Sources of the Stock Price Fluctuations in Chinese Equity Market

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Abstract: This paper proposes a latent factor approach based on a state-space framework in order to identify which factor, if any, dominates price fluctuations in the Chinese stock markets. We also illustrate the connection of such stock price decomposition with several general equilibrium asset pricing models and show that the decomposition results can potentially offer useful insights with regard to the empirical relevance of asset pricing models. We use quarterly data of the Chinese A-Share equity market over the period 1995Q3-2011Q1 and find that the estimates of the state-space model suggest that the expected return is the primary driving force behind price fluctuations in the Chinese stock market. We show that the time-varying expected returns appear to be counter-cyclical and this result seems to be consistent with the habit formation model of Campbell and Cochrane (1999). However, we also note that there is a great deal of uncertainty with respect to this variance decomposition due to the resulting small signal-to-noise ratio in the estimated state-space model.

1. Introduction

A little more than ten years after the beginning of the reform and opening-up policy, China established the Shanghai Stock Exchange and Shenzhen Stock Exchange in order to further deepen the market-oriented policy reform in the financial sector. When Chinese stock exchange markets first opened in 1991 there were only a handful of companies listed in both markets. Over the next twenty years the world has witnessed rapidly-expanding Chinese equity markets. By the end of 2010, the Shanghai Stock Exchange has risen to become the 5th largest stock market measured by market capitalization with a value of about 2.7 trillion US dollars and there are over 2000 listed companies in both markets. Combining both the Shanghai Stock Exchange and the Shenzhen Stock Exchange, the Chinese stock market has become the 3rd largest stock market in the world.

Despite its respectful size the Chinese stock exchange market has a number of important features that distinguish it from the other well developed equity markets and naturally render it an intriguing subject of study. First of all, since its advent, the Chinese stock exchange markets have been very volatile and heavily influenced by government policies. This high volatility is partly the result of the intrinsic characteristics of the Chinese economy as an emerging economy. Since the stock market was first instituted many relevant security laws and regulatory institutions were not immediately available at the beginning but were only gradually established during the twenty years of development. Second, because the Chinese economy has been a transition economy, many listed companies previously were wholly owned by the state before being listed in the stock exchange market and resulting in a mixture of ownerships. The state-owned shares were not allowed to be freely traded until 2005. The coexistence of the non-tradable and tradable shares prior to that point in time had been an important characteristic of the Chinese stock markets. Lastly, owing to a need for capital controls, the Chinese stock markets have separate classes of shares, namely the domestic-only shares (aka A-share) and the foreign-only shares (aka B-share). Prior to 2001, domestic investors are primarily restricted to the investment in A-share market while the foreign investors can only invest in B-share market. Fernald and Rogers (2002) document a few anomalies between the prices of these two separate classes of shares.

In this paper we focus our work primarily on the A-share market in order to study sources of the price fluctuations of those shares that are accessible by the domestic investors. In particular we rely on several general equilibrium asset pricing models to decompose stock prices into various components and build a latent factor[1] model based on a state-space framework to identify the primary driving force behind fluctuations in the Chinese stock prices. Although such a study is interesting in its own right, we also aim to shed light on the controversial topic in finance related to whether it is the cash flow component or the discount factor that dominates aggregate stock price fluctuations.

Asset pricing theory shows us that stock prices fluctuate as a result of movements in either expected future dividend growth or expected future returns (the discount rate). The work of Campbell and Shiller (1988a, 1988b) show that if a valuation measure such as the price dividend ratio can predict stock returns, this implies that expected future returns will have some contribution to movements in the price-dividend ratio. However, the low R^2 found in these stock return predictability regressions implies that a large portion of stock price movements remain unexplained. Unexpected variations in stock prices must be due to revisions in investors' expectations about future dividends and/or revisions to expected returns. Campbell (1991) notes that if one assumes no speculative bubbles, then unexpected stock returns can be decomposed into changes in expectations of future dividend growth, real interest rates, and excess stock returns. Campbell (1991), employing a vector autoregressive (VAR) return decomposition approach, notes that the impact of revisions in expectations of future expected returns on current stock prices depends not only on the degree of return predictability, but also on the time series properties of expected returns. Specifically, even if stock return predictability is low, news about expected future returns can have a large effect on stock price movements provided that expected returns are persistent.

