INFERENCE USING QUALITATIVE AND QUANTITATIVE INFORMATION WITH AN APPLICATION TO MONETARY POLICY

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I propose a framework for drawing inferences about an unobserved variable using qualitative and quantitative information. Using this framework, I study the timing and persistence of monetary policy regimes and compute probabilistic measures of the qualitative indicator's reliability. These estimates suggest that (1) it is over one and one-half times more likely that monetary policy is not restrictive at any point in time, (2) Boschen and Mills's [1995] policy index is a reliable indicator of the stance of monetary policy, and (3) certain qualitative indicators of monetary policy improve interest rate forecasts that are based on linear forecasting models. (*JEL* C22, E52)

I. INTRODUCTION

There has been a revival of interest in the use of qualitative information in macroeconomic analysis recently. An impetus for this revival is the apparent inability of modern statistical analyses that use only quantitative information to resolve significant macroeconomic controversies. For example, the direction of causality between money and output continues to be the subject of considerable debate. The use of qualitative information in macroeconomic analysis has a long tradition. Mitchell [1927] and Burns and Mitchell [1946] use the descriptions in Thorp's [1926] annals and several statistical series to identify the unobserved phase of the business cycle.[1] In their chapters on the Federal Reserve, Friedman and Schwartz [1963] use diaries, policy records, and monetary aggregates to identify the stance of monetary policy. The essence of this traditional method is that it is prudent to use *both* qualitative and quantitative information in the process of inference because of the potential gain in confidence associated with cross verification. Both types of information are needed to identify the asymmetries and nonlinearities that are characteristic of business cycles, policy initiatives, and other economic phenomena.

Questions concerning the interpretation of results using qualitative information, however, have been raised.[2] A source of unease is the difficulty of assessing a researcher's distillation of the information in descriptive materials. No obvious metric for evaluating the coding of a qualitative variable exists.

I present an alternative framework for combining qualitative and quantitative information in order to draw inferences of an unobservable variable. Quantitative information is an observable time-series variable. Qualita-

* I thank James Hamilton for correspondence and discussion that initiated this research. I also thank Michael Boldin, Phillip Cagan, John Campbell, Jordi Gali, Nicola Jefferson, David Romer, Paul Ruud, Joe Tracy and seminar participants at Berkeley, Board of Governors of the Federal Reserve System, Columbia, the Federal Reserve Banks of New York and San Francisco, and the Eastern Economic Association meetings for helpful comments and suggestions. The work of two anonymous referees and the editor (Frank Wykoff) improved substantially the final version. This research is supported by NSF Grant SES-9223476.

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1. In the introduction to Thorp [1926] Mitchell writes, "What we have in our business annals and our indexes of general business conditions, then, are different approaches to the problem of recording the fluctuations of economic activities—approaches each of which has its uncertainties as well as its merits. We cannot expect them to agree perfectly. When they disagree we cannot say that the discrepancy necessarily means error in one or all; it may mean merely that the different activities reflected by the various approaches really did not change in quite the same way. But if we find a general consilience among the results we shall feel increased confidence in the reliability of both approaches, and may regard the occasional discrepancies as presenting genuine problems from the study of which fresh knowledge may be gained."

2. For example, in his discussion of Romer and Romer's [1989] analysis of monetary policy shocks, Friedman [1989] questioned whether there was a close correspondence between monetary policy decisions and monetary policy actions.

Economic Inquiry
(ISSN 0095-2583)
Vol. XXXVI, January 1998, 108–119

tive information is an indicator variable (coded by a researcher) that reflects the distillation of literary materials. Motivated by the traditional method, I consider the case where both types of observable information are imperfect representations of an unobserved state variable. An iterative algorithm that uses quantitative and qualitative information to draw inferences of the unobservable variable is constructed. The algorithm produces an inference of the unobservable state variable for each sample period using the two types of information. It also produces a probabilistic assessment of whether the qualitative indicator is a reliable indicator of the true unobserved state. As discussed in more detail below, this algorithm is closely related to those of Cosslett and Lee [1985] and Hamilton [1989].

The algorithm is applied to the problem of determining the stance of monetary policy. A goal is to confront a problem that economic agents may actually face because of the secrecy surrounding the monetary policy process. A description of that problem is: How can observable information—qualitative and quantitative—be combined to infer the stance of monetary policy? Also, can the reliability of the qualitative information (or a distillation of it) be measured? I implement the algorithm using two prominent indicators of monetary policy.

The paper is organized as follows. The alternative framework for using qualitative and quantitative information to draw inferences of an unobservable variable is presented in the next section. The application to the problem of inferring the stance of monetary policy is presented in section III. In this section, indicators of policy are introduced, the model is estimated, and the relationship between the dynamic conditional monetary policy inferences and an important forecaster of macroeconomic activity is explored. Section IV concludes.

II. AN ALTERNATIVE FRAMEWORK FOR INFERENCE

Stochastic Structure

My alternative framework is based on a particular conception of the statistical model underlying the traditional method. Let y_t denote a quantitative variable and I_t denote a (0,1) qualitative variable. Further, let S_t denote an unobservable variable that influences y_t and I_t. A stylized version of the underlying statistical model is

$$(1)\qquad y_t = a_0 + a_1 S_t + (a_2 + a_3 S_t)\varepsilon_t$$

$$I_t = b_0 + b_1 S_t + \nu_t.$$

The a's and b's are constant parameters, while ν_t and ε_t denote disturbances. The disturbance ε_t is assumed to be independent of S_t. The disturbance ν_t is conditionally dependent on S_t (see below).

