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Capturing the Impact of Latent Industry-Wide Shocks with Dynamic Panel Model*

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Abstract

Expanding the panel model of Pesaran (2006) and Bai (2009), we propose a dynamic panel specification with Bayesian approach to capture the impact of unobservable industry-wide shocks to stock price movements. We employ fundamental accounting information to control company specific shocks and equity market index to capture market wide common shocks. Our model is designed to resolve the potential multicollinearity problem that is known to exist when the industry factors are considered by extracting the industry-wide shocks using Bayesian method.

JEL classification: C11, C13, G12

Keywords: Common Factor Structural Error; Common Shocks; Stock Price Movements; Accounting Fundamentals; Bayesian Gibbs Sampler

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1. Introduction

This paper proposes a dynamic panel model with Bayesian approach to capture the impact of industry-wide shocks in explaining stock price movements (SPM). Company specific shocks are captured by an equity valuation model that takes advantage of financial statement information, while market wide common shocks are captured by equity market index. The major contributions of this paper are in two aspects.

The technical contribution of our paper is that we propose Bayesian estimation technique to evaluate the unobservable common shocks and add more explanatory power to the traditional panel data set-up. The empirical contribution is that we present a model to control the company specific accounting information and the market wide shocks to investigate industry-wide shocks, which good proxies are often unavailable.

This paper has two motivations. Firs motivation is the needs to pay more attention to role of industry-wide shocks in explaining SPM. Fundamental analysts primarily investigate the financial statements of a company and its competitors so that they can estimate the future development of the value of the company. The advantage of fundamental analysis is that it has an intuitive explanatory link to SPM. It ought to, at least in theory, characterize the long-term, fundamental value of a stock. If the information on financial statements accurately reveals the fundamental value of a company, then the accounting information for a company, should explain a significant proportion of SPM.

However, results from previous studies show that the capability of these accounting variables in explaining the SPM is limited. Chen and Zhang (2007) show that, at individual stock level R^2 of the linear regressions of stock returns on accounting variables with different model specifications, are all less than 0.25. Bettmanet et al. (2009) and Hong and Wu (2014) present portfolio level evidence that the explanatory power of Ordinary Least Square (OLS) models using accounting variables to explain portfolio returns are much lower than when

other momentum variables are included. These results indicate that a model explaining SPM, with fundamental variables only is likely to suffer from omitted variable bias.

In order to overcome the potential omitted variable bias, an obvious solution is to include market index return as an explanatory variable. The Capital Asset Pricing Model (CAPM) states that the market excess return captures the systematic exposure of individual stock's excess return. Therefore, market index return is likely to have statistical significance in explaining the SPM (see Lessard, 1974). If market-wide common shocks exist, the same could happen within an industry.

Hao et al. (2011) use an extended Cournot and Bertrand completion model to demonstrate the sensitivity of SPM to industry-level news. They theoretically and empirically found that SPM are sensitive to industry-level news, and that the returns of less profitable companies in an industry are more sensitive to industry-level news than those of the more profitable companies. Harford (2005) also find the relevance of industry-specific economic shocks to SPM. However, it argues that the proxy variables for industry-specific economic shocks are highly correlated within an industry, which may cause multicollinearity if simultaneously included in a regression model. To address this, Harford (2005) extract the first principal component from seven observable economic shock variables.

However, Harford (2005) also notes the disadvantage as common shock variables are unobservable or have no reasonable proxy variables. Furthermore, the impacts of these common shocks on stock returns are different across different companies. In such cases, the proxy variables, or principal component analysis, may not be effective. Such modelling difficulty may explain why there is limited attention to the role of industry-wide shocks in explaining SPM. In order to fill this gap, we propose a new method of aggregating the unobserved industry-wide factors and treat it as a latent factor to overcome such issues. This is our first objective / contribution.

Our second motivation is to take advantage of Bayesian model. Instead of employing the conventional estimation methods proposed by Pesaran (2006) or Bai (2009), we adopt the Bayesian estimation method in this paper. Common shocks, which exist in many industries and social activities, could be a significant feature of both cross-sectional and panel data sets (Andrew, 2005; Bai, 2009). The last decade has seen considerable research (see Pesaran, 2006; Bai, 2009; Moscone and Tosetti, 2009) into the effects of common shocks on panel-data model estimation. Multifactor error structure has been introduced to conventional panel-data regression models to deal with the impacts of the unobservable common shocks.

To estimate the models, some try to filter out the effects of the common factor (Pesaran, 2006), or put restrictions on them (Bai, 2009), so that the coefficients of the observed variables can be estimated consistently. Algebraically the same as an exact factor structure, Ahn et al. (2001, 2013) consider panel data models with time-varying individual effects using Generalized Method of Moments (GMM) technique. Meanwhile, many other parametric or nonparametric models have recently been provided to take into account the cross-sectional dependence (for example Sarafidis and Robertson (2009) and Chen et al. (2012)).

However, these models focus on estimating the coefficients of the regressors and avoid evaluating the effects of the common shocks. In this paper, we examine the heterogeneous impacts of both observed factors (accounting fundamentals and market-wide common shocks) and unobservable industry-wide shocks, by estimating a panel data model with both individual-varying slope coefficients and individual-varying time effects, captured by a common factor error structure. The priors are chosen to reflect the beliefs of people on this particular model of investigating industry-wide shocks.

We address three reasons why Bayesian approach is more appropriate in extracting industry-wide shocks under this paper's framework. First, industry-wide shocks are shared by all companies in the same industry. The number of companies typically runs from five to

fifteen for S&P100 and it would be much larger in S&P500. The current model has 7 explanatory variables for each company, 5 fundamental variables, two variables representing industry-wide and market-wide shocks. This leaves us with 105 parameters to estimate using monthly observations. Conventional maximum likelihood based methods cannot handle this therefore we use Bayesian method.

Second, Gibbs sampling, with data augmentation, makes estimation of the common shocks at each time period and the reactions of the individual company to the latent shocks computationally much simpler compare to the conventional methods. The proposed method allows us to avoid the inefficient two-stage estimation suggested by Pesaran (2006). It also allows us to overcome the assumptions on factor structures introduced by Bai (2009).

Third, unlike maximum likelihood method, Bayesian estimation avoids evaluating the first and second derivates of the likelihood function when calculating the confidence interval. In Bayesian framework, the coefficients of determination can also be estimated conveniently after model estimation, which is rarely available in the literature because of the unavailability of estimation for factors and factor loadings. However, in empirical analysis, it is a valuable measurement for prediction accuracy and explanation power of model specification. Therefore, the second objective / contribution of our paper is to propose an enhanced econometric technique in capturing industry-wide shocks in explaining the SPM.