Campbell (1991) and Campbell and Ammer (1993) find that news about future excess returns is the primary factor behind movements in US stock returns, with news about future dividends, and real interest rates, contributing much less to movements in US stock returns. Cuthbertson et al. (1999) finds similar results for the UK. In particular, they employ annual data over the period 1918-1993 and find that news about future discount rates contributes about four times more to movements in UK stock prices than do news about future dividends. Furthermore Valckx (2004) decomposes US and Euro area excess stock and bond returns using similar methodology and finds that it is the future returns news that are primarily responsible for the returns fluctuations.

Recent work by Balke and Wohar (2002), and Binsbergen and Koijen (2010), employing US data, have applied an alternative estimation procedure to the VAR return decomposition pioneered by Campbell and Shiller (1988a, 1988b) and Campbell (1991) and discussed above. This estimation method is called a state-space model. This method can be preferable to the VAR return decomposition approach because it directly models and estimates the expectations processes of the variables of the model. The state-space framework has the advantages of modeling the expectations directly as latent factors and capturing the long-run serial correlations that a VAR model, with a finite number of lags, would have difficulty in doing. The latter point comes from the fact that the state-space model typically results in a moving averaging term in the reduced-form. Jiang, Rapach, Strauss, Tu, and Zhou (2011) find that various valuation ratios, including the price-dividend ratio, have predictive power for both aggregate as well as industry returns for China A-share stocks listed in Shanghai and Shenzhen stock exchanges.[2] As discussed above, this finding implies that expected future returns contribute to movements in the price-dividend ratio for China. This paper employs the state-space modeling methodology combined with the Campbell and Shiller (1988a) return decomposition technique to determine the relative contribution of the expected future returns and expected future dividend growth to Chinese equity price fluctuations.

This paper is organized as follows. Section 2 surveys several general equilibrium asset pricing models and provides a stock price decomposition model. Section 3 proposes a latent factor approach based in the state-space framework. Section 4 discusses data and presents the estimation results. Section 5 offers the stock price variance decomposition and discusses the uncertainty around such decomposition. Section 6 provides further economic analysis of the estimated time-varying expected returns. Section 7 concludes.

2. The Theoretical Framework of Stock Price Decomposition

Consider a contingent claim in an endowed economy that pays dividends D_{t+1} during the period *t+1*, with the equity price, P_{t+1} at the end of period *t+1*. The price of this equity at the end of period *t* is given by[3]:

$$P_t = E_t\left[M_{t+1} \cdot \left(P_{t+1} + D_{t+1}\right)\right] \quad (2.1)$$

Or

$$1 = E_t \left[M_{t+1} \cdot R_{t+1} \right] \quad (2.2)$$

Where, $R_{t+1} = \dfrac{P_{t+1} + D_{t+1}}{P_t}$ is the total equity return; M_{t+1} is the Stochastic Discount Factor (SDF), the covariance of and the payment of the contingent claim determines the price of the contingent claim in a stochastic environment. Therefore, only the part of the payment fluctuations that are correlated with the SDF will be priced in the equilibrium.

Depending on the utility specifications the SDF may involve different types of risks. For example, the standard CRRA (Constant-Relative-Risk-Aversion) utility specification as in Merha and Prescott (1985) implies the SDF involves only consumption risk:

$$m_{t+1} = \ln \delta - \gamma \cdot \Delta c_{t+1} \quad (2.3)$$

Throughout this paper, we use lowercase letters to denote the log variables, e.g., $m_{t+1} = \ln M_{t+1}$ and $c_{t+1} = \ln C_{t+1}$. Where, δ is the subjective discount factor, γ is the risk aversion parameter, and C_{t+1} is the aggregate consumption. Therefore, standard CRRA utility function offers only one type of risk source – consumption risk – and it has not been successful in explaining the equity price fluctuations, e.g., the equity premium puzzle of Merha and Prescott (1985) and the volatility puzzle of Shiller (1981).