Consider the case where the process for the unobserved true state follows the two-state Markov chain:

$$\text{prob}(S_t = 1 | S_{t-1} = 1) = p$$

$$\text{prob}(S_t = 0 | S_{t-1} = 1) = 1 - p$$

$$\text{prob}(S_t = 0 | S_{t-1} = 0) = q$$

$$\text{prob}(S_t = 1 | S_{t-1} = 0) = 1 - q$$

Suppose that y_t depends on S_t through a switching model:

$$(2)\qquad f(y_t | S_t = 0) = (1/\sigma_0\sqrt{2\pi})\exp[-(y_t - \mu_0)^2/2\sigma_0^2]$$

$$f(y_t | S_t = 1) = (1/\sigma_1\sqrt{2\pi})\exp[-(y_t - \mu_1)^2/2\sigma_1^2]$$

The variable I_t is an indicator (dummy) that is the researcher's distillation of relevant qualitative information. For example, if based on the qualitative information at the researcher's disposal, the researcher believes that $S_t = 1$, then at t the dummy variable is coded, $I_t = 1$. Thus, it is of interest to calculate

$$\text{prob}(I_t = 1 | S_t = 1) = g\,,$$

$$\text{prob}(I_t = 0 | S_t = 1) = 1 - g\,,$$

$$\text{prob}(I_t = 0 | S_t = 0) = h\,,\ \text{and}$$

$$\text{prob}(I_t = 1 | S_t = 0) = 1 - h\,.$$

The population parameters g and h indicate how reliable an indicator the random variable I_t is about the value of S_t on average.[3]

This stochastic structure is analogous to that in Hamilton [1989] and Cosslett and Lee [1985]. Cosslett and Lee extend the standard linear regression model with serial correlation to the case where included among the regressors is an indicator variable subject to measurement error. They model the indicator variable as a measurement of an unobserved indicator that follows a Markov process. Their main focus is to develop test statistics for the detection of serial correlation in such models. They formulate a recursive algorithm for likelihood function evaluation, and among their estimated parameters is a measure of the degree of measurement error in the observed indicator variable. Unlike in Cosslett and Lee, the likelihood function here is derived as a product of conditional likelihood values. This permits the computed inferences of the unobserved state variables at time t to depend only on information up to and including time t. Thus, these inferences are more closely associated with those that actual agents could have made at the time.

My framework is most closely related to Hamilton [1988; 1989] in that it depends on nonlinearities in the data for robust inference and estimation. He demonstrates how to draw inferences about whether and when discrete shifts in the distribution parameters of a nonstationary time series occurred. He models these potential shifts as the outcome of a Markov process. The only input to Hamilton's framework is a quantitative variable whose properties one wishes to learn more about. Hamilton [1989] demonstrates his technique using real GNP. A remarkable feature of his results is how well the regime shifts he identifies match-up with NBER business-cycle dating. What should be made of these correspondences? Are they spurious? What metric can be applied to them? Hamilton does not consider how qualitative information can be used and assessed in the inferential process.

The algorithm below describes precisely how y_t and I_t are used to draw inferences of S_t. The definition of conditional probability provides insight into the workings of the algorithm. Let A, B, and C be events. Suppose that we are most interested in the probability of two additional events: first, A, B, and C occur together and second, C occurs given that A and B have occurred. Using the definition of conditional probability, the probability of the first event is

$$P(ABC) = P(A|BC)P(B|C)P(C).$$

It follows that the probability of the second event is

$$P(C|AB) = \frac{P(A|BC)P(B|C)P(C)}{P(AB)}.$$

Analogues to these expressions recur below. In the first instance, the likelihood of occurrence of known values of I_t and y_t with a current and past value of the state variable is of interest. Given the Markov specification for the state, the conditional likelihood function for the observed data can be constructed and maximized numerically with respect to its parameters (μ_1, μ_0, σ_1, σ_0, p, q, g, and h). In the second instance, the probability of state S_t given I_t and y_t is of interest. It can be inferred once the maximum likelihood parameter estimates are in hand.

Those eager to get to the application and results may now prefer to leave the details in next subsection to a later reading.

Algorithm

Consider how qualitative and quantitative information can be used to form inferences of the state before considering estimation of the population parameters.

Let

$$\Omega_t \equiv \{y_t, I_t, y_{t-1}, I_{t-1}, \ldots, y_1, I_1\}$$

denote the data observed through date t. At date t, the filter for this composite process accepts as input[4]

3. The relation between the disturbance v_t and the unobserved variable S_t is as follows. In equation (1), set $b_0 = 1 - h$ and $b_1 = -1 + g + h$. Conditional on $S_t = 1$, v_t equals $1 - g$ with probability g and v_t equals $-g$ with probability $1 - g$. Conditional on $S_t = 0$, v_t equals $-(1 - h)$ with probability h and v_t equals h with probability $1 - h$.

4. The convention is that capital letters denote random variables and lower case letters denote realizations of random variables.

$$(3) \qquad \text{prob}(S_{t-1} = s_{t-1} | \Omega_{t-1})$$

and has as output

$$(4) \qquad \text{prob}(S_t = s_t | \Omega_t).$$

To move from equation (3) to equation (4) multiply equation (3) by $\text{prob}(S_t = s_t | S_{t-1} = s_{t-1})$ to obtain

$$(5) \qquad \text{prob}(S_t = s_t, S_{t-1} = s_{t-1} | \Omega_{t-1}) = \text{prob}(S_t = s_t | S_{t-1} = s_{t-1}) \times \text{prob}(S_{t-1} = s_{t-1} | \Omega_{t-1}).$$

Next, use equations (2) and (5) to compute the conditional joint-density distribution

$$(6) \qquad d(y_t, S_t = s_t, S_{t-1} = s_{t-1} | \Omega_{t-1}) = f(y_t | S_t = s_t) \times \text{prob}(S_t = s_t, S_{t-1} = s_{t-1} | \Omega_{t-1}).$$

