_t$ and $FFER_t$ exibit first order integration. $BILL_t$ and $FFER_t$ are cointegrated if there exists a β_1 that satisfies

$$BILL_t = \alpha + \beta_1 FFER_t + \varepsilon_t \tag{5}$$

This equation makes sense for our analysis because we know the T-bill rate prevailing in the treasury market should be equal to the federal funds rate plus a small constant (most likely negative in the case of T-bills) and an error term.

Table 2: Johansen Maximum Likelihood Cointegration Procedure for Variables: Federal Funds Effective Rate and 3-Month Treasury Bill Yields.

Cointegration likelihood ratio tests based on trace eigenvalue of the stochastic matrix (trace statistic)

Johansen tests for cointegration

Trend: constant — Number of obs = 347, Lags = 1

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	2	-433.80146	.	109.9359	15.41
1	5	-380.65096	0.26387	3.6349*	3.76
2	6	-378.8335	0.01042		

Note: * indicates the trace statistic corresponding to the maximum rank of cointegration. In this case the rank is 1.

Confirming cointegration will become pertinent as our analysis of T-bill rates continues. The most important lesson we can learn from this test is that the federal funds rate and T-bill rates actually co-move over long periods of time.

[1] The cointegration test used monthly data from 1983:1-2003:4. Sarno and Thornton (2003) find similar results over a comparable sample period.

Many papers have affirmed this relationship and attributed it to the idea that both rates are a product of the expectations hypothesis. e.g. Rudebusch (2001) and Woodford (1999). Thus, it is assumed the T-bill rate is similar to the market's expectation for the federal funds rate.

If the expectations hypothesis holds, or if markets are forward-looking at all, the federal funds rate will also have an effect on the latter portions of the term structure. According to findings by Cook and Hahn (1988), changes in the target rate have been followed by large movements in the same directions in the short-term market, moderate movements in intermediate-term rates and small, but significant movements in long-term rates.

The idea of "forward-looking markets" could possibly help us understand why the federal funds rate often follows (lags) behind T-bill rates. For example, if the market behaves in a way that drives up T-bill rates in expectation of a rise in the federal funds rate target, it may seem as though the federal funds rate is following the T-bill rate when in fact the opposite is true.[2]

Now we can begin to see how the Federal Open Market Committee (FOMC) has the ability to influence the interest rates of almost any short-term debt instrument in either direction by holding the power to literally anchor the short end of the term structure spectrum. Since we also know how closely the effective federal funds rate shadows the target rate set by the FOMC (contrast figures 1 and 2), we can theoretically model the prediction of T-bill rates by predicting decisions made by the FOMC regarding the target rate.

Modeling the Taylor Rule

We have already discussed the extent to which the federal funds target rate predicts the effective federal funds rate and demonstrated in the previous chapter that the effective federal funds rate is cointegrated with the rate of return on short-term securities (specifically T-bills). This suggests that the

[2] The federal funds rate tends to anchors the rates of short term government securities because of their similar liquidity and availability to banks. i.e. if a bank has excess reserves, they can opt to buy securities, or loan the reserves to other banks at the federal funds rate.

macroeconomic variables that influence the federal funds rate should also hold predictive power for T-bills. We therefore replace the federal funds rate in the Taylor rule with the T-bill rate to get an equation that can be used to predict the T-bill rate. Formally

$$BILL_t \cong i_t = \pi_t + a_\pi \langle \pi_t - \pi_t^* \rangle + a_y \langle y_t \rangle + 2 \qquad (6)$$

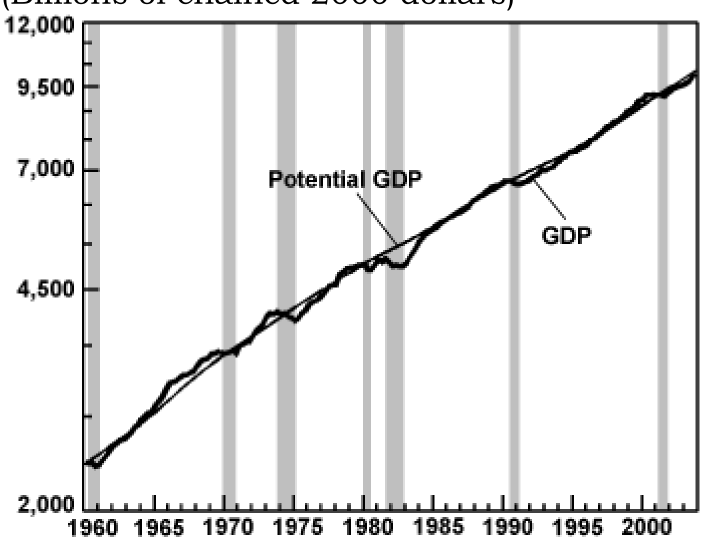
in econometric form:

$$BILL_t = \alpha + \beta_1 \pi_t + \beta_2 y_t + \varepsilon_t \qquad (7)$$

Results from simple forecasts like these should be interpreted with caution however. As Thomas (1999) points out, T-bill yields are often influenced by a number of factors aside from inflation and the output gap, including cyclical, liquidity, and "safe-haven" considerations. While one could in principle add more variables to the model to account for these factors, in practice we do not have data that capture such things as the "safe haven" hypothesis. If certain factors of the financial environment are behaving wildly, the forecasts form our model could be poor.

Figure 3: GDP and Potential GDP

(Billions of chained 2000 dollars)



Source: Congressional Budget Office.