The proposed method of investigating industry-wide unobservable variable has two advantages. First, it overcomes the potential model misspecification, such as omitted variable bias. Second, it allows us to investigate the sensitivity of the stock returns to commonly shared unobservable shocks, which has significant implications for the proper valuation of companies from the same industry. The sensitivity of a stock return to the unobserved common shocks could indicate how prone the company stock is to industry-wide trend or cyclicality. As companies in the same industry are often direct competitors, investigating the

sensitivity of the industry would enhance our ability to understand the industry-wide competitive relationship.

The rest of the paper is organized as follows. Section 2 explains the econometric model and the specifications of the empirical model of explaining SPM, Section 3 describes the data and run some preliminary test, Section 4 provides the empirical findings and Section 5 concludes the paper.

2. The Models

2.1 Econometric Model: Model Specification

The traditional panel data model can be written as

$$y_{it} = z_{it}'\theta + e_{it}, \tag{1}$$

where $i = 1,...,N$ indicates individuals; $t = 1,...,T$ indicates time periods; y_{it} represents the value of the dependent variable for individual i at time period t; z_{it} is a $s \times 1$ vector including all the explanatory exogenous variables; θ refers to the corresponding vector of coefficients; and e_{it} represents for the error term.

As noted above, we generalize the model in (1) from two aspects. First, to allow for heterogeneity, θ differs across i. Second, a factor structural error term is introduced to allow for cross-section dependence. The generalized model can be written as

$$\underset{1\times 1}{y_{it}} = \underset{s\times 1}{z_{it}'}\,\theta_i + e_{it}, \quad \text{where} \quad \underset{1\times 1}{e_{it}} = \underset{m\times 1}{\gamma_i'}\,f_t + \varepsilon_{it}. \tag{2}$$

Here θ_i's refer to the individual specific coefficients of variables z_{it}. The variable f_t's represent the unobservable common factors at time *t*. The variable γ_i's represent the individual specific impact of such common factors on the dependent variable. For identification, it is required that $m \le (N-1)/2$ (Geweke and Zhou, 1996).

Specifically, in the application of this paper, y_{it} represents the stock return of company i at time t; z_{it} includes all the accounting variables and the market index return; f_t represents the industry-wide shocks at time t; γ_i measures how each company reacts to the common shocks.

For simplicity, we write the above model in matrix form as follows.

$$\underset{N\times 1}{Y_t} = \underset{N\times Ns}{Z_t}\,\underset{Ns\times 1}{\theta} + \underset{N\times m}{\Lambda}\,\underset{m\times 1}{f_t} + \underset{N\times 1}{\varepsilon_t}, \tag{3}$$

where

$$Y_t = \begin{pmatrix} y_{1t} \\ \vdots \\ y_{Nt} \end{pmatrix}, \quad Z_t = \begin{pmatrix} \underset{1\times s}{z_{1t}'} & & \\ & \ddots & \\ & & \underset{1\times s}{z_{Nt}'} \end{pmatrix}, \quad \theta = \begin{pmatrix} \theta_1 \\ \vdots \\ \theta_N \end{pmatrix}, \quad \Lambda = \begin{pmatrix} \gamma_1' \\ \vdots \\ \gamma_N' \end{pmatrix} \quad \text{and} \quad \varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \vdots \\ \varepsilon_{Nt} \end{pmatrix}.$$

Then the following conditions are standard and necessary for the Bayesian analysis (Geweke and Zhou, 1996; Chan et al., 2013).

Assumption 1: *The error terms and factors are independent and identically distributed across t. Specifically,*

$$\begin{pmatrix} f_t \\ \varepsilon_t \end{pmatrix} \sim N(0, \Sigma), \quad \Sigma = \begin{pmatrix} I_m & 0 \\ 0 & \underset{N\times N}{\Sigma_\varepsilon} \end{pmatrix} \quad \text{and} \quad \Sigma_\varepsilon = diag\left(\sigma_1^2, \sigma_2^2, \ldots, \sigma_N^2\right).$$

Moreover, f_t *and* ε_t *are not correlated with* Z_t.

2.2 Econometric Model: Bayesian Estimation

Based on the model above, we present a Gibbs sampler that generalizes the algorithm of Geweke and Zhou (1996) for an *m*-factor model with large *T* and small *N* to accommodate a panel data regression model with individual-varying slope coefficients and factor structural error term. Both γ_i's and f_t's are treated as unknown parameters with values being drawn from their conditional posterior densities. Then, conditional on γ_i's and f_t's, the model of

(3) reduces to the standard linear regression model, facilitating draws from the conditional posterior densities for the parameters.

For prior densities of individual-varying slope coefficients and variances of random error terms, we consider a standard diffuse prior, that $\theta_i \propto 1_s$ and $h_i \propto \frac{1}{h_i}$, where $h_i = \frac{1}{\sigma_i^2} > 0$. For prior densities of unobservable factor loadings, we follow Geweke and Zhou (1996) to have $\gamma_i \propto 1_m$ for the case with large *T* and small *N*. Under these prior distributions and model specifications, the joint posterior density for all unknown parameters (such that θ_i, h_i, γ_i and f_t) can be written as

$$\begin{aligned} p(\Theta \mid Y_{1:T}, Z_{1:T}) = & \prod_{i=1}^{N}\prod_{t=1}^{T}(2\pi)^{-1/2} h_i^{1/2} \exp\left\{-\frac{h_i}{2}\left(y_{it} - z_{it}'\theta_i - \gamma_i' f_t\right)^2\right\} \\ & \cdot \prod_{i=1}^{N}\frac{1}{h_i} \cdot \prod_{t=1}^{T}(2\pi)^{-m/2} \exp\left\{-\frac{1}{2} f_t' f_t\right\}, \end{aligned} \tag{4}$$

where Θ represents for all unknown parameters.

From the joint posterior density (4) we can derive the full conditional posterior densities that can be used for Gibbs sampling. Particularly, we assume that all the rank conditions needed below are satisfied.