Based on the coding of the dummy variable, the researcher knows whether $I_t = 0$ or $I_t = 1$ at time t. The event of interest is the joint occurrence of $(I_t = i_t, y_t, S_t = s_t, S_{t-1} = s_{t-1})$. To evaluate the likelihood of this event, multiply equation (6) by $\text{prob}(I_t = i_t | S_t = s_t)$. This product gives

$$(7) \qquad d(I_t = i_t, y_t, S_t = s_t, S_{t-1} = s_{t-1} | \Omega_{t-1}) = \text{prob}(I_t = i_t | S_t = s_t) \times d(y_t, S_t = s_t, S_{t-1} = {}_{t-1} | \Omega_{t-1}).$$

Equation (7) embodies the important assumption that I_t is conditionally independent of y_t, s_{t-1}, and other history.[5] I maintain this assumption throughout the analysis. If this assumption is not true, then a potential source of bias is introduced. The four values of equation (7), one for each of the four possible configurations of s_t and s_{t-1}, are of the form $d(I_t = i_t, y_t, s_t, s_{t-1} | \Omega_{t-1})$. The sum of these four numbers is the conditional likelihood of the tth observation

$$(8) \qquad f(I_t = i_t, y_t | \Omega_{t-1}) = \sum_{s_t=0}^{1} \sum_{s_{t-1}=0}^{1} d(I_t = i_t, y_t, s_t, s_{t-1} | \Omega_{t-1}).$$

Dividing equation (7) by (8) yields an inference about s_t and s_{t-1} that makes use of the new observed data for date t:

$$\text{prob}(S_t = s_t, S_{t-1} = s_{t-1} | \Omega_t) = d(I_t = i_t, y_t, S_t = s_t, S_{t-1} = s_{t-1} | \Omega_{t-1}) / f(I_t = i_t, y_t | \Omega_{t-1}).$$

The desired output, equation (4), is found by summing over s_{t-1}:

$$\text{prob}(S_t = s_t | \Omega_t) = \sum_{s_{t-1}=0}^{1} \text{prob}(S_t = s_t, S_{t-1} = s_{t-1} | \Omega_t).$$

A by-product of the algorithm is the conditional likelihood, equation (8). The product of these conditional likelihoods can be maximized with respect to the parameters μ_1, μ_0, σ_1, σ_0, p, q, g, and h. The values of g and h tell us how reliable an indicator I_t is on average. Additionally, a comparison of $\text{prob}(S_t = 1 | \Omega_t)$ with I_t tells us how reliable is the inference for date t in particular.[6]

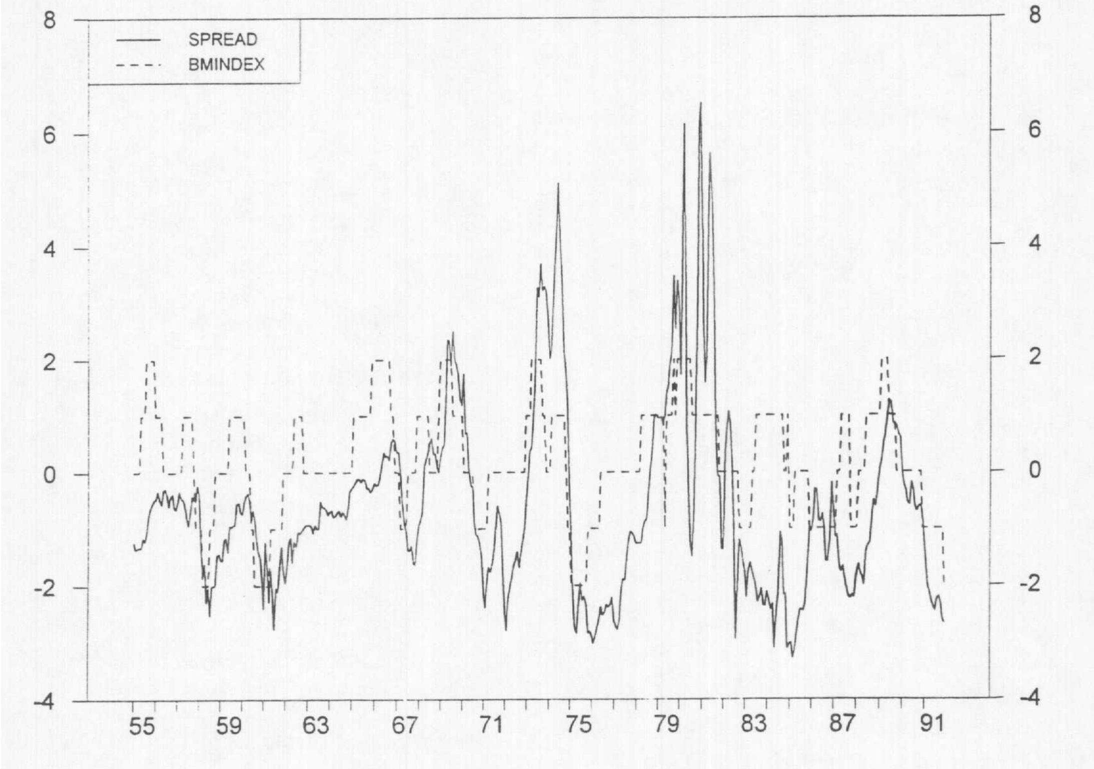
My statistical framework is distinguished by how it combines quantitative and qualitative information and its probabilistic assessment of the researcher's use of the qualitative information at the researcher's disposal.[7] The framework may be thought of as an objective

5. If this assumption is violated, then the first term on the right-hand side in equation (7) should be $\text{prob}(I_t = i_t | S_t = s_t, y_t, S_{t-1} = s_{t-1}; \Omega_{t-1})$. This would alter the interpretation of the parameters g and h substantively.