Alternative utility specifications have been proposed in the literature to introduce additional risk sources to help explain the equity price fluctuations. Campbell and Cochrane (1999) propose a type of habit-formation utility specification and highlight the discount factor as the primary driving force of the equity price variation. In their model the SDF involves not only consumption risk but also a type of habit risk:

$$m_{t+1} = \ln \delta - \gamma \cdot \Delta c_{t+1} - \gamma \cdot \Delta s_{t+1} \quad (2.4)$$

Where, s_{t+1} is defined as the relative size of current consumption to the average past consumption as a way to represent the habit formed by the economic agent. Because the habit variable is pro-cyclical it makes the equity price riskier. Therefore they show that the stock price variation may be largely driven by the discount factor.

Bansal and Yaron (2004) build upon the Epstein-Zin (1989) and Weil (1989) recursive utility function and stress the importance of the long run consumption risk. In their model the SDF involves not only consumption risk but the market portfolio risk:

$$m_{t+1} = \theta \ln \delta - \frac{\theta}{\psi} \Delta c_{t+1} - (1-\theta) r_{m,t+1} \tag{2.5}$$

Where, $\theta = \frac{1-\gamma}{1-{}^{1}\!/\!_{\psi}}$, ψ is the Intertemporal Elasticity of Substitution (IES), and r_m is the market portfolio return. Bansal and Yaron (2004) finds that the stock price variation may be largely explained by the consumption or dividends risks.

In this paper we adopt the methodology of Campbell and Shiller's (1988a) to decompose the price-dividend ratio into expected future dividends and expected future returns in order to quantitatively document and compare each of their contributions to stock price variation. Such decomposition exercise can potentially provide empirical support for either the habit-formation model or the long run risk model.

By definition the gross stock return is:

$$r_{t+1} = \ln\left(\frac{P_{t+1} + D_{t+1}}{P_t}\right) \tag{2.6}$$

After some algebra we can show the RHS takes the following expression:

$$r_{t+1} = \Delta d_{t+1} + \ln\left(1 + \exp\left(pd_{t+1}\right)\right) - pd_t \tag{2.7}$$

Where, $pd = \ln(P/D)$. Take a first-order Taylor expansion of the RHS around the steady state $E[pd]$, to obtain the following approximation:

$$r_{t+1} \approx \kappa + \Delta d_{t+1} + \rho \cdot pd_{t+1} - pd_t \tag{2.8}$$

Where, $\rho = \dfrac{\exp(E[pd_t])}{1+\exp(E[pd_t])}$, and the constant $\kappa = \log(1+\exp(E[pd_t])) - \rho \cdot E[pd_t]$. Plug (2.8) into (2.2) and assume log-normality to obtain:

$$\begin{aligned} pd_t &= E_t \Delta d_{t+1} - \left(-E_t m_{t+1} - Cov\left(m_{t+1}, \Delta d_{t+1} + \rho \cdot pd_{t+1}\right)\right) + \rho \cdot E_t pd_{t+1} \\ &+ \frac{1}{2} Var_t\left(m_{t+1}\right) + \frac{1}{2} Var_t\left(\Delta d_{t+1} + \rho \cdot pd_{t+1}\right) \end{aligned} \tag{2.9}$$

Where, the second line comes from the convexity adjustment term due to Jensen's inequality. The first term $E_t \Delta d_{t+1}$ on the RHS represents dividends endowment risk. The term $\left(-E_t m_{t+1} - Cov\left(m_{t+1}, \Delta d_{t+1} + \rho \cdot pd_{t+1}\right)\right)$ may be thought of as the equity return or the discount factor. Since the risk free rate is:

$$i_{t+1} = -E_t m_{t+1} \tag{2.10}$$

the term $-Cov\left(m_{t+1}, \Delta d_{t+1} + \rho \cdot pd_{t+1}\right)$ is essentially the equity risk premium. For equities whose payments are negatively correlated with the SDF, m_{t+1}, the risk-averse agent typically requires a positive premium to hold them and this is also why agents need to pay a premium to acquire any usual insurance plan that is typically positively correlated with SDF. Eq. (2.9) may be easily iterated forward to show that the price dividend ratio is the sum of discounted future dividend growth with the future discount rate being stochastic.