Output Gap and Inflation Dynamics

In the most heavily cited papers that estimate the Federal Reserve's policy rule, e.g. Taylor (1993) and Clarida, Gali, Gertler (2000), the output gap and inflation are the two key macroeconomic variables that influence FOMC behavior. This is reasonable, given that Congress has established the Federal Reserve's mandate as the pursuit of low and stable inflation and full employment. We now provide the reader with an empirical explanation of how these two variables are believed to behave with estimations constructed by Rudebusch and Svensson (1998).[3]

$$y_t = \alpha + \vartheta_1 y_{t-1} + \vartheta_2 y_{t-2} - \vartheta_3 \langle i_{t-1}^a - \pi_{t-1}^a \rangle + \varepsilon_t \qquad (8)$$

$$\pi_t = \alpha + \beta_1 \pi_{t-1} + \beta_2 \pi_{t-2} + \beta_3 \pi_{t-3} + \langle 1 - \beta_1 - \beta_2 - \beta_3 \rangle \pi_{t-4} + \beta_4 y_{t-1} + \varepsilon_t \qquad (9)$$

where $i_{t-1}^a = \frac{1}{4}\sum_{j=0}^{3} i_{t-j}$ and $\pi_{t-1}^a = \frac{1}{4}\sum_{j=0}^{3} \pi_{t-j}$. i_{t-1}^a and π_{t-1}^a are thought of as quarterly averages of the federal funds rate and the output gap respectively.

y_t is the output gap as a function of its own lagged values and of the differences between the average federal funds rate and inflation over the most recent four months. The third term of the equation is a sort of monetary transmission mechanism to help describe how policy-induced changes in the federal funds rate influence the output gap. As an illustration, consider an economy in which the Federal Reserve wishes to reduce the output gap. The Federal Reserve would raise the effective federal funds rate. According to the above equation, this action will trigger a decrease in the output gap due to the sign on ϑ_3 being negative.

π_t is Rudebusch's proposal for quantifying inflation as a function of lagged inflation and one lag of the output gap. Rudebusch and Svensson (1998)

[3] Nearly identical models are suggested by Svensson (1997)

estimate the above inflation model. They fail to reject the hypothesis that the coefficients of the four lags of inflation sum to one. This model implies an accelerationist Phillips curve (vertical in the long-run) on account of the reliance on lagged values of inflation itself (an unemployment variable is not included). The accelerationist curve assumes inflation is always backward-looking and there exists a “natural” rate of unemployment that corresponds to equilibrium. When unemployment is below its natural rate, inflation will be increasing; when it is above it, it will be decreasing

We have updated the regressions in Rudebusch and Svensson (1998) with data from 1983:1 to 2003:4 to get a feel for how stable the parameters are. First, coefficients estimated by Rudebusch and Svensson (1998) over the period 1961:1 to 1996:2 are reported for both inflation and the output gap (Tables 3 and 4). Next, we estimate the same models over the period 1983:1 to 2003:4 (tables 5 and 6). For the inflation model, *t*-tests show the first 3 lags of inflation and the output gap to be significant. However, the fourth lag of inflation is not significant. These results differ little from Rudebusch and Svensson (1998). For the output gap, *t*-tests show the first two lags of inflation to be significant. However, the monetary transmission mechanism $\langle i_{t-1}^{a} - \pi_{t-1}^{a} \rangle$ is insignificant at any conventional confidence level. Rudebusch and Svensson (1998) found this variable significant. Considering our dataset is more contemporaneous, it is possible that monetary policy has had less effect on the output gap in more recent years.

Table 3: Rudebusch's Estimates of Inflation Equation

$\boldsymbol{\pi_t = \alpha + \beta_1\pi_{t-1} + \beta_2\pi_{t-2} + \beta_3\pi_{t-3} + \beta_4\pi_{t-4} + \beta_4 y_{t-1} + \varepsilon_t}$		
Variable	**Coefficient**	**Standard Error**
π_{t-1}	0.70	0.08
π_{t-2}	-0.10	0.10
π_{t-3}	0.28	0.10
π_{t-4}	0.12	0.08
y_{t-1}	0.14	0.03

Notes: Observations: 84, Sample period: 1961:1-1996:2, Frequency: Quarterly

Table 4: Author's Estimates of Rudebusch's Inflation Equation

$\boldsymbol{\pi_t = \alpha + \beta_1\pi_{t-1} + \beta_2\pi_{t-2} + \beta_3\pi_{t-3} + \beta_4\pi_{t-4} + \beta_4 y_{t-1} + \varepsilon_t}$		
Variable	**Coefficient**	**Standard Error**
π_{t-1}	0.50	0.10
π_{t-2}	-0.21	0.10
π_{t-3}	0.32	0.10
π_{t-4}	0.12	0.10
y_{t-1}	0.14	0.01

Notes: Observations: 84, Sample period: 1983:1-2003:4, Frequency: Quarterly

Table 5: Rudebusch's Estimates of Output Equation

$\boldsymbol{y_t = \alpha + \vartheta_1 y_{t-1} + \vartheta_2 y_{t-2} - \vartheta_3\langle i^a_{t-1} - \pi^a_{t-1}\rangle + \varepsilon_t}$		
Variable	**Coefficient**	**Standard Error**
y_{t-1}	1.16	0.08
y_{t-2}	-0.25	0.08
$\langle i^a_{t-1} - \pi^a_{t-1}\rangle$	-0.10	0.03

Notes: Observations: 84, Sample period: 1961:1-1996:2, Frequency: Quarterly

Table 6: Author's Estimates of Rudebusch's Output Equation

$$y_t = \alpha + \vartheta_1 y_{t-1} + \vartheta_2 y_{t-2} - \vartheta_3 \langle i^a_{t-1} - \pi^a_{t-1} \rangle + \varepsilon_t$$

Variable	Coefficient	Standard Error
y_{t-1}	1.17	0.10
y_{t-2}	-0.29	0.10
$\langle i^a_{t-1} - \pi^a_{t-1} \rangle$	0.03	0.02

Notes: Observations: 84, Sample period: 1983:1-2003:4, Frequency: Quarterly

Dynamics of Leading Indicators

Finding useful leading indicators of changes in interest rates (T-bill returns) is not an easy task and the literature does not provide clear guidance about the selection of leading indicators. Wesley Mitchell and Arthur Burns are believed to be the first advocates of the idea that historical aggregates will yield predictive power for the macroeconomy. Mitchell and Burns (1938) employ 71 quarterly series to form a composite leading indicator. Indicators such as these have met with criticisms such as the "measurement without theory" notion, originally crafted by Koopmans (1947). Box and Jenkins (1976) have since shed many of these criticisms after the proposal of time-series based evaluation of leading indicators. Despite decades of discussion and arguments among authors, composite indicators such as these are still widely cited and used by economist in making cyclical trend predictions. Kaminsky, Lizondo and Reinhart (1998) conclude that certain economic indicators are useful predictors of currency crises. Stock and Watson (2002) provide a good theoretical analysis of how principle component analysis is useful for forecasting and leading indicator purposes.

