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MEASURING THE VALUE RELEVANCE OF STOCK RETURNS, EARNINGS, AND CASH FLOWS USING THE GIBBS SAMPLER

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In this paper we develop a new approach for assessing the value relevance of accounting and financial variables. Since changes in firm value are unobservable, previous research in accounting and finance assessed the value relevance of accounting and financial variables, such as earnings and cash flows, using stock prices or returns as a value benchmark. However, a growing body of empirical evidence has shown that stock returns might not be an efficient summary of all value-relevant information. In this paper, we formulate a probability model that incorporates unobservable changes in firm value. After estimating the value changes using the Gibbs sampler, we measure the extent to which alternative value proxies are related to the estimates. Our results show that stock return is not an efficient measure of firm value or its change, although it is more value-relevant than accounting-based value measures, i.e., accounting earnings and cash flows. We further show that accounting earnings are a better measure of firm value or its change than cash flows, a finding consistent with previous research.

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Keywords: Gibbs Sampler, Value Relevance, Stock Returns, Earnings, Cash Flows

1. INTRODUCTION

A central issue in accounting and finance is to evaluate the value relevance of alternative proxies for firm value. Since firm value or its change is unobservable, previous research typically assesses the value relevance of alternative proxies, such as earnings and cash flows, using stock prices or stock returns as a

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value benchmark (e.g., Dechow 1994). An important assumption underlying this approach is that stock prices or returns fully reflect all value-relevant information without delay. However, a growing body of empirical evidence has shown that stock prices or returns may not be an efficient summary of all value-relevant information (DeBondt and Thaler 1985; Bernard and Thomas 1989; Lakonishok, Shleifer and Vishny 1994; Ferri and Min 1996; Sloan 1996; and Bernard, Thomas and Wahlen 1997).

In this paper, we develop a new approach for assessing the value relevance of accounting and financial variables. The approach is based on an intuitive assumption that unanticipated changes in alternative proxies for firm value are serially uncorrelated (Samuelson 1965; Dichev 1997). Since alternative value proxies (e.g., stock returns, earnings, and cash flows) purport to measure the *same* underlying economic value or its changes, there should exist a value-relevant, common factor that triggers observed, unanticipated changes in alternative value proxies.

In particular, this paper has two objectives: First, we develop a formal probability model that allows us to estimate unobservable changes in firm value that are common to different value proxies. Unobservable changes in firm value are incorporated into the probability model, and are estimated using the procedure called the Gibbs sampler. By directly estimating unobserved changes in firm value without reference to a (potentially inefficient) value benchmark, our model provides empirical researchers with a concrete framework within which the value relevance of alternative proxies for firm value could be better assessed and compared. Second, we use our probability model to empirically assess the extent to which three commonly used proxies for firm value—stock returns, accounting earnings, and cash flows—capture our estimates of unobserved firm value. Put differently, we evaluate the value relevance of alternative value proxies by reference to their association with our value estimates, not a traditional value benchmark such as stock prices or stock returns.

Our results show that stock return is not an efficient measure of firm value or its change, albeit more value relevant than accounting-based value measures, i.e., accounting earnings and cash flows. We further show that accounting earnings are a better measure of firm value or its change than cash flows, a finding consistent with previous research (e.g., DeChow 1994; and Dichev 1997).

The rest of the paper is structured as follows. Section 2 formulates a model and explains the estimation method called the Gibbs sampler. Sample description and variable definitions are included in section 3. Section 4 presents the empirical results. Finally, section 5 concludes the paper.

2. MODEL AND ESTIMATION METHOD

2.1 Model

This study aims to evaluate the value relevance of three alternative proxies for firm performance, namely stock returns, earnings and cash flows. To do so, we formulate the following models in a framework of rational expectations hypotheses:

$$
\begin{aligned}
R_{it} - E(R_{it} \mid I_{i,t-1}) &= f(\Delta V_{it}) + u^{r}_{it} \\
X_{it} - E(R_{it} \mid I_{i,t-1}) &= g(\Delta V_{it}) + u^{x}_{it} \\
C_{it} - E(R_{it} \mid I_{i,t-1}) &= h(\Delta V_{it}) + u^{c}_{it}
\end{aligned}
\tag{1}
$$

where, for each firm i and in each period t, R, X, and C denote stock return on common share, accounting earnings, and cash flows, respectively; I denotes the information set available in each period; ΔV represents unobserved changes in firm value; and u denotes random factors. It is assumed that, given the information set $I_{i,t-1}$, unanticipated changes in R_{it}, X_{it} and C_{it} (i.e., expressions in the LHS of the above equation) should be, by its nature, random in each period, and thus, that they are serially uncorrelated. We posit that these unanticipated changes can be decomposed into two components: (1) the value-relevant, common component that simultaneously triggers unanticipated changes in observed value proxies (ΔV_{it}); and (2) the value-irrelevant component that is idiosyncratic to each value proxy (u_{it}). The value-relevant, common component, ΔV_{it}, is not observable, and it is defined in such a way that the comovements of observed value proxies arise solely from movements in ΔV_{it}. This unobserved value change thus accounts for contemporaneous correlations among the unexpected changes in R_{it}, X_{it} and C_{it}. In contrast, each idiosyncratic component is uncorrelated with the other idiosyncratic components and with the value-relevant, common component (ΔV_{it}) at all leads and lags.

