

The Impact of Weekly Money Supply Announcements on Stock Market Returns: A Multiprocess Mixture Model Approach

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Abstract

This study provides evidence concerning the impact of anticipated and unanticipated components of the weekly money supply announcements on stock market returns in the United States and Canada on the date after the announcement. The innovative aspect of this study is the use of a multiprocess mixture model recently proposed by Gordon and Smith (1990) for modeling time series that are subject to several forms of potential discontinuous change and outliers. The technique involves running multiple models in parallel with recursive Bayesian updating procedures which extend the standard Kalman filter. The results provide strong evidence in favor of the efficient markets hypothesis that only the unanticipated component of the money supply announcement influences the stock market returns in both the United States and Canada.

The use of OLS estimation in the present study produces results which suggest that both anticipated and unanticipated components of the money supply announcement exert a statistically significant influence on stock market returns in both countries. In contrast, the multiprocess mixture model estimation method produces results which support the efficient markets hypothesis. The difference in findings between OLS and multiprocess estimation methods is attributed to the ability of the multiprocess techniques to model discontinuous structural shifts in the parameters and accommodate outliers in the stock return-weekly money relationship. The multiprocess mixture method provides evidence that numerous discontinuities and outliers exist in the stock market returns-weekly money relation and produces posterior probabilities for the multiple models running in parallel. These probabilities suggest that the OLS model has low posterior probability relative to the structural shift and outlier models which suggest poor inferences regarding the significance of anticipated and unanticipated money arise from the use of OLS estimation techniques.

Introduction

The efficient markets hypothesis states that asset prices reflect expectations of fundamental variables including expectations of future money supply growth rates and inflation rates. Over time the availability of new information produces revisions in expectations and these changes are important determinants of movements in asset prices. A key assumption of the new classical macroeconomics is that only the unanticipated change in money supply should have an impact on stock prices.

There are two channels through which the negative

relationship between stock prices and unanticipated money announcements are purported to work. These are the anticipated liquidity effect and inflationary expectations effect. The anticipated liquidity hypothesis was suggested by Urich and Wachtel (1981) and is based on investor's expectations of future Federal Reserve responses to money surprises. If there is an unanticipated increase in money supply, market participants expect the Federal Reserve to slow money growth in the near future. This would increase real interest rates through the liquidity effect and thereby lower stock prices.

The alternative hypothesis is one of inflationary expectations. Unanticipated increases in money supply result in higher inflationary expectations. Fama (1981) and Geske and Roll (1983) propose a negative correlation between equity returns and the anticipated inflation rate resulting from changes in real variables. Similarly, Feldstein (1980) and Summers (1981) argue that share prices and the anticipated inflation rate should be negatively correlated because of interaction between inflation and the tax system. Both the anticipated liquidity and inflationary expectations hypotheses suggest lower stock prices in the face of unanticipated money supply announcements.¹

Empirical support for this proposition is found by Pearce and Roley (1983,1985), Berkman (1978), and Cornell (1983) who find that unanticipated increases in the money supply lead to a decline in stock prices. Anticipated changes in money supply are found to be statistically insignificant in explaining variation in stock prices.

Several authors found that both anticipated and unanticipated components of the money supply announcement have a statistically significant impact on financial assets prices. Urich and Wachtel (1984) and Belongia and Sheehan (1987) found that the anticipated component of the money announcement was significantly correlated with the rate of return on financial assets. Similarly, Sprinkel (1964), Homa and Jaffee (1971), and Hamburger and Kochin (1972) found that increases in the money supply resulted in higher stock prices.