In this paper we focus on the stock price decomposition approach of Campbell and Shiller (1988a). By iterating (2.8) forward, taking conditional expectations on both sides, and excluding the explosive solution, we obtain:

$$pd_t = \frac{\kappa}{1-\rho} + E_t \sum_{j=0}^{\infty} \rho^j \left(\Delta d_{t+1+j} - r_{t+1+j} \right) \qquad (2.11)$$

The price-dividend ratio measures current stock price and can tell whether a particular equity is pricey relative to its dividends payments. The stock price decomposition result in (2.11) essentially states that if the price-dividend varies, then the variation must be traced to either the agent's varying expectation of future dividends growth or future returns. It is important to study which component of the above two is primarily responsible for the price-dividend variation. From a theoretical perspective, the result of this investigation can tell us where most equity risks originate and thus direct us to essentially where all the risk sources are. It enables us to judge which type of asset pricing model is empirically more relevant. From a practical perspective, it makes sense to act as a fundamental investor in a world where the dividends are primarily driving the stock price variation.

In order to implement such variance decomposition we need to have knowledge of the RHS of (2.11). However, economists do not directly observe the agent's expectations of future dividends growth and future returns. Therefore, we must apply certain econometric techniques and use available information to estimate them. Most literature that decomposes the stock price into expected returns and expected dividend growth employs the decomposition procedure followed Campbell (1991) and employ the Vector Auto-Regression (VAR) type model to estimate the unobserved expectations for the price dividend variance decomposition. There are a number of advantages to using an alternative state-space approach over that of the VAR methodology. For example, the state-space model is very natural when it comes to estimating the unobserved expectations because it can directly model these expectations as latent factors and efficiently filter them out from the observed variables under certain restrictions. Furthermore, when compared with the VAR. Another favorable feature of the state-space model is that it can capture the long-run serial correlations potentially present in the data that a VAR (with finite number of lags) would have difficulty in doing since the state-space model usually corresponds to a reduced-form of the Vector Auto-Regressive-Moving-Average (VARMA) model.[4]

3. A State-Space Model of the Stock Price Decomposition

Suppose the latent expectations are defined as $g_t = E_t[\Delta d_{t+1}]$ and $\mu_t = E_t[r_{t+1}]$ and that they both follow the stationary AR(1) processes[5]:

$$(1-\phi_g L)\cdot(g_t - a_g) = \varepsilon_t^g \tag{3.1}$$

$$(1-\phi_\mu L)\cdot(\mu_t - a_\mu) = \varepsilon_t^\mu \tag{3.2}$$

Where, $\varepsilon_t^i, i = g, \mu$ are shocks to the expectation processes and $Var(\varepsilon_t^g) = \sigma_g^2, Var(\varepsilon_t^\mu) = \sigma_\mu^2$. We also have: $Cov(\varepsilon_t^i, \varepsilon_s^j) = 0$ if $t \neq s$ for $i = g, \mu$. Then the realized dividends growth and returns are the sum of their expected values and the realized (news) shocks:

$$\Delta d_{t+1} = g_t + \varepsilon_{t+1}^d \tag{3.3}$$

$$r_{t+1} = \mu_t + \varepsilon_{t+1}^r \tag{3.4}$$

Where, ε_{t+1}^d and ε_{t+1}^r are news shocks to the realized dividend growth and the realized returns, and with variances $Var(\varepsilon_{t+1}^d) = \sigma_d^2, Var(\varepsilon_{t+1}^r) = \sigma_r^2$. We also have: $Cov(\varepsilon_t^i, \varepsilon_s^j) = 0$ if $t \neq s$ for $i = d, r$.

We write out the variance matrix of the above four shocks:

$$Var\begin{pmatrix} \varepsilon_{t+1}^{g} \\ \varepsilon_{t+1}^{\mu} \\ \varepsilon_{t+1}^{d} \\ \varepsilon_{t+1}^{r} \end{pmatrix} = \begin{bmatrix} \sigma_g^2 & \times & \times & \times \\ \sigma_{g\mu} & \sigma_\mu^2 & \times & \times \\ \sigma_{gd} & \sigma_{\mu d} & \sigma_d^2 & \times \\ \sigma_{gr} & \sigma_{\mu r} & \sigma_{dr} & \sigma_r^2 \end{bmatrix} \tag{3.5}$$