The conditional posterior densities of the parameter θ_i's for $i = 1, \ldots, N$ are normal distributions, given by

$$\theta_i \mid Y_{1:T}, Z_{1:T}, \Theta_{-\theta_i} \sim N\left(\hat{\theta}_i, \frac{1}{h_i}\left(Z_i' Z_i\right)^{-1}\right), \tag{5}$$

where

$$\hat{\theta}_i = \left(Z_i' Z_i\right)^{-1}\left(Z_i' \tilde{Y}_i\right), \quad \underset{T\times s}{Z_i} = \begin{pmatrix} z_{i1}' \\ \vdots \\ z_{iT}' \end{pmatrix} \quad \text{and} \quad \underset{T\times 1}{\tilde{Y}_i} = \begin{pmatrix} y_{i1} - \gamma_i' f_1 \\ \vdots \\ y_{iT} - \gamma_i' f_T \end{pmatrix}.$$

The conditional posterior densities of h_i's for $i=1,\ldots,N$ are gamma distributions as follows.

$$h_i \mid Y_{1:T}, Z_{1:T}, \Theta_{-h_i} \sim G\left(s_h, s_c\right), \tag{6}$$

where the shape and scale parameters are $s_h = \frac{T}{2}$ and $s_c = 2 / \sum_{t=1}^{T}\left(y_{it} - z_{it}'\theta_i - \gamma_i' f_t\right)^2$ respectively. Specifically, if $z \sim G\left(s_h, s_c\right)$, then $p(z \mid s_h, s_c) = \frac{s_c^{-s_h} z^{s_h - 1}}{\Gamma(s_h)} \exp(-z / s_c)$.

The conditional posterior densities of f_t's and γ_i's are drawn in the same way as Geweke and Zhou (1996).

Rather than estimations for factors and factor loadings, we are more interested in evaluating proportions of variation in dependent variable y_{it} that can be attributed to both observed variables and unobserved common factors. Based on draws from conditional posterior distributions, it is straightforward to evaluate the coefficient of determination, R^2, of the model (3) taking into account for not only observable variables of Z_t's but unobservable factors of f_t's. Specifically, for the overall model,

$$R^2 = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\hat{y}_{it} - \bar{y}\right)^2}{\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it} - \bar{y}\right)^2} = 1 - \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{\varepsilon}_{it}^2}{\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it} - \bar{y}\right)^2}, \tag{7}$$

where $\bar{y} = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} y_{it}$ such that the average stock return over all companies and all time periods. We can also evaluate R^2 of model (3) for a particular individual/company as

$$R_i^2 = \frac{\sum_{t=1}^{T}\left(\hat{y}_{it} - \bar{y}_i\right)^2}{\sum_{t=1}^{T}\left(y_{it} - \bar{y}_i\right)^2} = 1 - \frac{\sum_{t=1}^{T}\hat{\varepsilon}_{it}^2}{\sum_{t=1}^{T}\left(y_{it} - \bar{y}_i\right)^2}, \tag{8}$$

where $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$ such that the average stock return of the *i*th company over all time periods. Though the estimations for common factors and factor loadings are not invariant in terms of the ordering of individuals, according to Chan et al. (2013), the estimations for R^2 are invariant. Therefore, the application results discussed in this paper are not influenced by changing the order of companies.

2.3 Fundamental Equity Valuation Model using Accounting Information

In order to capture the company-specific factors that influence stock returns, we employ the equity valuation model of Zhang (2000). This model is also expanded in Chen and Zhang (2007) and Hong and Wu in establishing the theoretical relationship between stock returns and accounting fundamentals. The model measures the characteristics of underlying operations of a company using the links between the future cash flows and the observed accounting data in valuing equity. Equity value is a function of two basic operational attributes: scale and profitability.

Let V_t be the value of an all equity-finance company at date *t*. B_t is the corresponding book value of equity. X_t is the earnings generated in period *t*, and g_t is the company's growth opportunities as perceived at *t*. g_t is defined as the percentage by which the scale of operations (capital invested) may grow. Let $q_t \equiv X_t / B_{t-1}$ as profitability at time *t*. Let $E_t(X_{t+1})$ be the expected next-period earnings, *k* is the earnings capitalization factor, and $P(q_t)$ and $C(q_t)$ are the put option to abandon operations and the call option to expand operations, respectively. $P(q_t)$ and $C(q_t)$ are normalized by the scale of operations, B_t. To simplify the analysis, assumes that profitability follows a random walk, $\tilde{q}_{t+1} = q_t + \tilde{e}_{t+1}$. Chen and Zhang (2007) derived the valuation function of equity as

$$V_t = B_t\left[q_t / r_t + P(q_t) + g_t C(q_t)\right] \equiv B_t \upsilon(q_t, g_t, r_t), \tag{9}$$

where $\upsilon(q_t, g_t, r_t) \equiv q_t / r_t + P(q_t) + g_t C(q_t)$. Now consider ΔV_{t+1}, the change in equity value from date t to date $t+1$. Define $\upsilon_1 \equiv \mathrm{d}\upsilon/\mathrm{d}q_t$ and $\upsilon_3 \equiv \mathrm{d}\upsilon/\mathrm{d}r_t$. $\mathrm{d}\upsilon/\mathrm{d}g_t$ is $E(q_t)$ and need not to be defined again. Let D_t be the dividends paid in period t+1. Chen and Zhang (2007) derived the period $t+1$ stock return, denoted R_{t+1} as

$$R_{t+1} = \left[\frac{X_{t+1}}{V_t}\right] + \upsilon_1\left[\frac{B_t}{V_t}\Delta q_{t+1}\right] + \left[\left(1-\frac{B_t}{V_t}\right)\frac{\Delta B_{t+1}}{B_t}\right] + C(q_t)\left[\frac{B_t}{V_t}\Delta g_{t+1}\right] + \upsilon_1\left[\frac{B_t}{V_t}\Delta r_{t+1}\right]. \quad (10)$$

Based on (10), Chen and Zhang (2007) run the following approximated regression.

$$R_{it} = \alpha + \beta x_{it} + \gamma\Delta\hat{q}_{it} + \delta\Delta\hat{b}_{it} + \omega\Delta\hat{g}_{it} + \phi\Delta\hat{r}_{it} + e_{it}, \quad (11)$$

where R_{it} is the annual stock return; $x_{it} = X_{it} / V_{it-1}$ is the earnings yield, divided by the beginning-of-period market value of equity; $\Delta\hat{q}_{it} = (q_{it} - q_{it-1})B_{it-1} / V_{it-1}$ is the change in profitability, adjusted by the beginning-of-period ratio of the book value of equity to the market value of equity, with profitability defied as the return on equity; $\Delta\hat{b}_{it} = [(B_{it} - B_{it-1}) / B_{it-1}](1 - B_{it-1} / V_{it-1})$ is capital investment, adjusted by one minus the beginning-of-period book-to-market ratio; $\Delta\hat{g}_{it} = (g_{it} - g_{it-1})B_{it-1} / V_{it-1}$ is the change in growth opportunities, adjusted by the beginning-of-period book-to-market ratio; $\Delta\hat{r}_{it} = (r_t - r_{t-1})B_{it-1} / V_{it-1}$ is the change in the discount rate, adjusted by company's beginning-of-period book-to-market ratio; and e_{it}'s are random error terms.