In this thesis, our first assumption is that leading indices are useful for predicting changes (turning points) of T-bill returns, rather than predicting explicit values. This notion of using leading indicators in a less theoretical manner is affirmed by Diebold and Rudebusch (1989) in their analysis of business cycles using Bayesian sequential probability forecasting. This thesis uses regression methods, thus it is pertinent to mention similar studies by Estrella and Mishkin (1998) and Staiger, Stock and Watson (1997). Standards for qualifying potential leading indicators in this thesis follow a structural method outlined in the methodology section to follow.

Methodology

The empirical work that follows uses a systematic method of eliminating insignificant variables from a pool of candidates. According to Estrella and Mishkin (1998), the more variables a model includes, the better the in-sample results. However, liberal inclusion of explanatory variables in the regression will not necessarily help -and frequently hurts- results when extrapolating beyond the sample's end. A model that has been overfit will yield little predictive power in out-of-sample testing. The empirical results of this thesis provide information about how advantageous a simple "Taylor-like" model can be when complemented with a limited number of significant variables.

The general purpose of this thesis is to examine simple financial variables that help predict T-bill returns. Thus, in addition to the variables entering the Taylor rule, other readily available and meaningful variables are presented in Table 7. Table 7 also contains the expected information lag in attaining data for the variables. To illustrate, managers will have no use for a predictive variable that makes a prediction about interest rates in 3 months if the data for that variable itself is not available before 3 months have expired.

Table 7: Variable Notation and Description

Series	Description	Info. Lag (Months)
FFTR	Federal Funds Target Rate	0
BILL	90-day T-bill	0
SPREAD	10 year-90-day Treasury Spread	0
SP500	S&P 500	0
M0	Monetary Base	1
M1	M1	1
M2	M2	1
GDPGP	GDP Gap	3
CPI	Consumer Price Index	3
INFEXP	Michigan Index of Expected Inflation	0
GND	Gross National Debt	0
UNEMP	National Unemployment Rate	0
HOUST	Housing Starts	1
CONCO	Consumer Sentiment/Confidence	0
GOLD	Prevailing Gold Price Per Troy Ounce	0

Basic Model and Criteria for Evaluating Results

When sorting through such a broad selection of financial variables, one must be careful not to include so many variables that the in-sample model is over-fit. Thus a variable selection model must be used.

As mentioned earlier, it is imperative to keep predictive models simple and composed of as few variables as possible, thus an exhaustive variable selection method is employed in this experiment. The first phase of the experiment will require running bivariate OLS regressions. The T-bill return will be regressed on each individual independent variable. This will give us an idea of which variables could possibly make up the model. After that, remarks will be made and the variables with significant test statistics will be used for further analysis. The second phase will involve regressing T-bill returns on the variables chosen in phase 1 in addition to each of the variables in Table 7. After the second phase, R-Squared and test statistics will be interpreted to assess the predictive power of each model. Significant lags of variables will be considered for inclusion. Beyond that, variables with the most impact on R-Squared will be sought for inclusion.[4]

CHAPTER 4 - Results

In-Sample Results

Results from Tables 8 and 9 reveal a number of expected as well as unexpected findings. First, the difference in dependant variables used in the two separate tables appears to yield little difference in results, this is to be expected considering the cointegration evidence. As per both tables, the results match the intuition that follows from the theoretical model proposed by Taylor (1993). In other words, both the output gap and the CPI series show significance at high levels with lags greater than 3 quarters.

[4] The Newey-West technique for correction of serial correlation and heteroskedasticity was deployed (Newey and West 1987). However, OLS results showed little difference in statistics. Thus OLS results are reported, as OLS is more precise in the absence of serial correlation and heteroskedasticity.

Table 8: Measures of Fit and *t*-statistics for In-sample Bivariate Models: BILL as Dependant Variable

	$BILL_{t+k} = \alpha + \beta_1 \varphi_t$							
	$k = Quarters\ Ahead$							
φ_t ***Variables***	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Treasury Spread								
R^2	0.02	0.00	0.00	0.00	0.00	0.01	0.02	0.02
t-stat	-1.42	-0.81	-0.25	0.27	0.56	0.91	1.32	1.31
S&P 500								
R^2	0.04	0.04	0.06	0.05	0.05	0.02	0.02	0.01
t-stat	1.77	1.96	2.38	2.07	2.13	1.54	1.28	1.08
M0								
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
t-stat	-0.50	-0.43	0.13	0.41	0.42	0.37	0.65	0.43
M1								
R^2	0.00	0.00	0.00	0.00	0.01	0.02	0.03	0.05
t-stat	-0.44	-0.28	0.14	0.64	0.93	1.21	1.57	2.13
M2								
R^2	0.04	0.05	0.05	0.06	0.07	0.07	0.06	0.05
t-stat	1.74	2.03	2.05	2.22	2.52	2.52	2.36	2.08
Output Gap								
R^2	0.02	0.03	0.06	0.10	0.15	0.21	0.25	0.28
t-stat	-1.16	-1.61	-2.31	-3.08	-3.90	-4.63	-5.26	-5.68
CPI								
R^2	0.19	0.17	0.15	0.14	0.10	0.08	0.10	0.12
t-stat	4.32	4.09	3.82	3.63	3.10	2.68	2.99	3.27
Inflation Expectations								
R^2	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
t-stat	0.42	0.24	0.45	0.49	0.72	1.09	0.92	-0.65
National Debt								
R^2	0.17	0.17	0.19	0.19	0.21	0.21	0.20	0.18
t-stat	4.06	4.13	4.36	4.33	4.73	4.70	4.46	4.28
Unemployment								
R^2	0.09	0.12	0.16	0.21	0.32	0.30	0.36	0.38
t-stat	2.83	3.36	4.00	4.66	4.66	5.96	6.58	7.14
Housing Starts								
R^2	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01
t-stat	-0.64	0.25	0.62	0.83	0.99	0.85	0.71	0.71
Consumer Confidence								
R^2	0.01	0.01	0.05	0.04	0.04	0.02	1.63	0.04
t-stat	0.64	1.06	1.97	1.90	1.75	1.42	1.28	1.78
Gold Price								
R^2	0.08	0.03	0.03	0.02	0.01	0.01	0.00	0.00
t-stat	-2.72	-1.62	-1.66	-1.25	-0.91	-0.95	0.14	-0.50