The model is a variant of the dynamic factor models considered by Geweke (1977) and Engle and Watson (1981). And the unobservable value change, ΔV_{it}, in the model is similar in spirit to the coincident index, an estimate of "the state of the economy," in Stock and Watson (1989, 1991).

As mentioned earlier, the common value change, ΔV_{it}, is defined as the common factor which triggers the unexpected changes in all of R_{it}, X_{it} and C_{it}, given the information set I_{it-1}. Then it represents not only current value changes, but also, if any, the lagged value changes that have not yet been reflected in $I_{i\,t-1}$. Since we are interested in assessing which of R, X and C contains most information about value changes that have not been captured by the three variables in previous periods, we include only their lagged variables $\{R_{i\,t-1}, X_{i\,t-1}, C_{i\,t-1}\}$ in the information set $I_{i\,t-1}$. Variables of lag orders higher than one did not add significant information to the information set $I_{i\,t-1}$. To operationalize model (1), we assume that a linear projection of each variable on $I_{i\,t-1}$ can sufficiently account for the value changes reflected in the information set $I_{i\,t-1}$. Then model (1) can be re-expressed as below:

$$\begin{aligned} R_{i\,t} &= \beta_{ro} + \beta_{r1} R_{i\,t-1} + \beta_{r2} X_{i\,t-1} + \beta_{r3} C_{i\,t-1} + \beta_{r4}\ \Delta V_{i\,t} + u^{r}{}_{i\,t} \\ X_{i\,t} &= \beta_{xo} + \beta_{x1} R_{i\,t-1} + \beta_{x2} X_{i\,t-1} + \beta_{x3} C_{i\,t-1} + \beta_{x4}\ \Delta V_{i\,t} + u^{x}{}_{i\,t} \\ C_{i\,t} &= \beta_{co} + \beta_{c1} C_{i\,t-1} + \beta_{c2} X_{i\,t-1} + \beta_{c3} C_{i\,t-1} + \beta_{c4}\ \Delta V_{i\,t} + u^{c}{}_{i\,t} \end{aligned} \qquad (2)$$

where $u^{k}{}_{i\,t}$ follows a normal distribution $N(0, \sigma_k{}^2)$, and is serially and mutually independent for $k = r, x$, and c.

Model (2) states that observed R, X, and C are a function of their lagged variables which capture information about firm value that have already been reflected in previous periods, unobservable value changes that simultaneously trigger changes in R, X, and C in the current period, and value-irrelevant, idiosyncratic random factors. For an identification of the scale of $\Delta V_{i\,t}$ a restriction of $\beta_{r4} + \beta_{x4} + \beta_{c4} = 1$ is imposed. This is only for normalization with no substantive implication.

2.2 Extimation Method

Model (2) cannot be estimated by the methods developed for multiple regression models because the value change variable $\Delta V_{i\,t}$ is not observed. However, if data on $\Delta V_{i\,t}$ can be generated by a simulation method, the model is just a set of regressions and the posterior conditional (on $\Delta V_{i\,t}$) density functions for β's and σ's are well defined in the Bayesian framework. Therefore, its parameters β's and σ's can be estimated. This strategy of augmenting data was introduced in Tanner and Wong (1987).

It is shown in the appendix that the unobserved value change $\Delta V_{i\,t}$ follows a normal distribution, conditional on values of β's and σ's generated from their posterior conditional density functions. Thus, the posterior conditional density function for $\Delta V_{i\,t}$ is well defined and can be used for generating data on $\Delta V_{i\,t}$.

Once the conditional density functions for the parameters (β's and σ's) and the unobserved variable ($\Delta V_{i\,t}$) are derived, the marginal density functions for

β's, σ's and ΔV_{it} can be estimated using the Gibbs sampler. The Gibbs sampler is a Markov chain Monte Carlo method that enables us to estimate marginal density functions using sampled draws from conditional density functions. This method is well discussed in Casella and George (1992) and Gelfand and Smith (1990), among others. Further, the applications of the Markov chain Monte Carlo method to various problems are found in Chiang et al. (1999), Chib (1996), McCulloch and Rossi (1994), Min (1998), Nakatsuma (2000), and the references cited therein.