Integrating the above specifications into the variance decomposition (2.11), we obtain:

$$E_t \sum_{j=0}^{\infty} \rho^j \left(\Delta d_{t+1+j}\right) = \left(1-\rho\phi_g\right)^{-1} \cdot g_t + \frac{a_g}{1-\rho} \tag{3.6}$$

$$E_t \sum_{j=0}^{\infty} \rho^j \left(r_{t+1+j}\right) = \left(1-\rho\phi_\mu\right)^{-1} \cdot \mu_t + \frac{a_\mu}{1-\rho} \tag{3.7}$$

Therefore (2.11) becomes:

$$pd_t = \frac{\kappa}{1-\rho} + \frac{a_g - a_\mu}{1-\rho} + \left(1-\rho\phi_g\right)^{-1} \cdot g_t - \left(1-\rho\phi_\mu\right)^{-1} \cdot \mu_t \tag{3.8}$$

Thus (3.8) states that sources of the stock price variations can come either from the expected future dividends growth ($\left(1-\rho\phi_g\right)^{-1} \cdot g_t$) or the expected future returns ($\left(1-\rho\phi_\mu\right)^{-1} \cdot \mu_t$) or the comovement between these two.

Cochrane (2008b) points out that the Campbell-Shiller identity implicitly imposes a restriction that ties together the four shocks $\varepsilon_{t+1}^{g}, \varepsilon_{t+1}^{\mu}, \varepsilon_{t+1}^{d}, \varepsilon_{t+1}^{r}$. Therefore the variance matrix (3.5) has a reduced rank and once we specify the variance matrix for any three of them the whole variance matrix of the four shocks can be readily derived. To explicitly show this restriction, we plug (3.3) and (3.8) into the identity (2.8) and obtain:

$$\varepsilon_{t+1}^{r} = \varepsilon_{t+1}^{d} + \rho\left(1-\rho\phi_g\right)^{-1} \cdot \varepsilon_{t+1}^{g} - \rho\left(1-\rho\phi_\mu\right)^{-1} \cdot \varepsilon_{t+1}^{\mu} \tag{3.9}$$

Also see Ma and Wohar (2011) for a general condition for any arbitrary number of lags.

Because of the identity, one only needs to choose two out of the three observed variables $\Delta d_{t+1}, pd_{t+1}, r_{t+1}$ to estimate the state-space model. The last variable can be easily backed out from the identity. We follow Binsbergen and Koijen (2010) and select the pair of $\Delta d_{t+1}, pd_{t+1}$ for the estimation.[6]

In this case the state-space representation can be written out as below:

Measurement equation:

$$\begin{bmatrix} \Delta d_{t+1} \\ pd_{t+1} \end{bmatrix} = \begin{bmatrix} c_g \\ A \end{bmatrix} + \begin{bmatrix} 0 & 1 & 0 & 1 \\ B_2 & 0 & -B_1 & 0 \end{bmatrix} \begin{bmatrix} g_{t+1} - c_g \\ g_t - c_g \\ \mu_{t+1} - c_\mu \\ \varepsilon_{t+1}^d \end{bmatrix} \tag{3.10}$$

Transition equation:

$$\begin{bmatrix} g_{t+1} - c_g \\ g_t - c_g \\ \mu_{t+1} - c_\mu \\ \varepsilon_{t+1}^d \end{bmatrix} = \begin{bmatrix} \phi_g & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & \phi_\mu & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} g_t - c_g \\ g_{t-1} - c_g \\ \mu_t - c_\mu \\ \varepsilon_t^d \end{bmatrix} + \begin{bmatrix} \varepsilon_{t+1}^g \\ 0 \\ \varepsilon_{t+1}^\mu \\ \varepsilon_{t+1}^d \end{bmatrix} \tag{3.11}$$

Where, $A = \frac{\kappa}{1-\rho} + \frac{a_g - a_\mu}{1-\rho}, B_1 = \frac{1}{1-\rho\phi_\mu}, B_2 = \frac{1}{1-\rho\phi_g}$; three shocks $\begin{bmatrix} \varepsilon_{t+1}^g & \varepsilon_{t+1}^\mu & \varepsilon_{t+1}^d \end{bmatrix}$ are explicitly modeled and the last one is implicitly determined by the restriction (3.9).