Notes: T-bill returns are regressed on each independent variable separately for up to 8 quarters ahead.
Observations: 84, Sample period: 1983:1-2003:4, Frequency: Quarterly
Results for the model: $\boldsymbol{BILL_{t+k} = \alpha + BILL_t + \beta_1 \varphi_t}$ are reported in Table 14.

Table 9: Measures of Fit and *t*-statistics for In-sample Bivariate Models: FFER as Dependant Variable

φ_t *Variables*	1	2	3	4	5	6	7	8
	$FFER_{t+k} = \alpha + \beta_1 \varphi_t$							
	$k = Quarters\ Ahead$							
Treasury Spread								
R^2	0.03	0.00	0.00	0.00	0.01	0.01	0.03	0.02
t-stat	-1.63	-0.88	-0.28	0.33	0.74	1.07	1.53	1.43
S&P 500								
R^2	0.04	0.05	0.06	0.05	0.06	0.03	0.02	0.01
t-stat	1.75	2.02	2.39	2.17	2.37	1.63	1.34	0.95
M0								
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01
t-stat	-0.55	-0.42	0.13	0.30	0.43	0.35	1.34	0.66
M1								
R^2	0.00	0.00	0.00	0.00	0.01	0.02	0.03	0.06
t-stat	-0.44	-0.19	0.24	0.73	1.06	1.29	1.72	2.19
M2								
R^2	0.04	0.05	0.06	0.06	0.08	0.09	0.06	0.06
t-stat	1.86	2.07	2.23	2.34	2.72	2.81	2.32	2.30
Output Gap								
R^2	0.01	0.02	0.05	0.09	0.13	0.18	0.23	0.26
t-stat	-0.81	-1.29	-1.98	-2.78	-3.57	-4.26	-4.89	-5.32
CPI								
R^2	0.19	0.17	0.13	0.12	0.09	0.07	0.09	0.10
t-stat	4.37	4.09	3.57	3.38	2.79	2.42	2.80	3.07
Inflation Expectations								
R^2	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.01
t-stat	0.28	0.21	0.44	0.47	0.62	1.15	0.82	-0.69
National Debt								
R^2	0.15	0.17	0.18	0.19	0.21	0.21	0.19	0.18
t-stat	3.85	4.03	4.19	4.40	4.67	4.68	4.45	4.27
Unemployment								
R^2	0.07	0.10	0.15	0.19	0.24	0.29	0.33	0.37
t-stat	2.53	3.09	3.74	4.42	5.11	5.72	6.36	6.92
Housing Starts								
R^2	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01
t-stat	-0.74	0.16	0.49	0.81	0.81	0.94	0.65	0.66
Consumer Confidence								
R^2	0.00	0.02	0.04	0.05	0.04	0.02	0.02	0.03
t-stat	0.52	1.13	1.78	1.97	`1.84	1.27	1.37	1.52
Gold Price								
R^2	0.07	0.03	0.03	0.02	0.01	0.00	0.00	0.00
t-stat	-2.39	-1.61	-1.54	-1.14	-0.82	-0.52	0.09	-0.38

Notes: Federal fund effective rates are regressed on each independent variable separately for up to 8 quarters ahead. Observations: 84, Sample period: 1983:1-2003:4, Frequency: Quarterly

Table 10 displays statistics found by running the Taylor Rule in addition to each separate variable found to perform well in the above regressions. The results show that the S&P 500, M2, National Debt and Unemployment all improve the standard Taylor equation significantly from 1 to 6 steps ahead.

Principle Component Analysis

It is possible that the analysis in Table 10 runs into the problem of using too many degrees-of-freedom. One approach to this problem is simple and has been used heavily in recent macroeconomic literature including Stock and Watson (2002), Bernanke and Boivin (2003) and Bernanke, and Boivin and Eliasz (2004). Dynamic-factor models are derived using principle component analysis where the observed endogenous variables are linear functions of exogenous covariates and unobserved factors. The use of such models allows for ease of use insofar as the number of variables is significantly decreased by grouping according to index. Also, the degrees-of-freedom problem will be solved if a single factor effectively summarizes all of the variables employed in the principle component analysis.

According to Jolliffe (28), "Principle component analysis (PCA) is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on." Less formally, we are trying to capture the similarity in movements among several series in a single series. In this thesis, the principle component is constructed using the following method. First, we should consider the matrix W.

$$\mathrm{W} = \begin{bmatrix} CPI_1 & GDPGP_1 & SP500_1 & M2_1 & GND_1 & UNEMP_1 \\ CPI_2 & GDPGP_2 & SP500_2 & M2_2 & GND_2 & UNEMP_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ CPI_T & GDPGP_T & SP500_T & M2_T & GND_T & UNEMP_T \end{bmatrix} \quad (10)$$

Where CPI, GDPGP, etc. are the explanatory variables we wish to use. If we believe these series are correlated, as is the case with many macroeconomic variables, we may wish to reduce the dimensions of the matrix W in order to reduce the degrees of freedom used by running a regression.