The idea behind the Gibbs sampler is to construct a Markov chain of conditional density functions. Let $\theta_1 = \{\beta's\ \sigma's\}$ and $\theta_2 = \{\Delta V_{it}$ for all i and $t\}$ be two random vectors. Suppose their conditional density functions are known and denoted by $p(\theta_1 \mid \theta_2)$ and $p(\theta_2 \mid \theta_1)$, respectively. Given an arbitrary starting value $\theta_1^{(0)}$, draw $\theta_2^{(1)}$ from $p(\theta_2 \mid \theta_1^{(0)})$ and $\theta_1^{(1)}$ from $p(\theta_1 \mid \theta_2^{(1)})$. Then repeat the drawing using $\theta_1^{(1)}$ as a new starting value. After K such iterations, we arrive at $(\theta_1^{(K)}, \theta_2^{(K)})$. Geman and Geman (1984) show that under regularity conditions, the marginal distributions of $(\theta_1^{(K)}, \theta_2^{(K)})$ converge to the marginal distributions of θ_1 and θ_2: i.e., as $K \to \infty, \theta_i^{(K)} \to \theta_i \sim p(\theta_i)$ for i=1,2.

After a burn-in period of K iterations, the Gibbs sampler is iterated additional M times. Then the mean of the marginal distribution of θ_1, which is used as a point estimate of θ_1, is estimated by $\Sigma_{i=1}^{M} \theta_1^{(K+i)}/M$ or by $\Sigma_{i=1}^{M} E(\theta_1 | \theta_2^{(K+i)})/M$ using conditional expectations. And the marginal distribution of θ_1 is approximated by the empirical distribution of $(\theta_1^{(K+1)}, \cdots, \theta_1^{(K+M)})$, or by $\Sigma_{i=1}^{M} p(\theta_1 | \theta_2^{(K+i)})/M$ using the information about conditional distributions.

Concerning the convergence issue, we follow a practical suggestion made in McCulloch and Rossi (1994), and plot the estimates of posterior densities over Gibbs iterations. If these estimated posterior densities show little variation with additional Gibbs iterations, we may conclude that the Gibbs sampler has converged to the posterior densities. We also conduct an analysis of the sensitivity of estimated posterior distributions to various, widely dispersed starting values, e.g., $\theta_2^{(0)}$. Theoretical discussions on the convergence issue can be found in Geweke (1992), McCulloch and Rossi (1994), Tierney (1994) and Zellner and Min (1995).

We now derive two posterior conditional density functions, $p(\beta's, \sigma's | \Delta V_{it}$, observed data) and $p(\Delta V_{it} | \beta's, \sigma's$, observed data), to implement Gibbs sampling.[1] First, the posterior conditional density function for $\beta's$ and $\sigma's$ can be easily obtained since model (2) becomes a set of multiple regression models when data on ΔV_{it} are given. Further, the disturbance terms u^r, u^x and u^c

[1] When we derive conditional density functions, we also use observed data on R_{it}, X_{it} and C_{it} and therefore call them posterior conditional density functions.

are mutually independent and thus, each regression equation can be estimated separately.

For expository simplicty, we define the following notations:[2]

$\underline{R}_T$ $=(N\text{x}1)$ column vector of R_{it} for all i and t,
$\underline{R}_{T-1}=(N\text{x}1)$ column vector of $R_{i,t-1}$ for all i and t,
$\underline{X}_{T-1}=(N\text{x}1)$ column vector of $X_{i,t-1}$ for all i and t,
$\underline{C}_{T-1}=(N\text{x}1)$ column vector of $C_{i,t-1}$ for all i and t,
$\Delta\underline{V}_T=(N\text{x}1)$ column vector of ΔV_{it} for all i and t.
$\underline{1}$ $=(N\text{x}1)$ column vector of 1's,
$\underline{0}$ $=(N\text{x}1)$ column vector of 0's,
$\underline{u}^r$ $=(N\text{x}1)$ column vector of $u^r{}_{it}$ for all i and t,
$\underline{\beta}_r$ $=(4\text{x}1)$ column vector of $(\beta_{ro}\ \beta_{r1}\ \beta_{r2}\ \beta_{r3})'$,
N $=$total number of observations.