Not all correlations are necessarily identified in the state-space model. Morley, Nelson and Zivot (2003) study the identification conditions for a univariate unobserved component model for trend and cycle decomposition for the output and find that rich dynamics (long lags p) is helpful in identifying the correlations. Cochrane (2008b) and Rytchkov (2008) study the state-space model that we adopt here and point out that the model is exactly identified with one additional restriction. Economic theory does not directly provide any clear instruction regarding which correlation to restrict. Binsbergen and Koijen (2010) impose an arbitrary restriction that the shocks to the expected dividends growth and realized dividends growth are orthogonal to each other. However, that leaves the possibility open that expected returns and expected dividends growth might be correlated with each other. The possibly correlated expected returns and expected dividends growth makes it less obvious how to attribute the stock price variation to each source. To circumvent this issue, we impose the restriction $\rho_{\mu g} = 0$ to not only achieve identification of the model but also make it easier to interpret the results.[7]

4. Data and Estimation

The data we use for our model estimation and the stock price decomposition is the DataStream China A Index, part of the DataStream Global Equity Index. The DataStream User Guide states that The China A Index consists of class A-share of mainland Chinese companies that are traded on the Shanghai and Shenzhen exchanges. We choose to study the class A-share market because it is accessible only by Chinese nationals and can reflect more accurately the investment behavior of the Chinese domestic investors as opposed to the class B-share market which receives the investment primarily from the foreign investors. We obtained the monthly capital gains and total returns of this particular index, from which we impute the dividends growth and the price-dividend ratios. To have a basic idea about how well this index has tracked the more standard indices such as the Shanghai Stock Exchange (SE) A Share price index, we plot these two in Figure 1. These two match each other very closely. We also observe that the correlation of the DataStream China A Index with the Shanghai SE A Share Index is about 0.98, and the correlation of that with the Shenzhen SE A Share Index is about 0.94. Overall, the

DataStream China A Index well represents the price fluctuations of the class *A* shares of the Chinese equity markets.

Based on the definition of total returns ($R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t}$) we compute the dividends:

$$D_{t+1} = P_t \left(R_{t+1} - \frac{P_{t+1}}{P_t} \right) \tag{4.1}$$

From here we compute the log dividends growth Δd_{t+1}, log price-dividend ratio pd_{t+1}, and also log total returns r_{t+1}.

To calculate quarterly dividends from monthly dividends we first add up the monthly dividends for each quarter. We then take a trailing average (to eliminate potential seasonality) of the past four quarter dividends to form dividends for the last quarter. We then divide the stock price for the last quarter by the dividend for that quarter and take the natural log to obtain the log price-dividend ratio. Similar calculations are done for other quarters. The log price-dividend ratio, dividends growth, and the total returns are all in annualized terms. The summary statistics are presented in Table 1. We choose to aggregate data to quarterly frequency because we notice that the monthly data is too volatile to work with[8].

Note that the A-Share market on average has delivered about 11% annual rate of return since 1995. Nonetheless, at the same time the Chinese stock market is also very volatile: the standard deviation of returns is 0.74, more than six times of the average return. In contrast, the standard deviation of US equity returns during the same period is only about 0.10. The price-dividend ratio is very persistent. However, the Augmented Dickey-Fuller test suggests that the series is stationary.

We write out the log-likelihood function of the above state-space model via the Kalman Filter (see Kim and Nelson (1999)), and maximize the function over the admissible parameter space, using our quarterly data. The state-space maximum likelihood estimation results are presented in Table 2.[9]

5. Variance Decomposition and Its Uncertainty

The estimations results reveal that the expected return is very persistent ($\hat{\phi}_\mu = 0.8280$). In contrast, the expected dividends growth is far less persistent ($\hat{\phi}_g = -0.3652$). The dynamics of the latent expectations have important consequences for stock price variation decomposition. To better understand these implications, consider equation (3.8) (dropping constants for illustration purpose):

$$pd_t = \frac{g_t}{1-\rho\phi_g} - \frac{\mu_t}{1-\rho\phi_\mu} \tag{5.1}$$

Taking the variance of both sides, we have the following variance decomposition result:

$$Var(pd_t) = \frac{1}{(1-\rho\phi_g)^2}\cdot Var(g_t) + \frac{1}{(1-\rho\phi_\mu)^2}\cdot Var(\mu_t) - \frac{2}{(1-\rho\phi_g)(1-\rho\phi_\mu)}\cdot Cov(g_t,\mu_t) \tag{5.2}$$