The growth opportunities, g, are often captured using long-term analysts' forecasts. The availability of these forecasts for an individual company is severely limited. The most popular alternative is to use industry-wide long-term growth forecasts instead of forecasts for individual companies. However, under the current model, this approach will introduce an identification problem as g is shared by all the companies that are in the same industry. Therefore, the logical solution is to drop g and let it be absorbed in the factor structure from the model, and take the four accounting variables as our fundamental variables.

We generalize model (11) to take account of individual-varying impacts of observed factors (accounting fundamentals and market-wide common shocks), and individual-varying impacts of the unobservable industry-wide shocks on stock returns, as follows:

$$\begin{aligned} R_{it} &= \beta_i x_{it} + \gamma_i \Delta\hat{q}_{it} + \delta_i \Delta\hat{b}_{it} + \phi_i \Delta\hat{r}_{it} + \alpha_i SP500 + e_{it} \\ e_{it} &= \gamma_i' f_t + \varepsilon_{it} \end{aligned} \tag{12}$$

From here on, we refer to this model as Model CF.

In this paper, we follow Geweke and Zhou (1996), Ahn et al. (2001) and Bai (2009) to assume the number of unobservable common factors is known. In particular, we are interested in consistently measuring the impact of observable factors on stock prices, and estimating the variation in stock returns that can be explained by both observable and unobservable factors.

3. Data and Preliminary Tests

3.1 Data Description and Data Issues

We base our analyses on the monthly returns of the 56 stocks across six industries in the S&P100 index between January 2003 and December 2012: 11 from the IT industry, 13 from the industrial industry, 8 from the energy industry, 10 from the finance industry, 11 from the health care industry and three from the utilities industry. In order to capture impact of industry-wide factors on stock returns, we conduct the analysis for each industry separately. We use analyst long-term forecasts from the Institutional Broker Estimate System (IBES) in this paper. We follow the approach of Hong and Wu (2014) in our sample construction except that we do not adopt portfolios for our analyses. This gives rise to a primary sample extending from 2003 to 2012, with 6552 (such that $N = 56$ and $T = 117$) monthly company-level observations. The company-level accounting data is available from the Compustat North America database and Thomson Reuters' Worldscope database. Stock prices

are sourced from Bloomberg and earnings forecasts data are extracted from the Institutional Broker Estimate System (IBES).

Many existing studies of using accounting information to explain stock returns become event studies as they collect stock returns on or around the earnings announcement date (see Chen and Zhang, 2007; Clement et al., 2011). While such practice has a clear benefit of isolating the impact of accounting information on stock returns (and hence shows higher statistical significances of the estimated coefficients), it refines the scope of regression analysis and does not allow the incorporation of other variables that may affect stock returns. As our main interest is in the industry-wide factors, we use monthly stock return data based on calendar dates. Although this expects to yield much lower statistical significance for the estimated coefficients of the accounting variables, such structure allows us to overcome the restrictions of the event study framework.

Mixed-frequency problem is another issue in our dataset, since accounting data are produced quarterly, while stock price data are produced monthly. In order to overcome this, we follow the method of Hong and Wu (2014). There are two different types of data in our sample: stock and flow. Stock data are snapshots of the measured variable at a given point in time, whereas flow data represent an accumulation over a given period. Stock return, profitability, growth opportunity and discount rate are stock variables, but earnings, yield and capital investments are flow variables. By accumulating monthly observations of flow variables over a quarter, they could then become the end of the quarter observation. This means the end of quarter observation for flow variables could be, at least in theory, reverse engineered and decomposed into monthly observations. However, this does not apply to stock variables. Since all our quarterly observed variables are flow variables, weighted average is used under this assumption.

3.2 Cross-Sectional Dependence Test and Number of Common Factors

Before we apply Model CF to the above stock return data, we conduct formal cross-section dependence (CD) tests to check our data set. For each industry, our panel data set has small *N* and relatively large *T*, therefore we adopt the CD test proposed by Breusch and Pagan (1980). This test is based on the following Lagrange multiplier (LM) statistic

$$CD_{LM} = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2 , \tag{13}$$

where $\hat{\rho}_{ij}$ is the sample estimated pair-wide correlation of the residuals. Specifically,

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T}\hat{e}_{it}\hat{e}_{jt}}{\left(\sum_{t=1}^{T}\hat{e}_{it}^2\right)^{1/2}\left(\sum_{t=1}^{T}\hat{e}_{jt}^2\right)^{1/2}}, \tag{14}$$

where $\hat{e}_{it}$ is the estimate of e_{it} by running OLS regression for each individual i. Breusch and Pagan (1980) show that under the null hypothesis of cross-sectional independence, CD_{LM} is asymptotically a chi-squared distribution with $N(N-1)/2$ degrees of freedom.

(Insert Table 1 here)

We conduct the CD test for each of the six industries, with Table 1 presenting the degrees of freedom and LM statistic, CD_{LM}, for each industry. The test results indicate that cross-sectional dependence exists for all industries, justifying the application of Model CF to our stock return data.

(Insert Table 2 here)

As previously stated, the number of common shocks, *m*, that can be identified is less than or equal to $(N-1)/2$. Since there are only three companies from the utilities industry, we could only identify one common factor for this industry. For the sake of comparison, we first set the number of industry-wide shocks as one for all industries. Due to the similarity across

estimations for different industries, we focus on the 11 stocks from the IT industry. Table 2 lists the 11 companies in the sample. Despite the difference in the sample period investigated, the descriptive statistics of our sample data is comparable to those of Chen and Zhang (2007). We also estimate models with two or three industry-wide shocks for all industries but the utilities industry, and we present and discuss the results in Section 5.4.

4. Empirical Results

4.1 Impact of Observable Factors on Stock Returns

We estimate Model CF separately for all six industries. When estimating each model, we generate 15,000 draws but discard the first 5,000 as a "burn-in".

(Insert Table 3 here)

Table 3 presents the posterior statistics, including posterior mean, standard deviation and 95 per cent credible interval (CI) for coefficients of observable accounting variables and market-wide common shocks (the S&P500 index), for each company from the IT industry. Although, due to space limitations, we will present the estimated coefficients of the IT industry only, this does not alter the findings of this paper, as results from all the industries have consistent implications (estimated results of other industries are available from the authors upon request). In order to assess the Gibbs sampler's performance, we present the sampled paths and autocorrelation functions (ACFs) of these sample paths for all estimated coefficients of Apple Inc. in Figure 1. These plots show that the sample paths are mixed well. The sampled paths and their ACFs of estimated coefficients for the other companies are very similar, and are not included here.