Using the above matrix notations, we express the regression equation for R_{it} in (2) for all the observations as follows:

$$\underline{R}_T=Z\underline{\beta}_r+\beta_{r4}\Delta\underline{V}_T+\underline{u}^r, \tag{3}$$

where $Z=(\underline{1}\ \underline{R}_{T-1}\ \underline{X}_{T-1}\ \underline{C}_{T-1})$ and $u^r \sim N(\underline{0},\sigma_r{}^2 I_N)$. It is well known that the posterior density function for $(\underline{\beta}_r,\sigma_r)$, conditional on β_{r4} and $\Delta\underline{V}_T$, is in the form of the product of normal densities and an inverted gamma (IG) density function (Judge et al. 1985, pp. 103-104).

$$p(\underline{\beta}_r,\sigma_r \mid \beta_{r4},\Delta\underline{V}_T,\underline{R}_T,\underline{R}_{T-1},\underline{X}_{T-1},\underline{C}_{T-1})\sim N[\hat{\underline{\beta}}_r,\sigma_r{}^2(Z'Z)^{-1}]\times IG(\nu,\hat{\sigma}_r{}^2) \tag{4}$$

where $\hat{\underline{\beta}}_r=(Z'Z)^{-1}Z'(\underline{R}_T-\beta_{r4}\triangle\underline{V}_T), \nu=N-5, \nu\hat{\sigma}_r^2=(\underline{\beta}_r-\hat{\underline{\beta}}_r)'Z'Z(\underline{\beta}_r-\hat{\underline{\beta}}_r)$ and IG deenotes an inverted-gamma density function with parameters ν and $\hat{\sigma}^2$.

Similarly, the posterior density functions for $(\underline{\beta}_x,\sigma_x)$ and $(\underline{\beta}_c,\sigma_c)$ conditional on $(\beta_{x4},\beta_{c4},\Delta V_T)$ are

$$p(\underline{\beta}_x,\sigma_x \mid \beta_{x4},\Delta\underline{V}_T,\underline{X}_T,\underline{R}_{T-1},\underline{X}_{T-1},\underline{C}_{T-1})\sim N[\hat{\underline{\beta}}_x,\sigma_x{}^2(Z'Z)^{-1}]\times IG(\nu,\hat{\sigma}_x{}^2) \tag{5}$$

$$p(\underline{\beta}_c,\sigma_c \mid \beta_{c4},\Delta\underline{V}_T,\underline{X}_T,\underline{R}_{T-1},\underline{X}_{T-1},\underline{C}_{T-1})\sim N[\hat{\underline{\beta}}_c,\sigma_c{}^2(Z'Z)^{-1}]\times IG(\nu,\hat{\sigma}_c{}^2) \tag{6}$$

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[2] Underlines are used to denote column vectors.

where , $\widehat{\underline{\beta}_x} = (Z'Z)^{-1}\underline{Z}'(\underline{X}_T - \beta_{x4}\Delta\,\underline{V}_T), \nu\widehat{\sigma_x}^2 = (\underline{\beta}_x - \widehat{\underline{\beta}_x})'Z'Z(\underline{\beta}_x - \widehat{\underline{\beta}_x})$

$$\widehat{\underline{\beta}_c} = (Z'Z)^{-1}Z'(\underline{C}_T - \beta_{c4}\Delta\,\underline{V}_T), \text{ and } \underline{\nu\widehat{\sigma_c}}^2 = (\underline{\beta}_c - \widehat{\underline{\beta}_c})'Z'Z(\underline{\beta}_c - \widehat{\underline{\beta}_c})$$

The conditional posterior density functions for $(\beta_{r4}, \beta_{x4}, \beta_{c4})$ will first be derived without the normalizing condition imposed. After drawing $(\beta^u_{r4}, \beta^u_{x4}, \beta^u_{c4})$ from the derived density functions, we will normalize the drawn values by dividing them by $\beta^u_{r4} + \beta^u_{x4} + \beta^u_{c4}$. The conditional posterior density function for β^u_{r4}, given $(\underline{\beta}_r, \sigma_r, \Delta\,\underline{V}_T)$, can be derived from equation (3).

$$p(\beta^u_{r4} \mid \underline{\beta}_r, \sigma_r, \Delta\,\underline{V}_T) \sim N[(\Delta\,\underline{V}'_T\Delta\,\underline{V}_T)^{-1}\Delta\,\underline{V}_T'(\underline{R}_T - Z\underline{\beta}_r), \sigma_r^2(\Delta\,\underline{V}_T'\Delta\,\underline{V}_T)^{-1}] \quad (7)$$

Similarly, the conditional posterior density functions for β^u_{x4} and β^u_{c4} are as follows.

$$p(\beta^u_{x4} \mid \underline{\beta}_X, \sigma_X, \Delta\,\underline{V}_T) \sim N[(\Delta\,\underline{V}_T'\Delta\,\underline{V}_T)^{-1}\Delta\,\underline{V}_T'(\underline{X}_T - Z\underline{\beta}_x), \sigma_x^2(\Delta\,\underline{V}_T'\Delta\,\underline{V}_T)^{-1}] \quad (8)$$

$$p(\beta^u_{c4} \mid \underline{\beta}_c, \sigma_c, \Delta\,\underline{V}_T) \sim N[(\Delta\,\underline{V}_T'\Delta\,\underline{V}_T)^{-1}\Delta\,\underline{V}_T'(\underline{C}_T - Z\underline{\beta}_c), \sigma_c^2(\Delta\,\underline{V}_T'\Delta\,\underline{V}_T)^{-1}] \quad (9)$$