Past studies point to limitations associated with the use of ordinary least-squares to estimate the stock returns-weekly money supply announcements relationship. The weekly data contains considerable noise coupled with the presence of outliers and structural shifts from changes in Federal Reserve behavior over time. First, Deaves, Melino, and Pesando (1987) provide evidence that outliers in the data distort the results for the anticipated money variable. When outliers were eliminated, they found that only unanticipated money remains significant. Second, Schinasi and Swamy (1987) point out that investors may not use information the same way over all time horizons and investors may also change their reactions to different policy regimes. To address this problem, Thornton (1989) partitions his data set and makes extensive use of dummy variables so that his model approximates a time varying parameter model. Finally, beginning on February 8, 1980 until February 1, 1984, money supply announcements were generally made on Fridays at 4:10 pm. Since stock markets close at 4:00 pm, it was necessary to examine the impact of money announcements using changes between Friday and Monday stock prices. Belongia and Sheehan (1987) note that the resulting change in stock

prices may contain both a "weekend" effect and an announcement effect. Gibbons and Hess (1981) show that changes in stock prices over the weekend may not be correlated with money announcements. The "weekend" effect may introduce a bias in the parameter estimates. Starting on February 16, 1984 money announcements were made on Thursdays.

This study uses a multiprocess mixture model introduced by Gordon and Smith (1990) to model the stock return-weekly money relationship in both the United States and Canada. This estimation procedure is capable of dealing with discontinuous shifts in regime over time and accommodating outliers, both of which have been noted as problems in past studies. In addition, the mixture procedure is better able to handle non-normally distributed data which Hinch and Roll (1981) find characterizes U.S. stock returns. The estimation methodology involves running in parallel four time-varying parameter dynamic linear models of the type introduced by Harrison and Stevens (1976) and uses recursive Bayesian updating procedures which extend the standard Kalman filter. Specifically, Model I specifies a steady state relationship between the change in market returns between the open and close on the date after the announcement and anticipated and unanticipated money supply. This steady state relationship is re-estimated on a period by period basis from the beginning to end of the data sample. Since the parameters vary only due to the addition of one data observation at each time period, the steady state model is equivalent to the OLS estimation method employed in previous studies. Model II accommodates outliers, which were noted above as important; Model III allows for an intercept shift; and, Model IV allows for a slope shift in the relationship accommodating the changes in regime which are known to have taken place as well as changes in investors' reactions over time. These four models are run in parallel through time and posterior probabilities of the four models are used to "mix" together the output from the four models. In addition to the innovative estimation procedure, the data sample employed in this study covers a longer period, January 1980 to September 1988, than that employed in previous samples and includes both U.S. and Canadian stock returns.

Section 2 of the paper provides a brief description of the multiprocess mixture model with the interested reader referred to Gordon and Smith (1988,1990) for more details. The results from estimation of the model are presented in Section 3 where the focus is on a time-varying log of the odds ratio for two models which relate to the hypothesis of anticipated versus unanticipated components of the money supply announcements. We find evidence that only unanticipated money matters and exerts a significant influence on stock market returns in both the United States and Canada.

The Multiprocess Mixture Model

Several authors have adopted random walk time-varying parameter (TVP) methods when confronted with estimating money announcement relationships which are thought to be subject to changes in regime (see for example, Hafer and Sheehan, 1990 and Belongia, Hafer and Sheehan 1988). The mixture model approach employed here differs greatly from random walk TVP methods such as that proposed by Garbade (1977) or Swamy and Tinsley (1980). A direct comparison of the two approaches using the weekly money announcements data can be found in LeSage (1992). This comparison study concluded that the mixture model performed well in the face of outliers and abrupt shifts in regime, while the TVP model performed poorly. LeSage (1992) concluded that random walk TVP estimation methods produce overly smooth parameter estimates because the estimate for the parameter variability represents an average based on the entire data sample. In the face of rapid discontinuous shifts in the parameters, this variance estimate is unrepresentative of the variability during periods of abrupt shift or transient observations. The excessive smoothing of TVP estimates was found to bias the resulting estimates against finding evidence of abrupt structural shifts, and to degrade the precision of the estimated timing of the shifts. Further evidence in support of these conclusions can be found in a Monte Carlo study by Gamble and LeSage (1991) which compares the performance of TVP and mixture models in the face of abrupt shifts and outliers.

This study develops a dynamic linear model (DLM) first suggested by Harrison and Stevens (1976) and later refined by West and Harrison (1989), to estimate time-varying parameters for the relationship between changes in stock market returns and the anticipated and unanticipated components of money supply changes. This section first introduces the DLM model from which the four multiprocess models are derived by adjusting the observation and system variances.