As a result the variation of the price-dividend ratio must come from either $\frac{1}{(1-\rho\phi_g)^2}\cdot Var(g_t)$ or $\frac{1}{(1-\rho\phi_\mu)^2}\cdot Var(\mu_t)$ or their covariance. One determinant to the relative size of the first two contributors is the relative variance of the expected dividends growth and the expected returns. The variance of these two latent factors in turn depends positively on the size of their expectations shocks and also the persistent dynamics of the expectations, i.e., ϕ_μ and ϕ_g, since

(3.1) and (3.2) imply directly $Var(g_t) = \sigma_g^2 / (1-\phi_g^2)$ and $Var(\mu_t) = \sigma_\mu^2 / (1-\phi_\mu^2)$. Furthermore, the relative size of the two contributors to the stock price variation are also positively influenced by their loadings $\frac{1}{(1-\rho\phi_g)^2}$ and $\frac{1}{(1-\rho\phi_\mu)^2}$. Interestingly, the persistence parameters ϕ_μ and ϕ_g can increase both the variance and their loadings. As a result, the more persistent expected return than the expected dividend growth ($\hat{\phi}_\mu >> \hat{\phi}_g$) tends to attribute most of the price-dividend variation to the expected returns but little to the expected dividends growth. Specifically, Table 3 presents the detailed stock price decomposition. The variation of expected return clearly dominates that of the expected dividends growth in explaining the price-dividend variation.

In efforts to further understand the uncertainties around these point estimates we follow Hamilton's (1986) approach that integrates both the filter uncertainty and parameter uncertainty through Monte Carlo simulations in order to construct confidence bands for both the variance decomposition and the estimated state variables. Specifically, for each simulation we take a random draw of the model parameters from a multivariate normal distribution that is centered on the parameter estimates in Table 2 with the estimated variance covariance matrix. We then use Kalman filter to calculate the filtered estimates and the filtered uncertainty. In the end we follow Hamilton's procedure to compute both the filter uncertainty and parameter uncertainty for all of the estimated state variables at each time point, and the total standard errors are the square root of the sum of these two uncertainties.

Figure 2 plots the realized dividends growth, the expected dividends growth and its lower and upper 95% confidence bands. Since the expected dividends growth is obtained by filtering out the news shock from the realized one, it is obviously less volatile. However, the difference between these two is not great, which indicates that a large part of the dividend growth is well expected and there is little surprise. This result is primarily driven by the estimated ratio signal-to-noise ratio $\sigma_g / \sigma_d = 0.5896$ as reported at the bottom of Table 2.[10]

Figure 3 plots the realized returns, expected returns and its lower and upper 95% confidence bands. It presents a very different picture from that of the dividends growth. The expected return is very persistent and appears much smoother than the realized one, which indicates that there is too much noise in the realized returns. This is much consistent with the small signal-to-noise ratio $\sigma_\mu / \sigma_r = 0.1282$ as reported at the bottom of Table 2.

Although the expected return is very smooth it appears to be able to explain the bulk of the stock price variation, primarily thanks to its high persistence as discussed above. To further visualize this we plot in Figure 4 the price-dividend ratio (pd_t), the contribution of the expected dividend growth ($\frac{g_t}{1-\rho\phi_g}$), and the contribution of the expected return ($-\frac{\mu_t}{1-\rho\phi_\mu}$), essentially the three terms in (5.1), along with the 95% confidence bands of the latter two estimates. Evidently, the contribution of expected return appears to track the price-dividend variation very well. Interestingly, although the confidence band for the estimated expected returns in Figure 3 tends to indicate that the estimation is very accurate here we notice that the contribution of the expected return is accompanied by a somewhat wider confidence band indicating a great deal of uncertainty.

The essential idea of the state-space approach is to filter out the expected return (signal) from the realized one (signal plus noise). The small signal-to-noise ratio for the expected return case is a concern and suggestive of potential uncertainty of the persistent estimate for the expected return dynamics. Intuitively, when the signal is too small relative to the noise there ought to be a great deal of uncertainty about the persistence estimate ϕ_μ. We resort to the inference strategy of Ma and Nelson (2010) to carefully document the potential uncertainty of the above variance decomposition.