Next, the conditional posterior density function for $\Delta\,\underline{V}_T$, given $(\underline{\beta}_r, \sigma_r, \underline{\beta}_x, \sigma_x, \underline{\beta}_c, \sigma_c)$ and the normalizing restriction of $\beta_{r4} + \beta_{x4} + \beta_{c4} = 1$, is a normal distribution, as shown in the appendix.

$$p(\Delta\,\underline{V}_T \mid \underline{\beta}_r, \sigma_r, \underline{\beta}_x\sigma_x, \underline{\beta}_c, \sigma_c, \underline{R}_T, \underline{X}_T, \underline{C}_T) \sim N(\underline{\mu}_{\Delta V}, \sigma_{\Delta V}{}^2\ I_N), \quad (10)$$

where $\underline{\mu}_{\Delta V} = (\underline{R}_T + \underline{X}_T + \underline{C}_T) - (\beta_{r0} + \beta_{x0} + \beta_{c0}) \cdot \underline{1} - (\beta_{r1} + \beta_{x1} + \beta_{c1}) \cdot \underline{R}_{T-1}$

$$- (\beta_{r2} + \beta_{x2} + \beta_{c2}) \cdot \underline{X}_{T-1} - (\beta_{r3} + \beta_{x3} + \beta_{c3}) \cdot \underline{C}_{T-1}, \text{ and}$$

$$\sigma^2_{\Delta V} = \sigma_r^2 + \sigma_x^2 + \sigma_c^2.$$

The posterior conditional density functions (4)-(10) complete a Markov chain for Gibbs sampling. Therefore, the Gibbs sampling can be implemented as follows:

1. Initialize $\underline{\beta}_r, \sigma_r, \underline{\beta}_x, \sigma_x, \underline{\beta}_c$ and σ_c.
2. Sample $\Delta\,\underline{V}_T$ using (10).
3. Sample $(\underline{\beta}_r, \sigma_r, \underline{\beta}_x, \sigma_x, \underline{\beta}_c, \sigma_c)$ using (4), (5) and (6), respectively.
4. (i) Sample $(\beta^u_{r4}, \beta^u_{x4}, \beta^u_{c4})$ using (7), (8), and (9), respectively.
   (ii) Obtain $(\beta_{r4}, \beta_{x4}, \beta_{c4})$ by imposing the normalizing condition: i.e., $\beta_{i4} = \beta^u_{i4} / (\beta^u_{r4} + \beta^u_{x4} + \beta^u_{c4})$, for $i = r, x, c$.
5. Repeat steps 2, 3 and 4.

3. SAMPLE DESCRIPTION AND VARIABLE DEFINITIONS

3.1 Somple

The sample consists of all firm-year observations for which necessary data are available on the Center for Research in Security Prices (CRSP) 1997 and the Compustat 1997 databases. Financial institutions (SIC 6000 to 6999) are excluded since the data required to compute total accruals are not available. Firms are required to have a December 31 fiscal year-end. Because model (2) contains lagged variables, the sample is restricted to those firms that have at least two consecutive years of data on all necessary variables. There are 28,447 firm-year observations available from 1979 to 1996. Observations whose stock returns, earnings, or cash flows lie outside 0.05% or 99.5% of their respective distributions are deleted to avoid undue influence of extreme observations. This reduces the final sample to 26,606 firm-year observations, with a loss of 1,841 observations (6.47% of the original sample).

3.2 Variable Definitions

Annual stock returns (R) are measured as compounded monthly stock returns for a twelve-month period ending the end of the fiscal year of the firm. Earnings (X) are defined as earnings before extraordinary items and discontinued operations (Compustat item number 18). Accruals are computed as follows:[3]

$$\text{Accruals} = (\Delta\text{CA} - \Delta\text{Cash}) - (\Delta\text{CL} - \Delta\text{STD}) - \text{Dep},$$

where ΔCA = change in current assets (Compustat item number 4),
ΔCash = change in cash/cash equivalents (Compustat item number 1),
ΔCL = change in current liabilities (Compustat item number 5),
ΔSTD = change in debt included in current liabilities (Compustat item number 34),
Dep = depreciation and amortization expenses (Compustat item number 14).

Cash flows (C) are measured as the difference between earnings (X) and accruals. Earnings, accruals, and cash flows are all deflated by total assets at the beginning of the period.