For simple exposition of the DLM model we work with a model which contains only a single explanatory variable and let $X_t' = (1, UM_t)$ denote the explanatory variable vector containing an intercept term and the unanticipated money supply variable, UM_t , at time t . The unanticipated component can be derived from the Money Market Services Survey or through a one-step-ahead econometric forecast, both of which have been done in previous studies. Let y_t denote the dependent variable, the change in the stock market from open to close on the date following the money supply announcement. The DLM can be expressed as shown in (1).

$$\begin{aligned} y_t &= X_t' \theta_t + \varepsilon_t \\ \theta_t &= \theta_{t-1} + \omega_t \end{aligned} \tag{1}$$

In (1), $\theta_t' = (\alpha_t, \beta_t)'$, a parameter vector containing the time-varying intercept and slope parameters. In addition, we assume that $\text{var}(\varepsilon_t) = E_t = \sigma^2 R_\varepsilon$, $\text{var}(\omega_t) = W_t = \sigma^2 R_\omega$, and that $\sigma^2 = \lambda^{-1}$ is unknown. By virtue of the two parameters in the θ_t vector we also assume that:

$$R_\omega = \begin{pmatrix} R_\alpha & 0 \\ 0 & R_\beta \end{pmatrix} \tag{2}$$

Using a procedure suggested by West and Harrison (1989) and recommended by Gordon and Smith (1990) to deal with the case of unknown σ^2 , we assume that:

$$\begin{aligned} \theta_0 &\sim N(m_0, \sigma^2 C_0) \\ (\theta_t | D_t, \lambda) &\sim N(m_t, \lambda^{-1} C_t) \\ (\lambda | D_t) &\sim G\left(\frac{1}{2} n_t, \frac{1}{2} r_t\right) \end{aligned} \tag{3}$$

In (3) N denotes the normal distribution and G the gamma. This set of distributional assumptions forms a natural conjugate prior for the estimation problem, allowing the posterior distribution from one time period to be used as the prior for the next in a recursive estimation procedure based on an extended Kalman filter. The recursions shown in (4) determine m_t , C_t , n_t , and r_t along with the predictive density, $p(y_t | D_{t-1})$, necessary to derive the multiprocess probabilities. The term D_{t-1} indicates that the predictive density is conditional on data up to time $t-1$.

$$\begin{aligned} \hat{f}_t &= X_t' m_{t-1} \\ e_t &= y_t - \hat{f}_t \\ P_t &= C_{t-1} + W_t \\ F_t &= X_t' P_t X_t' + E_t \\ S_t &= P_t X_t' (F_t)^{-1} \\ m_t &= m_{t-1} + S_t e_t \\ C_t &= P_t - S_t F_t S_t' \\ n_t &= n_{t-1} + 1 \\ r_t &= r_{t-1} + e_t' (F_t)^{-1} e_t \\ p(y_t | D_{t-1}) &\sim F_t^{-1/2} |_{X_{t-1}}^{- (1/2) n_{t-1}} |_{X_t}^{- (1/2) n_t} \end{aligned} \tag{4}$$

One point to note concerning previous studies that used fixed parameter estimation methods is that the model in (1) subsumes these as a special case since it allows for parameter variation over time. Roley (1983) provided empirical evidence that the interest rate-weekly money supply relation was a time-varying relationship.

It is shown that the multiprocess mixture model nests the model shown in (1) as a special case, by using three additional models derived from (1). Following Gordon and Smith (1990), change point models are derived from the basic model in (1) by adjusting the observation and system variances, that is, $\text{var}(\varepsilon_t) = E_t = \sigma^2 R_\varepsilon$ and $\text{var}(\omega_t) = W_t = \sigma^2 R_\omega$ respectively, without changing the underlying model structure. This is accomplished by considering the following four specifications regarding $\sigma^2 R_\varepsilon$ and $\sigma^2 R_\omega$.

Steady State -- Model I.

Let $R_\epsilon = 1$ and $R_\alpha = 0, R_\beta = 0$. This represents the steady state model where there is no parameter variation in α and β except for that due to the addition of another observation at each time period to update the estimates of the model.

Outlier -- Model II.

Let $R_\epsilon = \phi$ and $R_\alpha = 0, R_\beta = 0$, where ϕ is a large number. This reflects a large value for ϵ_t and a transient observation or outlier at time t .