6. In practice, the algorithm is started up with the unconditional probability of s_0 given by the limiting probability of states 0 and 1. Additionally, the probabilities p, q, g, and h are parameterized as $x = \exp(-\theta_x^2)$ for $x = p, q, g, h$ to ensure that the likelihood function is well defined. See Hamilton [1994] for more on these points.

7. Interestingly, the use of qualitative information plays a significant role in Hoover's [1991] study of causality between money and prices. Although causality is not directly related to what concerns us here, it is clear that in his framework the efficient use of qualitative information, stability of distribution parameters, and causality are intertwined.

FIGURE 1
Fed Funds–10 Year T-Bond Spread vs. Boschen-Mills Index



way of not only identifying regime changes but also of evaluating dummy variables thought to characterize those changes.

III. APPLICATION: THE STANCE OF MONETARY POLICY

Indicators of Policy

The application focuses on two indicators of monetary policy. The first is quantitative—the spread between the federal funds rate and the ten-year Treasury bond (hereafter denoted the spread). The second is qualitative—Boschen and Mills's [1995] policy index. Both indicators are shown in Figure 1. These indicators are chosen because of the attention they have attracted recently and because they appear to constitute a natural set of inputs into and motivation for the statistical model described above.

Laurent [1990] was among the first to propose the spread as an inflation expectations-corrected measure of the stance of monetary policy. The Treasury bond controls for inflation expectations. Presumably, the spread increases if the Fed starts to tighten. Bernanke and Blinder [1992] noted that most of the volatility in the spread is due to movements in the federal funds rate.

Boschen and Mills [1995; 1992] construct their index from a meticulous reading of Federal Reserve documents. They provide a classification of the stance of policy for each month from January 1953 to December 1991. Their index takes on integer values in the range –2 to 2. Negative values of the index imply that policy is anti-inflationary while nonnegative values are associated with a more neutral (or pro-growth) policy stance. In Figure 1, I multiplied the Boschen-Mills index by –1 in order to make its interpretation parallel that of the spread. Boschen and Mills [1995; 1992] compare the Romers' [1989] indicator with their own and other indicators based on qualitative information proposed by Poole

[1971], Uselton [1974], Potts and Luckett [1978], and Kimelman [1981]. They find that these disparate indicators generally are highly correlated and that they contain marginal predictive power for many monetary aggregates and interest rates. The Boschen-Mills index is used to represent monetary policy by Romer and Romer [1994] and Ball and Croushore [1994].

The spread and Boschen and Mills's index have proven to be among the most robust policy indicators available. Yet, they have not been directly contrasted. If they are complimentary, then it may be worthwhile to explore ways of combining them to draw inferences of the unobserved true policy process. If they both are representations of the true policy process, then it may be possible to construct an acceptable metric by which the reliability of the qualitative indicator can be assessed.

Figure 1 conveys the impression that movements of the spread are not altogether unrelated to the Boschen-Mills index. High levels of the index appear to be associated with high or increasing levels of the spread. Low levels of the index appear to be associated with low or decreasing levels of the spread. Taken separately, each indicator suggests that there are distinct swings in the stance of policy. The spread, for instance, has remained above (below) its sample mean (=–.611) for some time and then switched to values below (above) its sample mean in one or two months. Similar swings are marked in Boschen-Mills index by transitions from a restrictive (expansionary) policy stance to an expansionary (restrictive) policy stance where the index takes on the zero value in only one (or fewer) months.

Figure 1 also suggests that it might be difficult to find parsimonious linear representations of policy. For example, I attempted to fit a series of low-order ARMA models for the spread.[8] The Box-Ljung Q-statistics for randomness overwhelmingly rejected the null hypotheses. Frequently, pure AR representations for the spread are used in forecast equations and VAR analysis. Residuals from AR(12), AR(24), and AR(36) specifications, however, yielded evidence against independent.[9]

These statistical results concerning the spread need not be surprising when considered from the qualitative index viewpoint. The perspective that emerges from this literature is more episodic. Policy is a series of initiatives—some more active than others. The Boschen-Mills index is representative of this qualitative regime-oriented approach to inference. From this viewpoint, it should require a significant number of AR parameters to smooth over a potentially nonlinear policy process.

Estimation and Interpretation

In the application, I assume that the spread is influenced by the unobservable state variable, S_t. That is, denote the spread as y_t in equation (1).[10] In this specification, the only source of persistence is the autoregressive structure of S_t itself.[11] This specification appears to be the most consistent with both Boschen and Mills' experiment of inferring the underlying policy stance at each point in time and the use of the level of the spread as a point in time indicator of policy.[12] For the coding of I_t, this assumption implies that S_t summarizes all past information and that Boschen and Mills do not refer to the spread contemporaneously. In the application, the in-

8. In the monetary policy literature, the level of the spread, not its changes, usually represents policy. This is why I do not consider integrated processes here.

9. The test statistic is $Q(P) = T(T+2) \quad \Sigma_{\tau=1}^{P} (T-\tau)^{-1}\{r(\tau;\varepsilon_t^2)\}^2 \sim \chi_P^2$ (see McLeod and Li [1983]). The sample size is 444. For the AR(12), AR(24), and AR(36) models, the $Q(50)$ statistics are 182.46, 164.25, and 152.91 respectively. The significance level is 0.0 in each case.

10. Heuristically, S_t may be thought of as the regime in effect at time t as indicated by a policy directive that was agreed upon in secret. The philosophy underlying my specification is that of Lucas [1976]: "a *policy* is viewed as a change in the parameters, ..., or in the function generating the values of policy variables at particular times."