[3] The cash flows have been reported in the statement of cash flows since 1987 by SFAS No 95. Since the time period examined in this paper is from 1979 to 1996, the accrual component is

3.3 Descriptive Statistics

Table 1 presents descriptive statistics about the variables used in the analysis. Stock returns have a mean of 0.143 while their median is 0.085, indicating that the distribution is skewed to the right. With a relatively large standard deviation of 0.499, only 59.4% of the observations have positive stock returns. In contrast, earnings and cash flows have tighter distributions than stock returns, their standard deviations being 0.109 and 0.119, respectively. And more than 75% of the observations have positive earnings and cash flows. Accruals are negative on average, with a mean of -0.040 and a median of -0.042. Only 24.5% of the observations have positive accruals.

[Table 1] Descriptive Statistics of the Variables

Variable	Mean	Std. dev.	Median	Upper quartile	Lower quartile	% positive
	All observations (n=26,606 from 1979 to 1996)					
Stock returns (R)	0.143	0.499	0.085	0.348	-0.085	59.4
Earnings (X)	0.024	0.109	0.042	0.080	0.001	75.6
Cash flows (C)	0.064	0.119	0.079	0.131	0.017	79.1
Accruals	-0.040	0.088	-0.042	-0.001	-0.084	24.5

4. EMPIRICAL RESULTS

The discussion of the empirical results is divided into two sections. Section 4.1 provides the results of the model estimation. Section 4.2 examines the value relevance of stock returns, earnings and cash flows using the estimates of changes in firm value obtained from Section 4.1.

4.1 Model Estimation

The Gibbs sampling has been repeated for 2,000 times using the posterior conditional density functions (4) - (10). As discussed in Section 2.2, we run the first 1000-time iterations to make sure that the Gibbs sampler has converged while we use the data drawn at the 1,001st through 2,000th iterations to produce the estimates in Tables 2, 3 and 4. The data drawn from the Gibbs iterations satisfy the convergence criteria described in Section 2.2.

Estimates of model (2) are reported in Table 2. As expected, lagged stock returns ($R_{i\,t-1}$) are useful in explaining the variations of earnings ($X_{i\,t}$), with a significant coefficient estimate of 0.017. The earnings variable has a significant coefficient for its own lagged variable, its estimate being 0.571 with a standard

calculated using information from the balance sheet and income statement.

error of 0.006. A significant autocorrelation of earnings is also reported by Dichev (1997) and Sloan (1996). For cash flows, an estimate of its own lagged variable is 0.262 and its standard error is 0.007, indicating that cash flows are highly autocorrelated. With respect to the value changes variable, ΔV_{it}, earnings and cash flows have significant coefficient estimates of 0.079 and 0.076, respectively, implying that they reflect changes in firm value.

[Table 2] Estimates of the Coefficients in Model (2) Using 1,000 Values Drawn by Gibbs Sampling

$$
\begin{aligned}
R_{it} &= \beta_{ro} + \beta_{r1} R_{it-1} + \beta_{r2} X_{it-1} + \beta_{r3} C_{it-1} + \beta_{r4} \Delta V_{it} + u^{r}{}_{it} \\
X_{it} &= \beta_{xo} + \beta_{x1} R_{it-1} + \beta_{x2} X_{it-1} + \beta_{x3} C_{it-1} + \beta_{x4} \Delta V_{it} + u^{x}{}_{it} \\
C_{it} &= \beta_{co} + \beta_{c1} R_{it-1} + \beta_{c2} X_{it-1} + \beta_{c3} C_{it-1} + \beta_{c4} \Delta V_{it} + u^{c}{}_{it}
\end{aligned} \tag{2}
$$

Independent Variable	Dependent variable					
	Stock Returns (R_{it})		Earnings (X_{it})		Cash Flow (C_{it})	
	estimate	s.e.	Estimate	s.e.	estimate	s.e.
Intercept	0.120	0.005	-0.002	0.001	0.038	0.001
$R_{i,t-1}$	-0.017	0.011	0.017	0.001	-0.002	0.001
$X_{i,t-1}$	0.019	0.069	0.571	0.006	0.315	0.008
$C_{i,t-1}$	0.386	0.063	0.098	0.005	0.262	0.007
ΔV_{it}	0.845	0.002	0.079	0.001	0.076	0.001

4.2 The Relative Value Relevance of Stock Returns, Earnings and Cash Flows

The evidence reported in the previous section indicates that all three proxies for firm value examined in this paper are value relevant. The next stage of the analysis is which of the value proxies reflects most closely our estimates of unobserved changes in firm value. Since changes in firm value are not observable in nature, previous studies have adopted indirect approaches to evaluate value relevance of alternative value measures. Dechow (1994) uses stock returns as a proxy for value changes and evaluates the value relevance of earnings and cash flows based on their associations with stock returns. Dichev (1997) uses the unpredictability of changes in value measures as a benchmark for value relevance, noting that a good measure of firm value should change only in response to new information.