Intercept Shift -- Model III.

Let $R_\epsilon = 1$ and $R_\alpha = \phi, R_\beta = 0$, where ϕ is a large number. This reflects a shift in the level or intercept of the model consistent with a large value for the disturbance to the parameter α at time t .

Slope Shift -- Model IV.

Let $R_\epsilon = 1$ and $R_\alpha = 0, R_\beta = \phi$, where ϕ is a large number. This reflects a shift in the slope term of the model consistent with a large value for the disturbance to the parameter β at time t .

The model shown in (1) is rewritten to include a superscript denoting the four models derived from the different observation and system variance assumptions stated above. This is done in (1').

$$\begin{aligned}
 y_t &= X_t' \theta_t + \epsilon_t^{(j)} \\
 \theta_t &= \theta_{t-1} + \omega_t^{(j)} \quad j=1, \dots, 4 \\
 E_t &= \text{var}(\epsilon_t^{(j)}) = \lambda^{-1} R_\epsilon^{(j)} \\
 W_t &= \text{var}(\omega_t^{(j)}) = \lambda^{-1} R_\omega^{(j)}
 \end{aligned} \tag{1'}$$

The recursions shown in (4) could also be rewritten to depict the four models differing only in the choice of elements for R_ϵ and R_ω . These new recursions would reflect the fact that, when the four models are estimated in parallel, of a combinatorial set of possible state transitions must be monitored. For example, in moving from time t to $t+1$ we have a joint model for state I in period $t+1$ and four possible states in the previous time period t . Similarly, for state II in period $t+1$ and four previous period t states and so on, for a total of sixteen models. To avoid the four-fold increase in the number of models under consideration as we move through time, we invoke an approximation which collapses the sixteen models back to four at each time period. The approximation procedure used by Gordon and Smith (1990), is to use the posterior probabilities of the models in order to produce a mixture of the sixteen models into four models. The mixture densities which result from the approximation have desirable properties, such as minimizing the Kullback-Leibler distances discussed in

Titterton, Smith, and Makov (1985). In addition to the desirable theoretical properties associated with this mixture approximation, in numerous applications the method appears to work well in practice (West and Harrison, 1989).

The mixture approximation procedure works as follows. Let $\pi_t^{(j)}$ denote the posterior probability of model j at time t and $\pi_t^{(ij)}$ the joint probability of model j in time t and model i in time $t-1$. In addition, let the predictive density of y_t for model j in time t and i in time $t-1$ be as shown in (5).

$$z_t^{(ij)} \sim [F_t^{(ij)}]^{-1/2} [r_{t-1}^{(i)}]^{(1/2)n_{t-1}} [r_t^{(ij)}]^{-(1/2)n_t} \tag{5}$$

The sixteen models, denoted by the ij superscripts, are collapsed to four models designated with j superscripts using the following probability weighing scheme:

$$\pi_t^{(j)} = \sum_{i=1}^4 \pi_t^{(ij)} \tag{6}$$

where

$$\pi_t^{(ij)} = z_t^{(ij)} \pi_0^{(j)} \pi_{t-1}^{(i)} / \sum_{i=1}^4 \sum_{j=1}^4 z_t^{(ij)} \pi_0^{(j)} \pi_{t-1}^{(i)} \tag{7}$$

The $\pi_0^{(j)}$ terms in (7) represent prior probabilities over the four models assigned by the investigator. The posterior probability weights, $\pi_t^{(j)}$ in (6), are calculated and used to collapse the $m_t^{(ij)}, C_t^{(ij)}$ and $r_t^{(ij)}$ terms associated with the sixteen models during each step of the recursion as shown in (8).

$$\begin{aligned}
 m_t^{(j)} &= \sum_{i=1}^4 \left(\frac{\pi_t^{(ij)}}{\pi_t^{(j)}} \right) m_t^{(ij)} \\
 C_t^{(j)} &= \sum_{i=1}^4 \left(\frac{\pi_t^{(ij)}}{\pi_t^{(j)}} \right) [C_t^{(ij)} + (m_t^{(ij)} - m_t^{(j)}) (m_t^{(ij)} - m_t^{(j)})'] \\
 [r_t^{(j)}]^{-1} &= \sum_{i=1}^4 \left(\frac{\pi_t^{(ij)}}{\pi_t^{(j)}} \right) [r_t^{(ij)}]^{-1}
 \end{aligned} \tag{8}$$