The process of making this dimensional reduction requires us to find matrices U and V such that W=UV. This can be described by the following equation.

$$\mathrm{W} = \begin{bmatrix} CPI_1 & GDPGP_1 & SP500_1 & M2_1 & GND_1 & UNEMP_1 \\ CPI_2 & GDPGP_2 & SP500_2 & M2_2 & GND_2 & UNEMP_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ CPI_T & GDPGP_T & SP500_T & M2_T & GND_T & UNEMP_T \end{bmatrix} \quad (11)$$
$$= \begin{bmatrix} u_{11} & \cdots & u_{61} \\ \vdots & \ddots & \vdots \\ u_{1T} & \cdots & u_{6T} \end{bmatrix} \begin{bmatrix} v_{11} & \cdots & v_{61} \\ \vdots & \ddots & \vdots \\ v_{61} & \cdots & v_{66} \end{bmatrix}$$
$$= \begin{bmatrix} U_1 & \cdots & U_6 \end{bmatrix} \begin{bmatrix} V_1 & \cdots & V_6 \end{bmatrix}$$

U is a matrix constructed as described below. $V_1 - V_6$ are the eigenvectors of *cov*(W) arranged so that V_1 has the largest associated eigenvalue. $U_1 - U_6$ are the actual principle components. The first principle component is the vector of interest in our analysis since it explains most of the co-movement among the variables of interest. The reason this is true is because U_1 is a function of V_1, and V_1 is the eignvector with the largest eigenvalue. In practice, U_2 through U_6 may explain very little of the variance among the variables. We will only use U_1 in our analysis.

The principle component analysis in this thesis takes the following form: First, the first principle component is calculated for the variables (CPI, GDPGP, SP500, M2, GND, UNEMP). Second, regressions are run using BILL as the dependant variable and the component as the independent variable. Results from these regressions will be compared to results obtained by similar regressions using a component composed of 16 (ten more than the original) randomly chosen macroeconomic variables. Results show that the 6-variable principle component series clearly outperforms the test series composed of 16 variables. This suggests the variables chosen as "good fits" outperform the randomly chosen variables composing the test series. See figures 4 and 5 (appendix).

Table 10: Measures of Fit and *t*-statistics For In-sample models: variables with CPI and GDP Gap

$$\boldsymbol{BILL_{t+k} = \alpha + \beta_1 \pi_t + \beta_2 y_t + \beta_3 \varphi_t}$$

$\boldsymbol{\varphi_t\ Variables}$	$\boldsymbol{k = Quarters\ Ahead}$							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
S&P 500								
$\boldsymbol{R^2}$	**0.27**	**0.26**	**0.28**	**0.29**	**0.30**	**0.30**	**0.34**	**0.38**
t-stat π_t	4.97	4.60	4.33	4.03	3.38	2.89	3.06	3.40
t-stat y_t	-2.27	-1.23	-1.81	-2.82	-3.60	-4.28	-4.86	-5.33
t-stat φ_{1t}	2.58	2.67	3.08	2.71	2.69	2.22	2.01	1.93
M2								
$\boldsymbol{R^2}$	**0.32**	**0.31**	**0.29**	**0.31**	**0.31**	**0.32**	**0.34**	**0.37**
t-stat π_t	5.71	5.24	4.64	4.46	3.67	2.93	2.91	3.15
t-stat y_t	-1.30	-1.12	-1.58	-2.36	-3.08	-3.82	-4.44	-4.96
t-stat φ_{1t}	3.64	3.59	3.18	3.16	2.95	2.61	2.05	1.64
National Debt								
$\boldsymbol{R^2}$	**0.30**	**0.28**	**0.28**	**0.27**	**0.29**	**0.30**	**0.34**	**0.37**
t-stat π_t	3.69	3.30	3.11	2.97	2.33	1.93	2.38	2.73
t-stat y_t	0.61	0.58	-0.12	-1.12	-1.75	-2.47	-3.21	-3.84
t-stat φ_{1t}	3.28	3.08	2.98	2.38	2.42	2.14	1.79	1.30
Unemployment								
$\boldsymbol{R^2}$	**0.31**	**0.34**	**0.34**	**0.35**	**0.35**	**0.36**	**0.38**	**0.44**
t-stat π_t	3.10	2.92	2.60	2.75	2.33	1.91	1.59	2.20
t-stat y_t	3.64	3.95	3.79	3.00	2.33	1.74	1.45	1.34
t-stat φ_{1t}	4.63	5.10	5.07	4.55	4.12	3.74	3.66	3.76

Notes: T-bill returns are regressed on inflation, the output gap, and each φ variable for up to 8 quarters ahead.
Observations: 84, Sample period: 1983:1-2003:4, Frequency: Quarterly

Table 11: Measures of Fit and *t*-statistics for In-sample Bivariate Models: BILL as Dependant Variable; Principle Components as Independent (6 variables)

$BILL_{t+k} = \alpha + \beta_1 \varphi_t$								
	$k = Quarters\ Ahead$							
φ_t $Variable$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Component U_1								
R^2	0.10	0.13	0.19	0.23	0.29	0.32	0.35	0.37
t-stat	3.05	3.52	4.34	4.90	5.72	6.24	6.61	6.92

Notes: T-bill returns (up to 8 quarters ahead) are regressed on a principle component found using Stata.
Observations: 84, Sample period: 1983:1-2003:4, Frequency: Quarterly
Results for the model: $BILL_{t+k} = \alpha + BILL_t + \beta_1 \varphi_t$ are reported in Table 15.