In contrast, the probability model developed in this paper allows us to estimate directly unobserved value changes, ΔV_{it}, so that the value relevance of alternative value proxies such as stock returns, earnings and cash flows can be evaluated directly by reference to their associations with estimates of ΔV_{it}.

The advantage of this approach is that the adoption of an imperfect value benchmark, such as stock returns, is no longer needed in evaluating the value relevance of alternative value measures.

To assess the value relevance of three alternative firm performance measures, R^2s of the following regression are calculated and compared for stock returns, earnings and cash flows using generated data on ΔV_{it}. This is similar to the approach adopted by Dechow (1994). An important difference is that the dependent variable in the regressions here is our estimates of unobserved changes in firm value, ΔV_{it}, not a stock returns variable. For $A = R_{it}, X_{it}, C_{it}$,

$$\Delta V_{it} = \gamma_0 + \gamma_1 A + \eta_{it} \tag{11}$$

[Table 3] Estimates of Coefficients and R^2 When Regressing Value Changes (ΔV_{it}) on Stock Returns, Earnings and Cash Flows, Using 1,000 Values Drawn by Gibbs Sampling

	Independent variable							
	Stock Returns (R_{it})		Earnings (X_{it})		Cash Flows (C_{it})		$\%(R_R^2 > R_X^2)^a$	$\%(R_X^2 > R_C^2)^b$
	estimate	s.e.	estimate	s.e.	estimate	s.e.		
γ_0	-0.154	0.005	-0.051	0.005	-0.110	0.005		
γ_1	1.079	0.004	2.104	0.038	1.718	0.029		
R^2	0.659	0.004	0.120	0.004	0.095	0.003	100	100

The estimated regression is $\Delta V_{it} = \gamma_0 + \gamma_1 A + \eta_{it}$ where $A = R_{it}, X_{it}, C_{it}$

[a] Percentage of the iterations at which R_R^2 is greater than R_X^2, where $R_R^2(R_X^2)$ is the R^2 when regressing ΔV_{it} on $R_{it}(X_{it})$.

[b] Percentage of the iterations at which R_R^2 is greater than R_C^2, where $R_X^2(R_C^2)$ is the R^2 when regressing ΔV_{it} on $X_{it}(C_{it})$.

Table 3 reports the results of the three simple regressions. Table 3 shows that stock returns have a mean R^2 of 0.659, much smaller than 1, indicating that the stock returns variable is not an efficient measure of value changes. The mean R^2 of earnings (0.120) is smaller than that of stock returns, but larger than that of cash flows (0.095). To check the significance of the differences, their R^2s were compared at each iteration of the Gibbs sampling. For all (100%) of the total iterations, the R^2 of stock returns was larger than the one of earnings, and the R^2 of earnings was larger than the one of cash flows. Therefore, it is concluded that stock returns are more value relevant than earnings and cash flows, and that earnings are a better measure of changes in firm value than cash flows.

To understand the importance of accruals, the observations are grouped into quintiles based on the absolute value of accruals. The estimation results in Table 4 confirm that the value relevance of earnings vis-à-vis cash flows increases as the absolute value of accruals grows. In quintile 1, where the absolute value of accruals is small, the R^2 on earnings is 0.097 and the R^2 of cash flows is also 0.097. However, when the absolute value of accruals grows (in quintile 5), earnings have a R^2 of 0.159, while cash flows have a R^2 of 0.104. In quintile 1, only 22.7% of the total iterations had a larger R^2 for earnings than cash flows. In contrast, for the other quintiles the percentage is 100%, suggesting that accruals make earnings better measures of firm value than cash flows. This finding is consistent with the results of previous research that accruals improve the value relevance of earnings by mitigating the timing and matching problems inherent in the measurement of cash flows.

[Table 4] Estimates of R^2 When Regressing Value Changes (ΔV_{it}) on Stock Returns, Earnings and Cash Flows for Each Quintile, Using 1,000 Values Drawn by Gibbs Sampling

Quintile[a]	Independent variable			$\%(R_R^2 > R_X^2)^b$	$\%(R_R^2 > R_C^2)^c$
	Stock Returns (R_{it})	Earnings (X_{it})	Cash Flows (C_{it})		
1	0.714	0.097	0.097	100	22.7
2	0.697	0.095	0.091	100	100
3	0.700	0.119	0.103	100	100
4	0.667	0.122	0.104	100	100
5	0.612	0.159	0.104	100	100

The estimated regression is $\Delta V_{it} = \gamma_0 + \gamma_1 A + \eta_{it}$ where $A = R_{it}, X_{it}, C_{it}$

[a] Quintiles are formed according to the absolute value of accruals. Quintile 1 contains firm-observations with the smallest absolute values of accruals, while quintile 5 contains firm-observations with the largest absolute values of accruals.