The approach taken here to estimating the stock return-weekly money supply relationship differs from that of Pearce and Roley (1983,1985) and others employing OLS estimation in a number of important ways. The steady state Model I is allowed to attach zero variation to the parameters during time periods where parameter variation does not exist. This is done by OLS estimation for all time periods. During periods of abrupt innovations in the noise of the system, the outlier Model II absorbs these large noise innovations keeping them from contaminating the steady state Model I parameter estimates. Similarly, for the intercept shift and slope shift Models III and IV, the mixture model attempts to keep the effects of these types of abrupt

shifts from impacting the parameter and variance estimates of the other models. Our model can be viewed as nesting the OLS procedures used in previous studies.

In conclusion, the mixture model approach produces estimates using the Kalman recursions based only on sample data through the current time period, allowing us to examine the impact of anticipated and unanticipated money on stock returns in a time-varying setting. Inferences are drawn from a mixture of four models where the weights used to produce the mixture purport to represent a model that is most appropriate at each time period.

Results from the Multiprocess Mixture Model

Before turning attention to the results from the multiprocess mixture model, we present ordinary least-squares estimates of the relationship between changes in both U.S. and Canadian stock returns and anticipated and unanticipated money. These estimates presented in Table 1, confirm the significance of both

anticipated and unanticipated money supply similar to that found in numerous other studies. For the results shown in Table 1, the money announcements were decomposed into anticipated and unanticipated components using the Money Market Services Survey, following other studies. The stock returns used to produce the estimates represent changes in U.S. and Canadian stock prices from open to close on the day after the announcement, with the sample covering the period January 4, 1980 to September 8, 1988. The U.S. stock prices used represent a value weighted market portfolio obtained from the CRSP tapes.² CRSP uses the New York Stock Exchange and American Stock Exchange as the market portfolio to derive a stock price index. Canadian stock returns were derived from price index data obtained from Morgan Stanley Capital International. Dates for which missing observations existed were omitted from the sample, a practice used by others, resulting in a sample of 425 weekly observations. Table 1 shows least-squares results for the entire data sample in part A, the early sample during which weekend effects were in place in part B and the end of the sample which excludes weekend effects in part C.

Table 1. Least-Squares Estimates

<i>A. Using the Entire Sample</i>				
Explanatory Variable	U.S. Stock Market		Canadian Stock Market	
	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic
Intercept	-0.0313	(0.605)	-0.1139	(2.134)**
Expected Money	0.0442	(1.842)*	0.0578	(2.329)**
Unanticipated Money	-0.0511	(2.317)**	-0.0579	(2.546)**
R-Squared	0.0166		0.0222	
<i>B. Using the Early Sample (includes Weekend Effects)</i>				
Explanatory Variable	U.S. Stock Market		Canadian Stock Market	
	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic
Intercept	-0.1034	(1.380)	-0.2556	(3.522)**
Expected Money	0.0780	(1.678)*	0.0959	(2.130)**
Unanticipated Money	-0.0767	(2.318)**	-0.0678	(2.114)**
R-Squared	0.0338		0.0368	
<i>C. Using the Later Sample (excludes Weekend Effects)</i>				
Explanatory Variable	U.S. Stock Market		Canadian Stock Market	
	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic
Intercept	-0.0496	(0.694)	-0.0381	(0.489)
Expected Money	0.0199	(0.712)	0.0303	(0.993)
Unanticipated Money	-0.0232	(0.787)	-0.0419	(1.304)
R-Squared	0.0041		0.0099	

* - indicates significance at the 10% level

** - indicates significance at the 5% level

The least-squares results based on the entire sample are similar to those found by other authors in that both expected and unanticipated money variables exert a statistically significant impact on stock prices for Canada and the United States. These results are contrary to the efficient markets hypothesis. There is a difference in the significance of expected and unexpected money during the early and later sample periods. The early sample results are identical to those based on the entire data sample. In the later sample period both expected and unanticipated money are insignificant for Canada and the United States. This suggests that the weekend effect played a role in earlier studies of money announcements and stock prices, a point made by Gibbons and Hess (1981). Nevertheless, OLS does not produce results consistent with efficient markets hypothesis in either the full sample or sub-samples. The mixture model procedure used here does produce such results suggesting, that in addition to weekend effects, outliers and structural shifts also played a role in affecting earlier findings based on least-squares.