Table 12: Measures of Fit and *t*-statistics for In-sample Bivariate Models: BILL as Dependant Variable; Principle Components as Independent (14 variables)

$BILL_{t+k} = \alpha + \beta_1 \varphi_t$								
	$k = Quarters\ Ahead$							
φ_t $Variable$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Component U_1								
R^2	0.02	0.04	0.08	0.10	0.16	0.18	0.21	0.21
t-stat	1.32	1.88	2.63	2.95	3.89	4.20	4.70	4.67

Note: T-bill returns (up to 8 quarters ahead) are regressed on a principle component found using Stata.
Observations: 84, Sample period: 1983:1-2003:4, Frequency: Quarterly

Out-of-Sample Results

Why do out-of-sample model evaluation? Most forecasters agree that in-sample goodness-of-fit is just not enough evidence to conclude a variable is a good predictor. The performance of a model on data outside that used in its construction remains the touchstone for its utility in all applications (Fildes and Makridakis p. 293, 1995). When one makes a forecast, it is always done in an out-of-sample fashion. It is natural to assess a model based on how it would have done in the past.

Difference among in-sample and post-sample conclusions may arise for a number of reasons. First, overfitting is a problem faced by those using econometrics to explain relationships. Beyond that, structural changes often cause a model that was once effective to perform poorly when the underlying parameters change. An out-of-sample test will easily assess how much a model is affected by parameter instability.

The out-of-sample results in this thesis are constructed in the following manner. First, an autoregressive model is run for the fit-period 1980:1-2003:4. The optimal lag length is determined by AIC. As discussed in Liu and Enders (2003), the AIC is designed to combat the problem of overfitting by adding a penalty term for each estimated parameter. Considering out-of-sample testing is sensitive to overfitting, AIC is one method for model selection of our forecasting models.

$$BILL_t = \alpha + \beta_2 BILL_{t-1} + \cdots + \beta_h BILL_{t-h} + \varepsilon_t \tag{12}$$

where φ_t denotes the variable being tested for predictive capacity and h is the optimal lag length chosen by the Akaike information criterion method proposed by Akaike (1974).

Once the fit-period model is estimated, it is used to make out-of-sample predictions across the forecast horizon 2004:1-2008:4. The Mean Squared Error (MSE) between actual out-of-sample values and the predictions generated by the autoregressive model will be computed as a benchmark for determining predictive power in the next step of the process. Next, bivariate VARs are run using the same fit-period in order to make forecasts for the same forecast horizon as the AR model.

$$\begin{aligned} BILL_t = \alpha &+ \beta_2 BILL_{t-1} + \cdots + \beta_h BILL_{t-h} + \vartheta_1 \varphi_{t-1} + \cdots + \vartheta_h \varphi_{t-h} \\ &+ \varepsilon_t \end{aligned} \tag{13}$$

In Table 13, the MSE of the autoregressive model is divided by the MSE of the respective vector autoregressive model. A number exceeding 1 indicates the variable is useful for predicting T-bill returns.

After analyzing the results of Table 6, we see evidence both affirming and negating the evidence gathered from earlier tables. As expected, the output gap and unemployment rate come out on top, easily outperforming the univariate AR model. The output gap increased the predictive power of the model across most forecast periods tested; where unemployment was effective after five steps ahead. The in-sample regressions yield very similar results.

A surprising performance was that of the S&P 500. At this point it is somewhat clear that the stock market holds predictive power about future interest rates from 4-8 months out. The economic intuition most likely goes as follows: First, we know from Table 4 that the S&P 500 has a positive effect on interest rates. Consider this narrative as an explanation: Given that declines in the stock market often closely follow sharp drops in output (Note: declines in output lead to the Federal Reserve lowering rates via the Taylor Rule), one could assume that interest rates should go down following a drop in the stock market as well.

Although a phenomenal performer in the in-sample regressions, including the CPI led to worse forecasts than with the AR model. One possible explanation for the underperformance of CPI could be due to the volatility of the series. Predictions using models constructed from volatile data often yield large errors.

Robustness

Given that the CPI shows no out-of-sample forecasting power in our analysis, we will also consider a core PCE deflator series. The purpose of this is to capture a less volatile measure of inflation. Additionally, on February 17, 2000 the Federal Reserve announced they would be abandoning the CPI index in favor of a chain-type PCE deflator (Monetary Policy Report, 2000). The advantage of the core PCE index is that it does not include food and energy prices (these series tend to be seasonal and very volatile). For this reason the series is more robust to price shocks that cause influential outliers in our forecasts.

The results in Table 13 indicate the core PCE deflator is extremely predictive of T-bill rates and yields a small MSE for the period forecasted. The MSE for this variable is almost suspiciously small. To double-check this result, we also used a rolling window method to find the MSE of forecasts using many different fit periods. Results are similar to those found in Table 13 for both CPI and the core PCE deflator. Rolling windows is a process by which an MSE is computed over every possible forecast horizon. This process gives a researcher the ability to further check the stability of the forecast errors over time.

As for the other variables, we test their robustness by using a rolling windows technique also. However, we found little difference between forecast errors from periods other than our chosen out-of-sample period (2004:1 to 2008:4). As for the variables that did differ somewhat, we elected to ignore the differences in favor of taking data from the most up-to-date horizon.

We find that the AR model performs better than the VAR model for the first 2 steps ahead in the case of almost every variable. We can say this is so for a couple reasons. First, the Federal Reserve is forward-looking according to the findings of Clarida, Gali, and Gertler (2000). If economic conditions more than 2 quarters ago are the main determinants of inflation and output in the near future, it makes sense the Federal Reserve actually reacts to changes in economic conditions from more than 2 quarters prior. As an illustration, consider a large increase in output in time t. Under the assumption that prices are sticky and take 1 year to adjust, the inflation caused by the increase in output will not be realized until $t+4$. The Federal Reserve will predict this inflation in $t+3$ and change the federal funds rate as soon as possible. Thus we see the poor performance at short horizons. Second, and arguably the most important for us to consider, AR forecasts are well suited for predicting short horizons because they capture the “momentum” of the series at hand. However, after a few periods, this momentum often leads forecasts in an incorrect direction.