[b] Percentage of the iterations at which R_R^2 is greater than R_X^2, where $R_R^2(R_X^2)$ is the R^2 when regressing ΔV_{it} on $R_{it}(X_{it})$.

[c] Percentage of the iterations at which R_R^2 is greater than R_C^2, where $R_X^2(R_C^2)$ is the R^2 when regressing ΔV_{it} on $X_{it}(C_{it})$.

5. CONCLUSION

In this paper, we first develop a formal probability model that allows us to directly estimate unobserved changes in firm value that are commonly reflected in three alternative value measures, namely stock returns, earnings and cash flows. Unobserved changes in firm value are modeled as a common factor causing changes in alternative value measures, and are estimated using the procedure called the Gibbs sampler.

Second, we assess the value relevance of stock returns, earnings, and cash flows against the estimates of changes in firm value obtained from the model. Our results show that the stock returns are not an efficient measure of changes in firm value, although stock returns are more value relevant than earnings and cash flows. Our results also show that earnings are a better measure of firm value or its change than cash flows, and that accounting accruals increase the value relevance of earnings, a finding consistent with previous research (e.g, DeChow 1994; and Dichev 1997).

The contribution of this paper is to provide a new approach for assessing the value relevance of alternative measures of firm performance. The approach taken in this paper differs significantly from that adopted in previous research. Most previous studies use stock market prices or stock returns as a value benchmark against which value relevance of alternative value measures, such as earnings and cash flows, is evaluated. The usefulness of this traditional approach is limited when the market is not informationally efficient and when market prices of equity shares are unavailable (as is the case for unlisted firms). Unlike the traditional approach, the new approach allows researchers to directly estimate unobserved changes in firm value, enabling the assessment of the value relevance of accounting and financial variables without reference to an inefficient value benchmark. This renders a value relevance analysis possible even when stock returns or prices are not readily available.

APPENDIX

In this appendix we explain that the posterior conditional density function for $\Delta \underline{V}_T$ is a normal distribution. Adding the three regression equations in (2) and imposing a normalizing restriction of $\beta_{r4}+\beta_{x4}+\beta_{c4}=1$, we obtain the following expression which does not include β_{r4}, β_{x4}, and β_{c4}:

$$\begin{aligned}\Delta \underline{V}_T = & (\underline{R}_T+\underline{X}_T+\underline{C}_T)-(\beta_{r0}+\beta_{x0}+\beta_{c0})\cdot \underline{1}-(\beta_{r1}+\beta_{x1}+\beta_{c1})\cdot \underline{R}_{T-1} \\ & -(\beta_{r2}+\beta_{x2}+\beta_{c2})\cdot \underline{X}_T-1-(\beta_{r3}+\beta_{x3}+\beta_{c3})\cdot \underline{C}_{T-1} \\ & -(\underline{u}^r+\underline{u}^x+\underline{u}^c)\end{aligned} \tag{12}$$

where the notations defined in the text are used. Given values of $\underline{\beta}_r, \sigma_r, \underline{\beta}_x, \sigma_x$, $\underline{\beta}_c$ and σ_c, the only random variables in (12) are $\underline{u}^r, \underline{u}^x$ and $\underline{u}^c$ whose distributions are multivariate normal with mean $\underline{0}$. Since $\underline{u}^r, \underline{u}^x$ and $\underline{u}^C$ are mutually independent and their covariance matrices are $\sigma_r^2 I_N, \sigma_x^2 I_N$ and $\sigma_c^2 I_N$, respectively, the posterior conditional density function for $\Delta \underline{V}_T$, given values of $(\underline{\beta}_r, \sigma_r, \underline{\beta}_x, \sigma_x, \underline{\beta}_c, \sigma_c)$, is the following normal distribution:

$$p(\Delta \underline{V}_r \mid \underline{\beta}_r, \sigma_r, \underline{\beta}_x, \sigma_x, \underline{\beta}_c, \sigma_c, \underline{R}_T, \underline{X}_T, \underline{C}_T) \sim N(\underline{\mu}_{\Delta V}, \sigma^2_{\Delta V} I_N) \tag{13}$$

where

$$\begin{aligned}\underline{\mu}_{\Delta V} = & (\underline{R}_T+\underline{X}_T+\underline{C}_T)-(\underline{\beta}_{r0}+\underline{\beta}_{x0}+\underline{\beta}_{c0})\cdot \underline{1}-(\beta_{r1}+\beta_{x1}+\beta_{c1})\cdot \underline{R}_{T-1} \\ & -(\beta_{r2}+\beta_{x2}+\beta_{c2})\cdot \underline{X}_{T-1}-(\beta_{r3}+\beta_{x3}+\beta_{c3})\cdot \underline{C}_{T-1}, \text{ and}\end{aligned}$$

$$\sigma^2_{\Delta V} = \sigma_r^2+\sigma_x^2+\sigma_c^2.$$

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