11. The AR representation for S_t is $S_t = (1-q) + (-1+p+q)S_{t-1} + \omega_t$. Conditional on $S_{t-1} = 0$, ω_t equals $1-p$ with probability p and ω_t equals $-p$ with probability $1-p$. Conditional on $S_{t-1} = 1$, ω_t equals $-(1-q)$ with probability q and ω_t equals q with probability $1-q$.

12. An alternative specification is to introduce AR parameters for the spread. Under this alternative specification, S_t pertains to the parameters of an autoregression. It is not clear, however, whether Boschen and Mills consider any additional sources of serial correlation beyond that in the perceived underlying state variable. Therefore, I consider the specification where the Boschen-Mills index and the level of the spread form a composite process.

dicator variable I_t is set to one when Boschen-Mills index is positive and zero otherwise.

The sample period is January 1955 to December 1991.[13] The results of maximizing the conditional likelihood function, equation (8), are presented in Table I, column 1.[14]

States 0 and 1 are persistent in a probabilistic sense. The probability of making a transition from a state to that same state in the next period is over 92%. If these estimates of p and q remain stable through time, we may calculate the long-run proportions of the time that monetary policy is relatively restrictive ($S_t = 1$) or less restrictive ($S_t = 0$).[15] For the example under consideration,

$$\pi_0 = (1-p)/(2-q-p) = .61 \qquad (9)$$

and

$$\pi_1 = (1-q)/2-q-p) = .39.$$

An interpretation of equation (9) is that it is over one-and-a-half times more likely that the stance of monetary policy is not restrictive at any point in time than it is restrictive.

The long-run average rate at which transitions from less to more restrictive policy occur is

$$\pi_0(1-q) = .0281. \qquad (10)$$

Also, the long-run average rate at which transitions from more to less restrictive policy occur is

$$\pi_1(1-p) = .0277. \qquad (11)$$

Equations (9), (10) and (11) can be used to compute the average duration of monetary policy regimes. The average duration of less restrictive policy regimes is

$$\pi_0/\pi_0(1-q) = 1/(1-q) = 21.74$$

months. Conversely, the average duration of more restrictive policy regime is

$$\pi_1/\pi_1(1-p) = 1/(1-p) = 14.08$$

months.

An interpretation of the estimates of g and h is as follows. If $g = 1$, then I_t is a perfectly *reliable* indicator of state 1 in a probabilistic sense. That is, $I_t = 1$ when $S_t = 1$ with probability one. If $g = .5$, then the researcher could have done just as well by coding the dummy variable by flipping a fair coin. If $g < .5$, then the researcher has the facts exactly backward. The parameter h is interpreted analogously except that it pertains to state 0. Returning to Table I, we see that g is .958 while h is .997. These results suggest that the Boschen and Mills index is a very reliable indicator of policy in a probabilistic sense.[16]

When the spread is in state 0 its mean and standard deviation are –1.327 and .920, respectively. When the spread is in state 1 it means is 177 basis points higher and its standard deviation is more than twice as large.

Figure 2 graphs prob($S_t = 1|\Omega_t$) for each sample period. Let the process be in state x when the probability of being in that state is greater than or equal to .5. Several episodes of state 1 are identified. Not surprisingly, they correspond closely with the anti-inflationary episodes identified by Boschen and Mills.

Consideration of varying policy regime duration is crucial for interpreting the reliability of qualitative inferences. Study of the duration of particular episodes of monetary tightening (or loosening) receives less attention in the monetary policy literature.[17] A conjecture for the relative neglect is that the lagged effects of the initiation of a monetary episode make it difficult to analyze satisfactorily termination dates. I attempt to overcome this dif-

13. The sample period is bounded from below by the availability of the spread and from above by the last date Boschen and Mills [1995] used in their study.

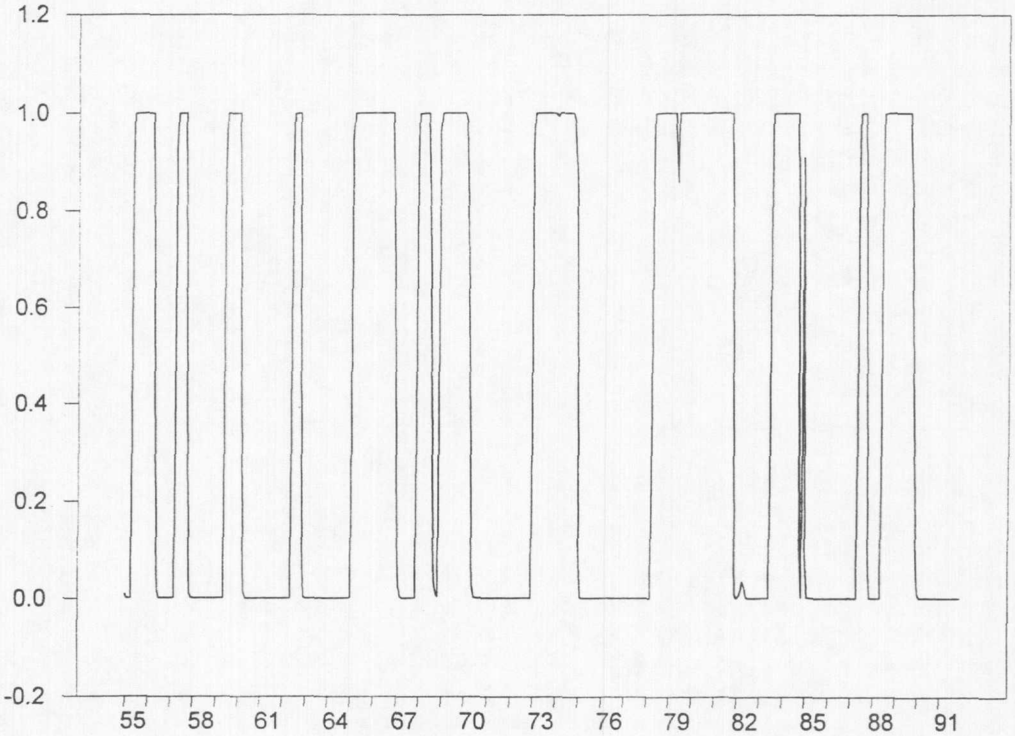
14. The standard errors for the probabilities are approximations calculated from the standard errors for θ_x (see footnote 6). They should be interpreted cautiously for the probabilities near the boundary of the parameter space.