Table 13: Out-of-sample Forecast MSE (AR) / MSE (VAR)

$$\textbf{VAR: } BILL_{t+k} = \alpha + \beta_2 BILL_{t-1} + \cdots + \beta_h BILL_{t-h} + \vartheta_2 \varphi_{t-1} + \cdots + \vartheta_h \varphi_{t-h} + \varepsilon_t$$
$$\textbf{AR: } BILL_t = \alpha + \beta_2 BILL_{t-1} + \cdots + \beta_h BILL_{t-h} + \varepsilon_t$$

	$k = Quarters\ Ahead$							
$\varphi_t\ Variables$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
S&P 500	0.228	0.510	0.806	1.047	1.209	1.280	1.384	1.365
M2	0.153	0.343	0.540	0.737	0.796	0.817	0.877	0.864
Output Gap	0.383	0.580	0.733	0.966	1.178	1.298	1.380	1.385
CPI	0.078	0.189	0.339	0.495	0.614	0.688	0.778	0.842
Core PCE deflator	1.376[5]	1.581	1.364	2.175	1.414	1.343	1.346	1.398
National Debt	0.185	0.436	0.733	0.994	1.057	0.985	0.938	0.916
Unemployment	0.099	0.258	0.461	0.708	0.907	1.033	1.184	1.272
Component U_1	0.087	0.223	0.431	0.690	0.891	0.987	1.071	1.075

Notes: AR denotes Autoregression; VAR denotes Vector Autoregression
Observations: 115, Sample period: 1980:1-2008:4, Frequency: Quarterly
This table reports the mean squared error found in the AR forecasts divided by the mean squared error found in the VAR forecasts. A value exceeding 1 tells us the additional variable is useful for predicting T-bill rate movement.

CHAPTER 5 - Conclusions

This thesis developed methods for identifying leading indicators for T-bill interest rate movements. From the extensive scope of variables tested, six variables exhibit performance worth noting: S&P 500, M2, output gap, CPI, national debt and unemployment.

These variables were supported first by simple OLS regressions. Then, analysis of out-of-sample forecasting errors provided additional evidence of predictive ability. A noteworthy feature of these six variables is that, if

[5] The errors used for the calculation of this figure are plotted together in Figure 6 (appendix). The AR is outperformed by the VAR according to MSE.

reduced to a single dynamic factor, the factor is statistically significant, especially when contrasted with models containing more variables.

A few of these variables have been identified in the literature previously. The output gap and inflation rate are the two most popular. We found the core PCE deflator more useful than the CPI at forecasting interest rates however. This is likely the series the Federal Reserve pays most attention to.

Overall, this thesis provides a good deal of evidence suggesting the unemployment rate and stock market performance are two series worth consideration in addition to the output gap and inflation. These four variables not only showed a good in-sample fit, but also improved the accuracy of our out-of-sample forecasts considerably.

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Appendix

Figure 4: Plot of Residuals (6 variables) $BILL_{t+5} = F(\alpha + \beta_1 \varphi_t)$

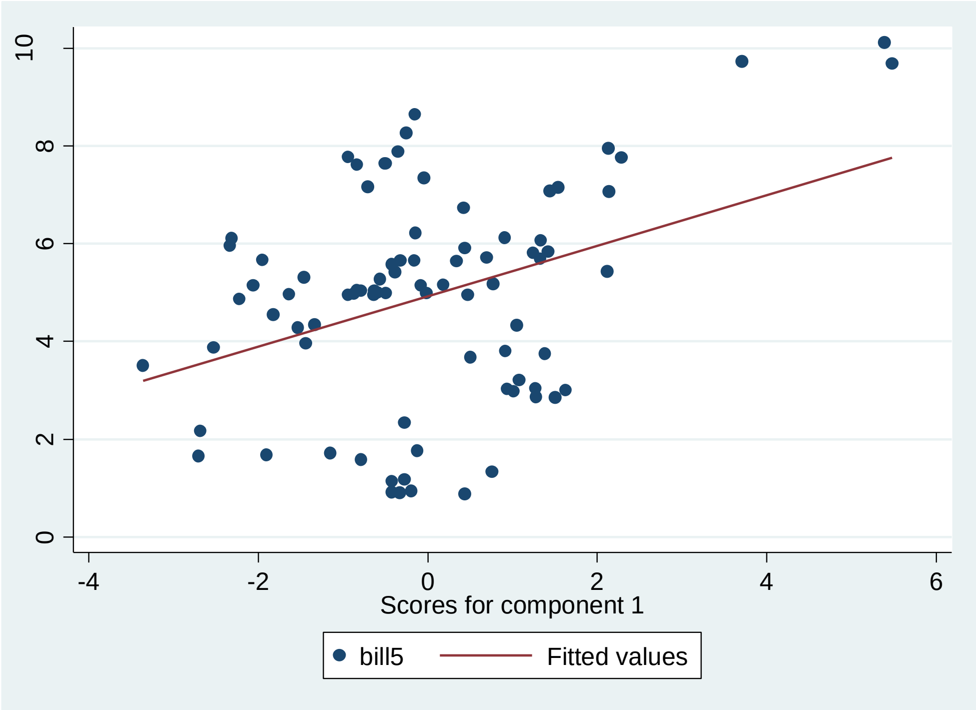

Figure 5: Plot of Residuals (14 variables) $BILL_{t+5} = F(\alpha + \beta_1 \varphi_t)$