Table 2 presents results from a robust regression procedure based on Huber (1977). Robust estimation procedures downweight outlying data points since least-squares is known to be sensitive to these outlier observations. The robust estimates presented in Table 2 represent an attempt to determine whether outliers alone are responsible for the inconsistency of least-squares estimates with the efficient markets hypothesis. From Table 2 we see that for the United States, robust estimates based on the full sample produce results consistent with the efficient markets hypothesis, but the results for the two U.S. sub-samples are not. None of the results for the Canadian data are consistent with the efficient markets hypothesis. This suggests that outliers may represent part of the problem, but structural shifts need to be taken into account as well as outliers.

The multiprocess mixture model results provide an interesting contrast to the least-squares and robust estimates presented in Tables 1 and 2. The differences in inference regarding the significance of anticipated and

Table 2. Robust (Huber) Estimates

<i>A. Using the Entire Sample</i>				
Explanatory Variable	U.S. Stock Market		Canadian Stock Market	
	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic
Intercept	0.0475	(1.11)	-0.0307	(0.78)
Expected Money	-0.008	(0.41)	0.0091	(0.53)
Unanticipated Money	-0.044	(2.41)**	-0.0126	(0.73)
<i>B. Using the Early Sample (includes Weekend Effects)</i>				
Explanatory Variable	U.S. Stock Market		Canadian Stock Market	
	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic
Intercept	-0.0898	(1.41)	-0.0219	(3.65)**
Expected Money	0.0124	(0.42)	0.0047	(0.17)
Unanticipated Money	0.0508	(1.82)*	-0.0316	(1.21)
<i>C. Using the Later Sample (excludes Weekend Effects)</i>				
Explanatory Variable	U.S. Stock Market		Canadian Stock Market	
	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic
Intercept	0.0864	(1.84)*	-0.0104	(2.49)**
Expected Money	-0.0203	(1.05)	0.0196	(1.15)
Unanticipated Money	-0.0210	(1.08)	-0.0138	(0.81)

* - indicates significance at the 10% level
 ** - indicates significance at the 5% level

unanticipated money are attributed to the influence of outliers and regime shifts which adversely impact the least-squares estimates.

The approach taken to testing the significance of anticipated versus unanticipated money in the stock return-weekly money relationship was to form two multiprocess mixture models and compute a Bayes factor or log-of-the-odds ratio for the two models. Model 1 involved only unanticipated money and an intercept term as the explanatory variables, whereas Model 2 employed a constant term, and both anticipated and unanticipated money as explanatory variables. If the weight of the evidence is in favor of only unanticipated money (indicating that anticipated money is unimportant) in explaining variation in stock returns, we would find that the log-of-the-odds ratio favors Model 1 containing only unanticipated money.

To implement the multiprocess estimation procedure, prior information was used in setting initial values for parameters, noise and system variances in both Models 1 and 2. Some experimentation was involved in order to find settings which produced good one-step-ahead forecasts. One could view this procedure as representing an informal rough grid alternative to specifying formal prior distributions over these aspects of the estimation problem (see Doan, Litterman and Sims, 1984). Intuitively, a good fit is desirable since the recursive Kalman relations make decisions regarding the relative importance of the alternative models and determine the posterior probabilities as a function of the predictive density function. The prior settings are fairly diffuse, yet still proper, and the amount of sample data is large, making the impact of the prior settings within reasonable ranges fairly unimportant.