(Insert Figure 1 here)

In general, we find that the market-wide common shocks, represented by the S&P500 index, have statistically significant and larger impacts on stock returns compared to the impacts of

the individual company's accounting fundamentals. S&P500 has a positive impact on stock returns for all the IT industry companies, with none of the 95 per cent CIs containing zero, suggesting significant positive impacts. On the other hand, most CIs of estimated coefficients for accounting fundamentals include zero, indicating no significant impacts from accounting fundamentals on stock returns. In addition, we find that the impacts of observed accounting fundamentals on stock returns vary across companies. For example, Δb, the adjusted capital investment, only has significantly positive impact on stock returns for three companies: Apple Inc., Intel Corporation and Qualcomm Inc., but has no significant impact for the other eight IT companies. Furthermore, the magnitudes of such significant impacts are different, ranging from 1.5060 to 2.0254. The impacts of market-wide common shocks, indicated by S&P500 index, also vary across companies from 0.7510 to 1.3613, although these impacts are significantly positive for all companies. Therefore, the model specification of individual-varying coefficients of observable accounting fundamentals and market-wide common factors can be justified.

For model comparison, we progressively increase the set of independent variables to explain stock returns. In particular, we estimate another two models for all industries. The first model is

$$R_{it} = \beta_i x_{it} + \gamma_i \Delta\hat{q}_{it} + \delta_i \Delta\hat{b}_{it} + \phi_i \Delta\hat{r}_{it} + e_{it}. \quad (15)$$

This model is a conventional equity valuation model with individual-varying coefficients and random error term following normal distributions. In this model, only accounting fundamentals are included as explanatory variables for stock returns. We refer to this model (15) as Model C1 in the following discussion. The second comparison model is

$$R_{it} = \beta_i x_{it} + \gamma_i \Delta\hat{q}_{it} + \delta_i \Delta\hat{b}_{it} + \phi_i \Delta\hat{r}_{it} + \alpha_i SP500 + e_{it}, \quad (16)$$

i.e. in the conventional equity valuation model besides accounting fundamentals, market-wide common shocks, indicated by S&P500, is included in as well. We refer to the above

model (16) as Model C2.

(Insert Table 4 here)

(Insert Table 5 here)

Tables 4 and 5 present the estimated coefficients for all companies from the IT industry by Model C1 and C2, respectively. (Model C1 and C2 are estimated by ordinary least square method rather than Bayesian MCMC method. Results for other industries are available upon request) From these tables we can see that the index return has statistically significant explanatory power in explaining the individual stock returns, and we may incur omitted variable bias by excluding the index return from the model. We observe three major findings by comparing the estimated results of the three models, CF, C1 and C2. First, Model C1 and C2 also show considerable variations in estimated coefficients across companies, which demonstrates that there exists strong individual heterogeneity within the IT industry.

Second, in terms of the estimated impacts of accounting fundamentals on stock returns, the results from Model C1 and Model C2 are consistent. In general, if a fundamental variable has significant impact in Model C1, it is likely to have a significant impact in Model C2, which includes S&P500 index return as an explanatory variable. However, when the unobserved industry-wide factor is taken into account, as in Model CF, such significant impacts almost disappear. This is important as it could be considered a sign of omitted variable bias. The accounting fundamentals could seem to capture some of the shocks from the unobserved industry-wide factors, when the factors are ignored. The results, without such factors as an explanatory variable, would be inaccurate because the major driver behind the stock price movement is unobserved industry-wide factors rather than accounting fundamentals. These empirical results imply that the seemingly statistical significance of the company specific accounting variables may be misleading.

Third, estimated impacts from S&P500 index on stock returns by Model C2 and Model

CF are almost identical. Therefore, the explaining power of S&P500 index to stock price movement is robust, and an IT company's reaction to unobserved industry-wide shocks seems to be uncorrelated to its reaction to the S&P500 index — an indicator for market-wide common shocks.

4.2 Impact of Unobservable Common Shocks on Stock Returns

(Insert Table 6 here)

In this section, we examine the impact of unobservable industry-wide shocks. We do this by comparing the coefficient of determination, R^2, of various econometric models estimated by Eq. (8). Results are presented in Table 6. We find that Model C1 has the lowest R^2 measures among the three model specifications. In Model C1, Accenture has the lowest R^2 and Qualcomm has the highest R^2. Such low level of R^2 measures indicates that the accounting fundamentals have very limited explanatory power on explaining SPM. It should also be noted that such low explanatory power is partially due to different return computing methodology. As previously discussed, many existing studies that use accounting information to explain stock returns become event studies as they collect stock returns on or around the earnings announcement date. We use monthly stock return data based on calendar dates. Although it is expected that this will yield much lower statistical significance for the estimated coefficients of the accounting variables, such structure allowed us to overcome the restrictions of the event study framework.

S&P500 index return, which is designed to capture the market-wide systematic shocks to the individual stock returns, is taken into account in Model C2. The R^2 measures significantly increase in Model C2 compared to those in Model C1. R^2 ranges from 0.2404 for Apple Inc. to 0.4721 for Cisco System. Taking Cisco System as an example, R^2 of Model C1 is 0.0179 while that of Model C2 is 0.4721. The result indicates that the market-

wide systematic common shock has strong and statistically significant explanatory power on SPM. The explanatory power of our C2 models (measured by R^2) is comparable to those of Bettman et al. (2009) and Hong and Wu (2014), where SPM are explained by accounting variables and market-wide common shocks. Bettman et al. (2009) report a R^2 of 0.429 (Table 4 of Bettman et al., 2009) while Hong and Wu (2014) report a R^2 of 0.42 (Table 2 of Hong and Wu, 2014). This naturally leads us to suspect an omitted variable bias that we may need to consider for not only market-wide common shocks, but also industry-wide shocks.

When unobservable industry-wide shocks are taken into account in Model CF, we gain significantly increased R^2 for all companies. For example, EMC Corporation has R^2 of 0.6842 while the R^2 of the same company in Model C2 is only 0.3797. It can been seen that the accounting fundamentals and S&P500 index explains 37.97 per cent of the variation in the stock prices of EMC Corporation, and including unobservable industry-wide shocks can explain another 30.45 per cent of the variation in its stock prices. Similar improvements are seen in all the other S&P100 IT companies. However, the stock price of EMC Corporation is more sensitive to the IT industry-wide shocks than other IT companies.

These empirical results demonstrate the strength of Model CF in explaining SPM. The unobserved industry-wide factors have statistically significant explanatory power for SPM and, therefore, Model CF is more properly specified compared to the other two models. From this, we can conclude that the major drivers behind stock prices of IT companies are observed market-wide common shocks and unobserved industry-wide shocks, rather than the accounting fundamentals of an individual company.