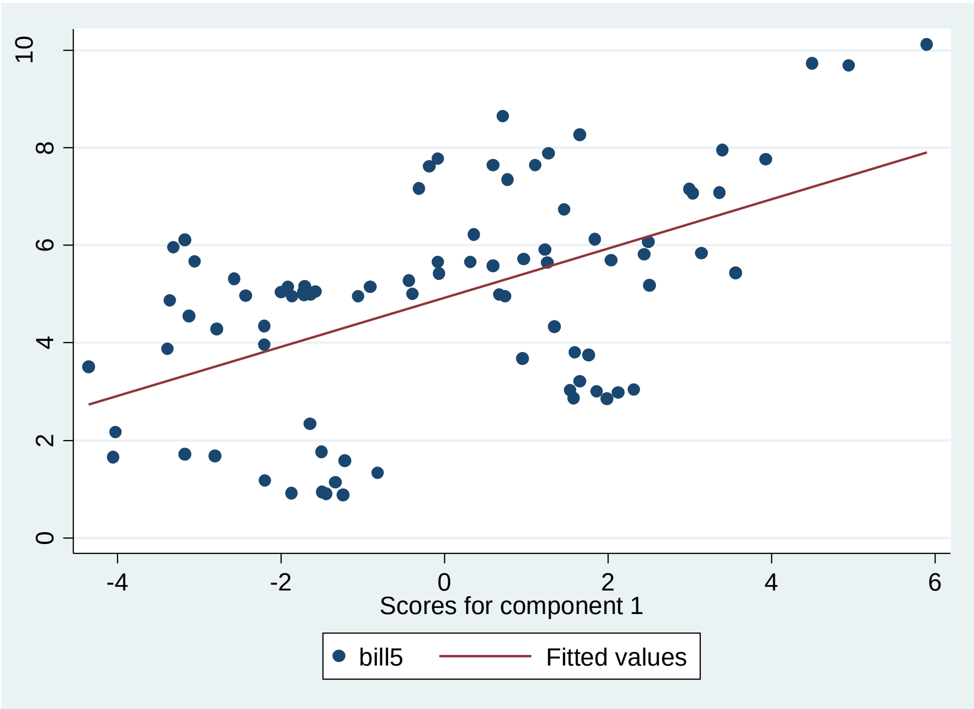

Figure 6: Core PCE Deflator VAR vs. AR Errors for 1 Period Lag.

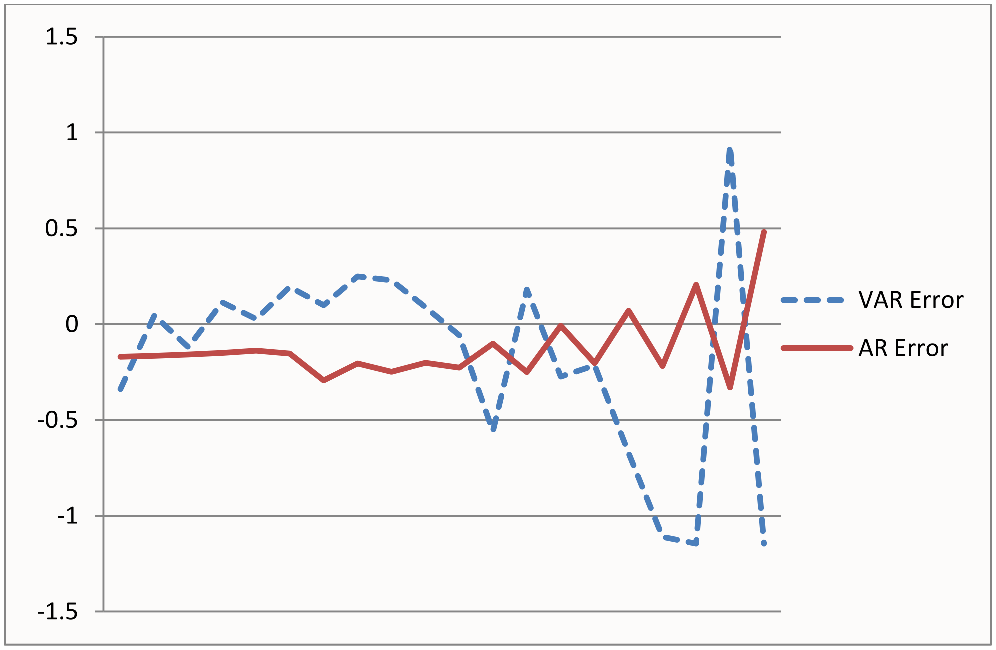

Table 14: Measures of Fit and *t*-statistics: Extra Models

$$BILL_{t+k} = \alpha + BILL_t + \beta_1 \varphi_t$$

	$k = Quarters\ Ahead$							
φ_t $Variables$	1	2	3	4	5	6	7	8
CPI								
R^2	0.95	0.85	0.75	0.64	0.54	0.43	0.33	0.23
t-stat	2.47	1.18	1.10	0.64	0.47	0.35	-0.08	-0.02
Output Gap								
R^2	0.94	0.85	0.75	0.64	0.55	0.45	0.36	0.28
t-stat	0.44	-0.08	-0.40	-0.94	-1.52	-1.88	-2.07	-2.29
S&P 500								
R^2	0.94	0.86	0.76	0.65	0.55	0.45	0.37	0.29
t-stat	1.69	1.27	1.19	1.58	1.82	2.05	2.26	2.14
M2								
R^2	0.94	0.85	0.75	0.64	0.53	0.43	0.33	0.24
t-stat	-0.49	-0.07	-0.43	-0.16	-0.11	-0.08	-0.23	-0.54
National Debt								
R^2	0.94	0.85	0.75	0.64	0.54	0.44	0.34	0.27
t-stat	-0.96	-0.48	0.99	0.45	1.13	1.34	1.60	1.91
Unemployment								
R^2	0.94	0.86	0.76	0.65	0.57	0.48	0.40	0.34
t-stat	0.35	0.91	1.28	1.89	2.42	2.79	3.10	3.54

Notes: T-bill returns are regressed on each independent variable separately for up to 8 quarters ahead. Observations: 84, Sample period: 1983:1-2003:4, Frequency: Quarterly

Table 15: Measures of Fit and *t*-statistics: Extra Models

$$BILL_{t+k} = \alpha + BILL_t + \beta_1 \varphi_t$$

$$k = Quarters\ Ahead$$

φ_t *Variable*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Component U_1								
R^2	0.94	0.85	0.75	0.65	0.56	0.46	0.38	0.31
t-stat	-0.20	0.34	0.70	1.33	1.99	2.35	2.60	2.94

Notes: T-bill returns (up to 8 quarters ahead) are regressed on a principle component found using Stata.
Observations: 84, Sample period: 1983:1-2003:4, Frequency: Quarterly