The prior values for the parameters (m_0) in both models 1 and 2 were set at 0.0 and the prior variances (C_0) for these parameters were set at $0.025(I_k) \phi$, where ϕ is a scalar hyperparameter used in the grid search for the best prior values and I_k is an identity matrix with k denoting the number of parameters. We set $n_0 = k+1$ and $r_0 = 0.05 \phi$ so that $E(\lambda^{-1}) = r_0 \phi / (n_0 - k) = \phi/20$. This reflects a prior belief that, when $\phi = 1$, parameter variability was one twentieth that associated with observational noise variability. The OLS estimation indicated a large amount of noise, motivating this setting. The prior noise estimate was set roughly equal to the noise estimate from OLS estimation of the stock return-weekly money relationship.

The prior probabilities for the four variants of Model 1, I-IV, were set at $\pi_0 = [.90 .05 .025 .025]$. This reflects a belief that the steady state Model I should be in effect 90% of the time, Model II outliers are anticipated to occur about 5% of the time, intercept and slope shifts 2.5% of the time each for nesting Model 2

with shifts allowed in both anticipated and unanticipated money variables as well as the intercept term we employed prior probabilities for the five variants, I-V of $\pi_0 = [.90 .025 .025 .025 .025]$. This larger model involves running five models in parallel and collapsing twenty five models back to five at each time period using the posterior probabilities. Values similar to those shown above for the prior model probabilities have been used fairly extensively in other multiprocess applications and are recommended by West and Harrison (1989). Monte Carlo evidence (Gamble and LeSage, 1991; Gordon and Smith, 1988; and West and Harrison, 1989), shows that these values are relatively unimportant. The results reported here were robust with respect to changes in these probabilities so long as the steady state probability remained above 0.80.

The settings used for the noise and parameter variances in Models I-IV derived from Model 1 and Models I-V derived from Model 2 are shown in Table 3. The role of the ϕ hyperparameter was to increase or decrease the prior settings for the parameter and noise variances in a systematic search for a setting which produced the best one-step-ahead predictions measured by the sum of squared one-step-ahead prediction errors.

Table 3. Prior Parameters Settings for Models I-IV

Model	R_ϵ	R_α	R_{β_1}	R_{β_2}
$j = 1$	1ϕ	0	0	0
$j = 2$	10ϕ	0	0	0
$j = 3$	1ϕ	1ϕ	0	0
$j = 4$	1ϕ	0	1ϕ	0
$j = 5$	1ϕ	0	0	1ϕ

The log-of-the-odds or Bayes' factor (West and Harrison, 1989) has been used extensively to compare alternative nested models such as those developed here including anticipated and unanticipated money supply components in a nested structure. This statistic takes a dynamic form when the predictive density function is evaluated on a period by period basis. At each time period, the Bayes factor reflects output from using only data up to the most recent time period. This approach to testing the impact of anticipated and unanticipated money differs from previous studies where the entire data sample was employed to perform a single test for significance.

The relative likelihood of Model 1 containing only anticipated money versus Model 2 containing both anticipated and unanticipated money based on observation y_t at time t is the ratio of the predictive densities based on data up to time $t-1$ shown in (9).

$$H_t = P_1(y_t | D_{t-1}) / P_2(y_t | D_{t-1}) \quad (9)$$

The overall Bayes' Factor is equivalent to the likelihood ratio and is based on the cumulative sum of the log of expression (9) over all periods. The traditional interpretation of the log Bayes factor introduced by Jeffreys (1961) is that evidence in favor of Model 1 containing only unanticipated money is indicated by a value of 1, with a value of 2 or more indicating strong evidence. On the other hand, a value of -1 indicates evidence in favor of Model 2, the model with both anticipated and unanticipated money. Similarly, a value of -2 indicates strong evidence in favor of this model, indicating that anticipated money matters as well as unanticipated.

A plot of the dynamic log Bayes factors for the stock returns-weekly money supply models for both the United States and Canada are shown in Figure 1. The horizontal lines in Figure 1 indicate +2 and -2 magnitudes so that, Bayes factors outside these lines provide strong evidence in favor of Model 1 or Model 2 respectively. Figure 1 shows that the evidence in favor of Model 1 containing unanticipated money alone (values above the +2 line) seems overwhelming over the 1980 through 1988 time period examined here for both the United States and Canada.