The results show that reactions to industry-wide shocks are varies for different companies. Some companies are more sensitive to industry-wide shocks, such as EMC Corporation. Some companies are not sensitive to industry-wide shocks, such as Microsoft.

4.3 Comparison across Various Industries

(Insert Table 7 here)

Having established the superiority of Model CF over the conventional Model C1 and Model C2 in explaining SPM for the IT industry, it would be meaningful to examine the robustness of Model CF's performance by investigating the R^2 of other industries. Table 7 presents the R^2 of Model CF and Model C2 for five other industries in S&P100 (estimated by Eq. (7)). For all industries, Model CF has higher R^2 than Model C2. This indicates that the findings in section 5.2 are robust. In particular, R^2 of Model C2 for the energy industry is 0.28, while that of Model CF is 0.59 — more than double of the former. For the utilities industry, R^2 of Model CF is more than triple of that of Model C2. For the finance and health care industries, Model CF can explain, approximately, an additional 20 per cent of variation in stock prices compared to Model C2. For the IT and industrial industries, more than 10 per cent additional variation in stock prices can be captured by Model CF.

It is shown that stock prices of companies from the energy, health care and utilities industries are more sensitive to industry-wide shocks. To a lesser extent, such common shocks also have an impact on stock prices of the IT, industrial and finance industries.

4.4 Robustness Test: Number of Common Factors

(Insert Table 8 here)

As we discussed in Section 4.2, since there are only three companies from the utilities industry in this study, we can only identify one common factor for this industry. For the sake of comparison we set a number of common shocks in Model CF as one for all industries and wanted to investigate the impact of such specifications on model performance in terms of fitting our stock return data. Table 8 reports R^2's of Model CF with one, two and three common shocks for all industries except for the utilities industry, which can only

accommodate models with one common factor. The results show that increasing the number of common shocks cannot make Model CF fit the data significantly better. In particular, for the IT industry, an increase in the number of common shocks has almost no impact on R^2 of the model. For the other four industries (industrial, energy, finance and health care), there is a minor improvement in R^2's when increasing the number of common shocks from one to two, such as an increase in R^2 from 0.52 to 0.59 for the industrial industry. Increasing the number of common factors from two to three has almost no impact, except the health care industry, and in some industries, such as energy and finance, R^2's are even reduced. These results demonstrate that our specification of one common shock is reasonable, and that increasing the number of shocks does not dramatically improve the model's performance.

5. Conclusion

This paper proposes a dynamic panel model with Bayesian approach to investigate the impact industry level shocks in equity markets. Company specific shocks are captured by an equity valuation model that takes advantage of financial statement information, while market wide common shocks are captured by equity market index. The model assesses unobserved industry level equity market shocks using a dynamic panel model with Bayesian approach.

There are four major findings from the empirical results of this study. 1) the impacts of observed accounting fundamentals and market-wide common shocks are heterogeneous across companies coming from the same industry. 2) Market-wide common shocks show more significant explanatory compare to accounting fundamentals. 3) Unobservable industry-wide shocks explain a considerable part of SPM. 4) The extents of reactions to unobservable industry-wide shocks are different across companies. Reactions to unobservable industry-wide shocks are also different across industries, with some industries, such as energy, health care and utilities, being more sensitive than the IT, industrial and finance industries.

Tables and Figures

Table 1 Breusch and Pagan's Test of Cross-Section Dependence

This table reports the cross-sectional dependence tests for six industries over period 2003-2012.

	IT	Industrial	Energy	Finance	Health Care	Utilities
Degree freedom	55	78	28	45	55	3
CD_{LM}	183	234	371	441	346	55

Table 2 Sample Companies from the IT Industry

This table reports the 11 sample companies in the IT Industry.

Apple Inc.	Dell	International Business Machines	Oracle Corporation
Accenture Plc.	EMC Corporation	Intel Corporation	Qualcomm Inc.
Cisco System	Hewlett Packard	Microsoft	

Table 3 Estimated Coefficients of Observed Factors for the IT Industry from Model CF

This table reports the estimation results of (15) for all 11 sample companies in the IT sector. Column 'Estimate' reports the estimated coefficients, Std reports the standard error of the estimated coefficients, CI reports the 95% confidence interval. Variable x is earnings divided by the beginning-of-period market value of equity; variable Δq is profitability change; capital investment, variable Δb, is the change in the book value of equity relative to the prior month; variable Δr is the discount rate (10-year US Treasury bond yield) change over the return period; variable SP500 is the S&P500 index return. The sample consists of 11 firm-year observations over the period 2003–2012.

Apple Inc

	Estimate	Std	95% CI
x	-1.6936	1.7674	(-5.1657, 1.7444)
Δq	-4.6425	6.5265	(-17.579, 8.3076)
Δb	2.0254	0.3939	(1.2574, 2.7924)
Δr	0.1426	0.2886	(-0.4243, 0.7073)
SP500	1.2218	0.2237	(0.7758, 1.6576)

Accenture plc

	Estimate	Std	95% CI
x	0.4542	0.3473	(-0.2254, 1.1313)
Δq	-0.7904	3.3818	(-7.3441, 5.7851)
Δb	-0.0217	0.0924	(-0.2028, 0.1577)
Δr	-0.0871	0.2839	(-0.6469, 0.4608)
SP500	0.9257	0.1144	(0.7001, 1.1511)

Cisco System

	Estimate	Std	95% CI
x	-0.3379	0.4660	(-1.2696, 0.5722)
Δq	10.3445	6.7426	(-2.8156, 23.708)
Δb	-0.0902	0.1559	(-0.3958, 0.2159)
Δr	-0.1777	0.1384	(-0.4508, 0.0946)
SP500	1.3435	0.1367	(1.0779, 1.6098)

Dell

	Estimate	Std	95% CI
x	-0.8304	0.7502	(-2.3010, 0.6343)
Δq	-0.8990	3.9800	(-8.6342, 6.9031)
Δb	-0.0994	0.1209	(-0.3406, 0.1398)
Δr	-0.0868	0.3423	(-0.7469, 0.5861)
SP500	1.3613	0.1642	(1.0379, 1.6801)

EMC Corporation

	Estimate	Std	95% CI
x	0.3083	1.0673	(-1.7994, 2.4126)
Δq	-3.2525	5.9631	(-14.793, 8.4963)
Δb	-0.0840	0.3460	(-0.7604, 0.5939)
Δr	-0.0667	0.0969	(-0.2554, 0.1228)
SP500	1.3198	0.1561	(1.0108, 1.6270)