15. Let $\pi_j = \lim_{n\to\infty} e^n_{jj}$, for $j \geq 0$ and $e_{ij} =$ the (i, j)th element of the estimated probability transition matrix. A well-known theorem (Karlin and Taylor [1975, 85]) establishes that the limiting probabilities, π_j, are the unique nonnegative solution to $\pi_j = \Sigma_{i=0}^{\infty} \pi_i e_{ij}, j \geq 0$ with $\Sigma_{j=0}^{\infty} \pi_j = 1$ and $\pi_j \geq 0$.

16. An alternative interpretation of g and h is that they indicate the amount of additional information about S_t derived from y_t. For example, g and h close to one may suggest that little additional information about S_t comes from y_t.

17. A noticeable exception is the period 1979 to 1982 where there appears to be a consensus as to when a monetary policy initiative began and when it ended.

FIGURE 2
Inferred Probability that $S = 1$



ficulty by drawing inferences from indicators that appear to respond to the beginning and end of policy initiatives.

Next, I examine the subsample robustness of these findings.

Subsample I: Fed Chairperson

The sample was divided using the dates of tenure for three of the five Federal Reserve chairmen that governed during the sample period. Columns 2 through 4 of Table I give the dates and parameter estimates for the chairmanships of Martin, Burns, and Volcker. The tenure of Miller and Greenspan were deemed too short to yield reliable estimates. The parameter estimates in Table I provide some indication of how sensitive the full sample parameters were to Fed leadership, which presumably could alter the conduct of monetary policy even in the face of institutional stability. Hakes [1990], for example, estimated policy reaction functions for Martin, Burns, and Volcker. He found that the objectives and priorities of monetary policy were sensitive to the identity of the Federal Reserve's chairman.

The parameter estimates exhibited subsample sensitivity that depended on the identity of the Fed chairman. Under Volcker, the estimates suggested that once policy took a stance it was very likely to persist: p and q were very high. In the Martin era, the spread exhibited relatively small average differences between restrictive and less restrictive policy. The persistence of regimes and volatility of the spread under Burns were intermediate to those of Martin and Volcker.

The Boschen-Mills index is an outstanding indicator of policy during the Martin era. It is a less accurate indicator of restrictive policy during Burns's chairmanship (g = .664). Finally, the Boschen-Mills index suggests that policy under Volcker is restrictive more often than it actually is (h = .705).

TABLE I
Maximum Likelihood Estimates of Parameters

Parameter	Full Sample	Martin [55:1–70:1]	Burns [70:2–78:1]	Volcker [79:8–87:8]	Target70s [74:9–79:9]	Target80s [84:3–91:12]
μ_0	–1.327 (0.059)	–1.004 (0.069)	–1.852 (0.092)	–1.636 (0.114)	–2.172 (0.103)	–1.472 (0.124)
$\mu_1 - \mu_0$	1.769 (0.155)	0.880 (0.127)	3.978 (0.307)	4.178 (0.460)	2.934 (0.259)	0.611 (0.275)
p	0.929 (0.019)	0.914 (0.032)	0.952 (0.038)	0.985 (0.020)	0.973 (0.030)	0.909 (0.055)
q	0.954 (0.013)	0.938 (0.023)	0.976 (0.018)	0.991 (0.010)	0.963 (0.029)	0.957 (0.025)
σ_0	0.920 (0.043)	0.709 (0.049)	0.708 (0.070)	0.965 (0.081)	0.617 (0.076)	1.001 (0.087)
σ_1	1.893 (0.101)	0.920 (0.075)	1.496 (0.207)	2.246 (0.314)	1.139 (0.169)	1.274 (0.171)
g	0.958 (0.018)	0.999 (—)	0.664 (0.095)	0.999 (—)	0.828 (0.082)	0.999 (—)
h	0.997 (0.005)	0.999 (—)	0.999 (—)	0.705 (0.054)	0.999 (—)	0.986 (0.017
log *LF*	–438.84	–94.93	–66.58	–116.60	–34.13	–78.52

Note: The data are the spread (= Federal Funds rate–10 year Treasury Bond rate) and the Boschen and Mills policy index. Standard errors in parentheses. Dashes indicate that the underlying point estimate is indistinguishable from zero.

Data source: Citibank database and Boschen and Mills (1995).

Suppose the Markov chain for each chairman is allowed to continue forever. What percentage of the time is policy restrictive or less restrictive? Calculation of the long-run state probabilities using equation (9) and the estimates of p and q for each chairman in Table I yields: Martin $\pi_0 = .58$, $\pi_1 = .42$; Burns $\pi_0 = .67$, $\pi_1 = .33$; Volcker $\pi_0 = .63$, $\pi_1 = .37$. Martin's numbers are close to those for the full sample. Policy under Burns is less restrictive 67% of the time. The values for Volcker are intermediate to those of Martin and Burns. It appears that, qualitatively and quantitatively, policy under Martin is unlike that under Burns which is unlike that under Volcker.