It is interesting to note that, during the beginning of the sample which represents the period following the regime shift of October 1979, Model 2 appears to gain favor relative to Model 1. The same is true of the time period following the regime shift of October, 1982 and the outlier introduced by the Stock market crash of 1987, Model 2 appears to gain favor relative to Model 1. The brief periods favoring a significant role for anticipated money may account for the OLS estimation results where both anticipated and unanticipated money components are found to be significant. Intuitively, after a shift in monetary regimes, survey responses used to measure anticipated versus unanticipated money may require some adjustment time.

A contention here is that the relatively conclusive findings in favor of Model 1 in this study are due to the ability of the multiprocess estimation procedure to take into account discontinuous structural shifts and outliers in the stock returns-weekly money relationship. Table 3 provides a distribution of the posterior probabilities for the steady state model from the estimated relationship containing unanticipated money.

Since the steady state model approximates procedures used in previous studies, Table 3 suggests that the posterior probability of this model relative to the outlier, intercept shift and slope shift model is relatively low for

a fair number of observations.³ Specifically, posterior probabilities are less than 90% for 14.3% of the observations for the United States and 13.2% for Canada. This suggests that inferences from previous studies that did not account for transient observations and structural shifts in the stock returns-weekly money relationship may be weak.

Table 4. Distribution of Steady State Model Probabilities

	U.S.	Canada
0 ≤ 10	5	5
10 ≤ 20	0	4
20 ≤ 30	2	3
30 ≤ 40	3	0
40 ≤ 50	4	2
50 ≤ 60	4	2
60 ≤ 70	8	3
70 ≤ 80	9	8
80 ≤ 90	26	29
90 ≤ 100	363	367

Conclusions

A multiprocess mixture model recently introduced by Gordon and Smith (1990) was used to analyze the stock returns-weekly money supply relationship. The technique accommodates outliers and abrupt structural shifts in time series by running multiple models in parallel in an effort to keep these events from contaminating a steady state model. The output from these multiple models is mixed together using the posterior probabilities of each model as a weighing factor.

Numerous transient observations and shifts in the intercept and slope parameters were found to exist in the stock return-weekly money relationship casting doubt on the inferences from OLS estimation used in previous studies. The multiprocess mixture model accommodated abrupt changes in time series relationships and produced results consistent with the efficient markets hypothesis providing evidence that only unanticipated components of the money supply announcement significantly impacted stock market returns on the date after the announcement. The results were consistent for both the United States and Canada.

The explanation for these findings is that the models derived from the DLM developed in this study subsume those from other studies as a special case. In addition to this nesting property, the multiprocess mixture method provides posterior probabilities for the importance of our models relative to those used in previous studies. This probabilistic information suggests that the mixture model dominates those employed in previous studies over a large number of observations.

Suggestions for Future Research

The multiprocess mixture model employed in this study should be capable of addressing the presence of outliers and structural shifts in a great number of empirical studies in business research. As indicated in this study, the statistical inferences drawn may depend heavily on the ability of empirical techniques to accommodate these types of change in the behavior of data series over time. Specifically, the multiprocess mixture model might be employed as an alternative to current event-study methods employed in finance.

Extensions of the DLM model (on which the mixture model demonstrated here is based) to the case of non-normally distributed data have been illustrated by West, Harrison, and Migon (1985). Future work to extend the mixture model along these lines would be of use for financial time-series which are known to exhibit non-normality.

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Footnotes

1. Thornton (1989) finds some support for the anticipated liquidity hypothesis over the inflationary expectations hypothesis using international assets.
2. The value-weighted stock index represents a portfolio with weights defined by the securities market portfolio as a proportion of the portfolio's total market value. The weights prevent movement in one stock from biasing the stock index as would occur in an equal-weighted index. The correlation between value-weighted and equal-weighted stock indices was very high so that the choice of this index should not influence the results reported here.
3. One might argue that Model 2 with both anticipated and unanticipated money is closer to the model employed in other studies. The distribution of posterior probabilities for the steady state model from Model 2 containing both anticipated and unanticipated money variables is essentially the same as that shown in Table 4 for Model 1 with unanticipated money alone. For both the United States and Canada the percentage of data observations with posterior probabilities less than 90% was 14.6%.

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