Hewlett Packard

	Estimate	Std	95% CI
x	0.2591	0.2746	(-0.2703, 0.8001)
Δq	0.6026	0.3785	(-0.1338, 1.3421)
Δb	-0.3546	0.2698	(-0.8817, 0.1792)
Δr	-0.0302	0.0865	(-0.1972, 0.1396)
SP500	1.1709	0.1343	(0.9072, 1.4375)

International Business Machines

	Estimate	Std	95% CI
x	0.3211	0.3658	(-0.4112, 1.0421)
Δq	-2.1763	1.3670	(-4.8392, 0.5149)
Δb	0.0044	0.0979	(-0.1885, 0.1986)
Δr	-0.0869	0.1265	(-0.3326, 0.1645)
SP500	0.7510	0.0956	(0.5617, 0.9386)

Intel Corporation

	Estimate	Std	95% CI
x	-0.5264	0.4407	(-1.3925, 0.3307)
Δq	4.6541	2.9327	(-1.0709, 10.441)
Δb	1.5060	0.7528	(0.0288, 2.9841)
Δr	-0.0968	0.1007	(-0.2940, 0.1017)
SP500	1.1706	0.1345	(0.9016, 1.4339)

Microsoft

	Estimate	Std	95% CI
x	-0.2348	0.3546	(-0.9304, 0.4510)
Δq	1.1018	2.2772	(-3.3573, 5.5670)
Δb	0.3644	0.2323	(-0.0993, 0.8194)
Δr	0.1579	0.1890	(-0.2152, 0.5212)
SP500	0.9204	0.1158	(0.6889, 1.1447)

Oracle Corporation

	Estimate	Std	95% CI
x	0.3819	0.4432	(-0.5117, 1.2434)
Δq	1.4581	2.6409	(-3.5877, 6.6771)
Δb	-0.1382	0.1720	(-0.4681, 0.2028)
Δr	-0.0787	0.1525	(-0.3802, 0.2237)
SP500	1.1977	0.1236	(0.9521, 1.4385)

Qualcomm Inc

	Estimate	Std	95% CI
x	-1.9100	1.1160	(-4.1181, 0.2935)
Δq	-0.1622	6.3623	(-12.703, 12.321)
Δb	1.8329	0.5274	(0.8054, 2.8707)
Δr	-0.4439	0.1869	(-0.8079, -0.0794)

SP500	1.0112	0.1721	(0.6695, 1.3405)

Table 4 Estimated Coefficients of Observed Factors for the IT Industry from Model C1

This table reports the estimation results of (18) for all 11 sample companies in the IT sector. Column 'Estimate' reports the estimated coefficients, Std reports the standard error of the estimated coefficients. Variable x is earnings divided by the beginning-of-period market value of equity; variable Δq is profitability change; capital investment, variable Δb, is the change in the book value of equity relative to the prior month; variable Δr is the discount rate (10-year US Treasury bond yield) change over the return period; variable SP500 is the S&P500 index return. The sample consists of 11 firm-year observations over the period 2003–2012.

	Apple Inc			Accenture plc			Cisco System		
	Estimate	Std	t-stat	Estimate	Std	t-stat	Estimate	Std	t-stat
x	-2.1898	1.6731	-1.3088	0.6654	0.3723	1.7873	0.0780	0.5602	0.1392
Δq	-2.2576	7.3073	-0.3090	-4.7480	4.1036	-1.1570	10.9510	9.7302	1.1255
Δb	2.5616	0.9197	2.7853	0.0760	0.1122	0.6774	-0.0045	0.2245	-0.0200
Δr	0.4460	0.3042	1.4661	0.4379	0.3339	1.3115	0.1484	0.1818	0.8163

	Dell			EMC corporation			Hewlett Packard		
	Estimate	Std	t-stat	Estimate	Std	t-stat	Estimate	Std	t-stat
x	-0.4294	0.4711	-0.9115	0.3538	0.8396	0.4214	0.2536	0.1702	1.4900
Δq	1.5334	5.3733	0.2854	5.1663	8.3891	0.6158	0.6996	0.5614	1.2462
Δb	0.0484	0.1598	0.3029	0.5956	0.4922	1.2101	-0.2756	0.3758	-0.7334
Δr	0.5932	0.4225	1.4040	0.0757	0.1148	0.6594	0.1209	0.1005	1.2030

	International Business Machines			Intel Corporation			Microsoft		
	Estimate	Std	t-stat	Estimate	Std	t-stat	Estimate	Std	t-stat
x	0.5190	0.2727	1.9032	-0.4070	0.4329	-0.9402	-0.0126	0.3624	-0.0348
Δq	-1.4852	1.7536	-0.8469	6.1426	3.9689	1.5477	2.0285	2.8121	0.7213
Δb	0.1345	0.1323	1.0166	2.6760	1.0311	2.5953	0.3940	0.2768	1.4234
Δr	0.1220	0.1532	0.7963	0.0770	0.1259	0.6116	0.4770	0.2379	2.0050

	Oracle Corporation			Qualcomm Inc		
	Estimate	Std	t-stat	Estimate	Std	t-stat
x	0.6939	0.5581	1.2433	-2.3679	1.0555	-2.2434
Δq	3.9501	3.7735	1.0468	6.7666	6.7856	0.9972
Δb	0.0876	0.2569	0.3410	2.8836	0.7755	3.7184
Δr	0.2776	0.1906	1.4565	-0.3230	0.2141	-1.5086

Table 5 Estimated Coefficients of Observed Factors for the IT Industry from Model C2

This table reports the estimation results of (19) for all 11 sample companies in the IT sector. Column 'Estimate' reports the estimated coefficients, Std reports the standard error of the estimated coefficients. Variable x is earnings divided by the beginning-of-period market value of equity; variable Δq is profitability change; capital investment, variable Δb, is the change in the book value of equity relative to the prior month; variable Δr is the discount rate (10-year US Treasury bond yield) change over the return period; variable SP500 is the S&P500 index return. The sample consists of 11 firm-year observations over the period 2003–2012.