Subsample II: Fed Operating Procedure

Since 1970, there have been two periods during which the Federal Reserve employed federal funds rate targets rather explicitly. Cook and Hahn [1989] identify the first period as September 1974 to September 1979. They examine the impact of perceived target changes on market interest rates. Rudebusch [1995] and Hamilton [1996] indicate that federal funds rate targets have also been a prominent feature of Federal Reserve policy since March 1984. Rudebusch [1995] uses information from durations between target changes to explicitly model the timing and direction of target changes. Hamilton [1996] uses post-March 1984 daily data to characterize the behavior of the federal funds rate during reserve maintenance periods under contemporaneous reserve accounting.

I estimated the model over each of these subperiods. The results are summarized in Table I, columns 5 and 6. The parameter estimates exhibit subsample sensitivity that depends on the targeting period.

The spread may be a particularly accurate measure of policy during a federal funds-rate control period.[18] Therefore, these periods provide a potentially ideal environment for evaluating the performance of Boschen-Mills index. Table I, column 5 suggests that the index is a very reliable indicator of less restrictive policy during the 1970s targeting period. It is a less accurate indicator of restrictive policy. Column 6 suggests that the index is a highly reliable indicator of policy during the 1980s (and early 1990s) targeting period. The index indicates restrictive policy in a few periods when policy was less restrictive. This causes the point estimate of $h(= .986)$ to be "relatively low."

There is considerable overlap in the Burns (column 3) and the 1970 targeting (column 5) subsamples. Essentially, they differ by a period of oil shock and recession. A comparison of the point estimates of g between columns 3 and 5 suggests that Boschen-Mills index is a less reliable indicator of restrictive policy under Burns due to the difficulty of inferring restrictive policy after the first oil shock.

Notice that there is considerable overlap in the Volcker (column 4) and the 1980s targeting (column 6) subsamples. The latter period excludes the 1979 oil shock and a severe recession in the early 1980s. A comparison of the point estimates of h between columns 4 and 6 suggest that the index is a less reliable indicator of less restrictive policy under Volcker due to the difficulty of inferring less restrictive policy during the second oil shock (and long recession). In summary, characterizing monetary policy qualitatively during turbulent economic periods is difficult.

Forecasting the Forecast Variable

Bernanke and Blinder [1992] find that lagged values of the spread contain marginal information for several real macroeconomic variables. They present evidence that federal funds-rate based measures of policy are preeminent within the class of forecasting variables they consider. Boschen and Mills, however, report that their policy index contains marginal information for many interest rates and growth rates of the monetary aggregates. In the previous section, I presented evidence that (1) a Markov model was not an unreasonable model for the spread and (2) a simple transformation of the Boschen and Mills index appeared to be a reasonable representation of the true unobserved state variable for the Markov process governing the spread. These two findings represent important clues as to why one should expect the Boschen and Mills qualitative indicator (and possibly other reliable ones like it) to have predictive power for particular interest rates in linear forecasting models.

Hamilton [1989] observed that if a Markov model is the true data-generating process for a variable, then pure autoregressive models for that variable would generate suboptimal forecasts. In my example, the basic intuition is that if equation (2) were the true model, then agents' forecast of the current value of the spread would differ according to whether policy was restrictive or expansionary in the previous period. This suggests that the dynamic conditional monetary policy inferences, $\text{prob}(S_{t-1} = 1|\Omega_{t-1})$, should contain significant marginal information for the spread when included in the AR models for the spread considered in section III. If $\text{prob}(S_{t-1} = 1|\Omega_{t-1})$ is found to be insignificant, then this is evidence against the Markov model.

To test whether $\text{prob}(S_{t-1} = 1|\Omega_{t-1})$ improves linear forecasts of the spread, I consider AR models for the spread of the form

$$spread_t = \alpha + \beta\text{prob}(S_{t-1} = 1|\Omega_{t-1}) + \sum_{s=1}^{k} \delta_s \; spread_{t-s} + e_t$$

for $k = 12$, 24, and 36. The standard errors from these regressions are not correct because $\text{prob}(S_{t-1} = 1|\Omega_{t-1})$ is a generated regressor. Therefore, the standard errors reported below are computed using results due to Murphy and Topel [1985] for two-step estimation with nonindependent random components. The estimates of β are (with correct standard errors in parenthesis)

$k = 12$	$k = 24$	$k = 36$
.2818	.2970	.3264
(.0682)	(.0702)	(.0734)

Suppose the probability that policy was restrictive last period increased from zero to

18. A referee brought this insight to my attention.

one. The estimates of β answer the question: By how many basis points should the forecast of the current spread be revised conditional on past values of the spread? For $k = 24$, for example, the answer is 30 basis points.

These results are in favor of the Markov model. Additionally, they provide some intuition as to why qualitative indicators of policy perform well in linear forecast models. These indicators capture nonlinearities in and the discreteness of the monetary policy process. These indicators are important and useful because they improve suboptimal forecasts that are based upon forecast equations that are in some sense misspecified.

IV. CONCLUSION

The coding of a qualitative variable can be interpreted as the researcher's evaluation of when a feature of the environment generating the data has changed. This evaluation may be based on a priori or extraneous information at the researcher's disposal. Assessment of the reliability of the qualitative variable is usually based on the degree to which one believes that its coding is consistent with shifts in the state of nature. Often, it is not clear how to evaluate the use of qualitative information. The framework proposed in this paper provides a way of constructing a probabilistic assessment of the researcher's use of qualitative and quantitative information.