	Apple Inc			Accenture plc			Cisco System		
	Estimate	Std	t-stat	Estimate	Std	t-stat	Estimate	Std	t-stat
x	-1.6423	1.5019	-1.0935	0.5105	0.3010	1.6960	-0.2605	0.4140	-0.6292
Δq	-6.0727	6.5831	-0.9225	-1.6415	3.3335	-0.4924	8.8070	7.1692	1.2284
Δb	2.0483	0.8293	2.4699	-0.0237	0.0914	-0.2593	-0.0542	0.1654	-0.3277
Δr	0.1283	0.2788	0.4602	-0.0822	0.2773	-0.2964	-0.1568	0.1374	-1.1412
SP500	1.2277	0.2285	5.3729	0.9210	0.1173	7.8517	1.3388	0.1364	9.8152

	Dell			EMC corporation			Hewlett Packard		
	Estimate	Std	t-stat	Estimate	Std	t-stat	Estimate	Std	t-stat
x	-0.7980	0.3735	-2.1365	0.4034	0.6653	0.6063	0.2913	0.1312	2.2203
Δq	-1.4026	4.2451	-0.3304	-2.2494	6.7081	-0.3353	0.6293	0.4325	1.4550
Δb	-0.0285	0.1261	-0.2260	-0.0324	0.3974	-0.0815	-0.3497	0.2896	-1.2075
Δr	-0.0457	0.3413	-0.1339	-0.0737	0.0928	-0.7942	-0.0322	0.0793	-0.4061
SP500	1.3521	0.1613	8.3825	1.3115	0.1591	8.2432	1.1725	0.1324	8.8557

	International Business Machines			Intel Corporation			Microsoft		
	Estimate	Std	t-stat	Estimate	Std	t-stat	Estimate	Std	t-stat
x	0.3730	0.2223	1.6779	-0.5723	0.3394	-1.6862	-0.1786	0.2931	-0.6093
Δq	-2.4030	1.4294	-1.6811	5.2574	3.1084	1.6914	0.8973	2.2731	0.3947
Δb	-0.0250	0.1094	-0.2285	1.8256	0.8132	2.2450	0.3154	0.2236	1.4106
Δr	-0.0782	0.1271	-0.6153	-0.0988	0.1007	-0.9811	0.1472	0.1964	0.7495
SP500	0.7529	0.0978	7.6984	1.1599	0.1363	8.5099	0.9210	0.1173	7.8517

	Oracle Corporation			Qualcomm Inc		
	Estimate	Std	t-stat	Estimate	Std	t-stat
x	0.4718	0.4174	1.1303	-1.8673	0.9498	-1.9660
Δq	1.0202	2.8348	0.3599	-2.0903	6.2961	-0.3320
Δb	-0.1286	0.1932	-0.6656	1.8864	0.7188	2.6244
Δr	-0.0752	0.1471	-0.5112	-0.4263	0.1927	-2.2122
SP500	1.1937	0.1254	9.5191	1.0183	0.1894	5.3765

Table 6 R^2 of Model CF, Model C1 and Model C2 for Companies from the IT Industry

This table reports the estimation of R^2 for all 11 sample companies in the IT sector for Model C1 and C2, indicated in equation (18) and (19), respectively. The sample consists of 11 firm-year observations over the period 2003–2012.

Company	Model CF	Model C1	Model C2
Apple Inc.	0.3369	0.0446	0.2404
Accenture Plc.	0.4015	0.0152	0.3650
Cisco System	0.6362	0.0179	0.4721
Dell	0.5614	0.0348	0.4070
EMC Corporation	0.6842	0.0033	0.3797
Hewlett Packard	0.5214	0.0735	0.4551
International Business Machines	0.4694	0.0357	0.3693
Intel Corporation	0.6288	0.0899	0.4473
Microsoft	0.4117	0.0414	0.3816
Oracle Corporation	0.6160	0.0163	0.4562
Qualcomm Inc.	0.3515	0.1178	0.2988

Table 7 R^2 of Model CF and Model C2 for All Industries

This table reports the estimation of R^2 for six industries over the period 2003–2012.

	IT	Industrial	Energy	Finance	Health Care	Utilities
Model C2	0.34	0.40	0.28	0.34	0.14	0.14
Model CF	0.51	0.52	0.59	0.56	0.35	0.49

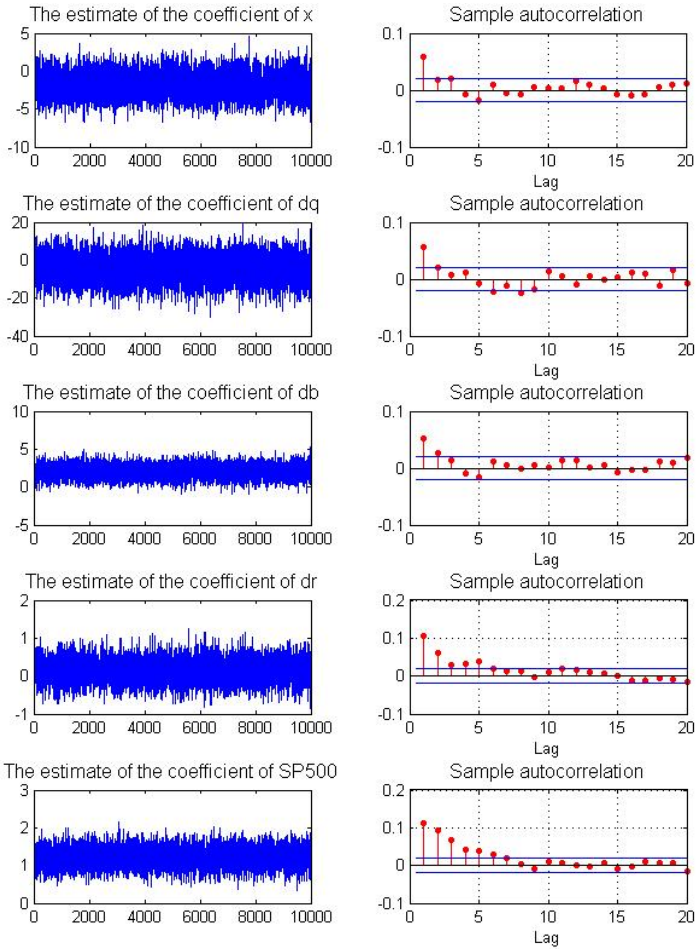
Table 8 R^2 of Model CF with Different Specification on Number of Common Shocks

This table reports the estimation of R^2 for six industries with different number of factors over the period 2003–2012.

	IT	Industrial	Energy	Finance	Health Care
Model CF (one factor)	0.51	0.52	0.59	0.56	0.35
Model CF (two factors)	0.51	0.59	0.65	0.63	0.37
Model CF (three factors)	0.51	0.60	0.63	0.62	0.42

Figure 1 MCMC Sample Paths and ACFs of Coefficients Estimated from Model CF for Apple Inc.

This figure reports the sample paths and ACFs of coefficients estimated from model CF for Apple company. Variable x is earnings divided by the beginning-of-period market value of equity; variable Δq is profitability change; capital investment, variable Δb, is the change in the book value of equity relative to the prior month; variable Δr is the discount rate (10-year US Treasury bond yield) change over the return period; variable SP500 is the S&P500 index return.



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