A description of the stance of monetary policy from 1955 to 1991 is that there were thirteen episodes of relative tightening. They were of varying duration and changes in stance were sudden. The standard deviation of an observable quantitative indicator of monetary policy (the federal funds rate minus the ten-year Treasury bond rate) is twice as large in its restrictive state. The conditional dynamic monetary policy inferences that are a by-product of the analysis improve linear forecasts of the spread between the federal funds rate and the ten-year Treasury bond by sensitively tracking underlying shifts in monetary regimes.

Recently, it has become common practice to analyze monetary policy using qualitative and quantitative information by reading policy documents, discerning shifts in policy, and then examining the behavior of financial quantitative variables shortly after inferred policy shifts or to use innovations in interest spreads (and rates) to represent shifts in monetary policy. The analysis of this paper suggests that, if such policy analysis is not be misleading, care must be taken to determine whether observed movements in financial variables represent innovations *within* policy regimes or true *shifts* in policy regimes.

REFERENCES

Ball, Laurence, and Dean Croushore. "Expectations and the Effects of Monetary Policy." Mimeograph, Johns Hopkins University, July 1994.

Bernanke, Ben, and Alan Blinder. "The Federal Funds Rate and the Channels of Monetary Transmission." *American Economic Review*, September 1992, 901–21.

Boschen, John, and Leonard Mills. "The Effects of Countercyclical Monetary Policy on Money and Interest Rates: An Evaluation from FOMC Documents." Mimeograph, College of William and Mary, May 1992.

______. "The Relation between Narrative and Money Market Indicators of Monetary Policy." *Economic Inquiry*, 33(1), 1995, 24–44.

Burns, Arthur F., and Wesley C. Mitchell. *Measuring Business Cycles*. New York: National Bureau of Economic Research, 1946.

Citibase. FAME Economic Database, 1946-present. New York, FAME, 1978–1994.

Cook, Timothy, and Thomas Hahn. "The Effect of Changes in the Federal Funds Rate Target on Market Interest Rates in the 1970s." *Journal of Monetary Economics*, November 1989, 333–51.

Cosslett, Stephen R., and Lung-Fei Lee. "Serial Correlation in Discrete Variable Models." *Journal of Econometrics*, January 1985, 79–97.

Friedman, Benjamin. "Comment," in O. J. Blanchard and S. Fischer eds. NBER *Macroeconomics Annual*. Cambridge, Mass.: MIT Press, 1989, 177–82.

Friedman, Milton, and Anna J. Schwartz. *A Monetary History of the United States* 1867-1960. Princeton: Princeton University Press, 1963.

Hakes, David R. "The Objectives and Priorities of Monetary Policy under Different Federal Reserve Board Chairman." *Journal of Money, Credit, and Banking*, 22(3), 1990, 327–37.

Hamilton, James D. "Rational Expectations Econometric Analysis of Changes in Regime: An Investigation of the Term Structure of Interest Rates." *Journal of Economic Dynamics and Control*, June/September 1988, 385–423.

______. "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle." *Econometrica*, March 1989, 357–84.

______. *Time Series Analysis*. Princeton: Princeton University Press, 1994.

______. "The Daily Market for Federal Funds." *Journal of Political Economy*, 104(1), 1996, 26–56.

Hoover, Kevin D. "The Causal Direction between Money and Prices: An Alternative Approach., *Journal of Monetary Economics*, 27(3), 1991, 381–424.

Karlin, Samuel, and Howard Taylor. *A First Course in Stochastic Processes*, 2d ed. New York: Academic Press, 1975.

Kimelman, Nancy Jo. *Post-War Monetary Policymaking in the U.S.* Ph.D. Thesis, Brown University, 1981.

Lucas, Robert E. "Econometric Policy Evaluation: A Critique." Carnegie-Rochester Conference Series on Pubic Policy, 1, 1976, 19–46.

Laurent, Robert D. "Term Structure Spreads, the Money Supply Mechanism, and Indicators of Monetary Policy." Working Paper Series No. WP-90-16, Macro Economic Issues, Research Department, Federal Reserve Bank of Chicago, September 1990.

McLeod, A. Ian, and W. K. Li. "Diagnostic Checking ARMA Time Series Models Using Squared-Residual Autocorrelations." *Journal of Time Series Analysis*, 4, 1983, 269–73.

Mitchell, Wesley C. "Business Cycles: *The Problem and Its Setting*. NBER, New York: National Bureau of Economic Research, 1927.

Murphy, Kevin M., and Robert H. Topel. "Estimation and Inference in Two-Step Econometric Models." *Journal of Business and Economic Statistics*, 3(4), 1985, 370–79.

Poole, William. "Rules of Thumb for Guiding Monetary Policy," in *Open Market Policies and Operating Procedures-Staff Studies*. Board of Governors of the Federal Reserve System, 1971, 135–89.

Potts, Glen, and Dudley Luckett. "Policy Objectives of the Federal Reserve System." *Quarterly Journal of Economics*, August 1978, 525–34.

Romer, Christina D., and David H. Romer. "Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz," in O. J. Blanchard and S. Fischer, eds. *NBER Macroeconomics Annual*. Cambridge, Mass.: MIT Press, 1989, 121–70.

______. "What Ends Recession?" in J. J. Rotemberg and S. Fischer, eds. *NBER Macroeconomics Annual*. Cambridge, Mass.: MIT Press, 1994, 13–57.

Rudebusch, Glenn D. "Federal Reserve Interest Rate Targeting, Rational Expectations, and the Term Structure." *Journal of Monetary Economics*, 35(2), 1995, 245–74.

Thorp, Willard L. *Business Annals*. NBER, New York: National Bureau of Economic Research, 1926.

Uselton, Gene. *Lags in the Effect of Monetary Policy: A Nonparametric Analysis*. New York: Marcel Dekker, 1974.