Ma and Nelson (2010) find that state-space models are often subject to ZILC (Zero-Information-Limit-Condition) as formulated by Nelson and Startz (2007), and when the signal is small relative to noise, the standard error of the persistence parameter would appear far too small. Readers are referred to Ma and Wohar (2011) for a detailed proof that ZILC holds in this type of model. Ma and Nelson (2010) propose a reduced-form test based on a linear approximation to the exact test of Fieller (1954) for a ratio of regression coefficients to deal with this issue. They also illustrate that the test is also an LM test in the spirit of Breusch and Pagan (1980) and the proposed test has more correct size coverage than the standard *t*-test in finite sample when the signal is small relative to the noise.

To implement this test, write out the VARMA representation of the dividends growth and price-dividend ratio as below:

$$\begin{bmatrix} (1-\phi_g L) & 0 \\ 0 & (1-\phi_g L)(1-\phi_\mu L) \end{bmatrix} \begin{bmatrix} \Delta d_{t+1} \\ pd_{t+1} \end{bmatrix} = \begin{bmatrix} (1-\theta_1 L) & 0 \\ 0 & (1-\theta_2 L) \end{bmatrix} \begin{bmatrix} u_{1t+1} \\ u_{2t+1} \end{bmatrix} \qquad (5.3)$$

Where, the shocks $[u_{1t+1} \quad u_{2t+1}]'$ may be correlated.[11]

The calculation of the test is in two steps. In the first step we estimate the restricted VARMA under the null hypothesis $\phi_\mu = \phi_{\mu,0}$. In the second step, we run the following regression and compute the *t*-statistic for the null $\lambda = 0$:

$$(1-\widetilde{\phi}_g L) pd_{t+1} = \tau \cdot \sum_{i=1}^{\infty} \phi_{\mu,0}^{i-1} \widetilde{u}_{2t+1-i} + \lambda \cdot \sum_{i=2}^{\infty} (i-1) \cdot \phi_{\mu,0}^{i-2} \widetilde{u}_{2t+1-i} \qquad (5.4)$$

Where, (5.4) is a first-order Taylor expansion of the second equation of (5.3) around the null $\phi_\mu = \phi_{\mu,0}$; $\tau = \phi_\mu - \theta_2$, $\lambda = \tau \cdot (\phi_\mu - \phi_{\mu,1})$, $\widetilde{\phi}_{g,1}$ and $\widetilde{u}_{2t+1}$ are the restricted estimates under the null. The intuition of the test is simple: if the null $\phi_\mu = \phi_{\mu,0}$ is true then the first term in (5.4) should be enough to capture all serial correlations and the second term should be insignificant.

To produce a confidence interval for ϕ_μ, we calculate the reduced-form test statistics corresponding to each possible null . The 95% confidence interval includes these null values that give test statistics less than the 5% critical value. We apply this test procedure to the dataset and Figure 5 plots the resulting *t*-statistic for a sequence of nulls for ϕ_μ. The 95% confidence interval for ϕ_μ rejects some regions in the admissible parameter space but it is much wider than that based on the standard inference. Since the contributions depend critically on the expectations dynamics, in particular the persistence estimate, these findings raise a concern that the uncertainty of the above stock price decomposition can be very large.

6. Further Economic Analysis

Since the estimation results tend to suggest that the expected return is the important driving force for the Chinese equity price fluctuations it is potentially interesting to investigate further the series of estimated expected return and find out whether there is any co-movement of it with the macroeconomic fundamentals and relevant government actions. To this end we obtain the real GDP, industrial production index, and various deposit rates for China from Datastream. We calculate the real GDP growth rates, industrial production growth rates, and the yield spread as defined by the difference between the 5-year deposit rate minus the 3-month deposit rate. Then we regress the expected returns onto its lagged level (due to its high persistence), the GDP growth rates, the industrial production growth rates, and the yield spread respectively. The results are given in Table 4.

First of all, since we are primarily interested in the correlation/co-movement between the expected returns and the macroeconomic indicators the usage of the contemporaneous variables does not invalidate the regression results. The estimation results seem to suggest that there is a negative correlation between the economy activity and the expected returns. In Model 2 where the industrial production growth rate is an explanatory variable it turns out to be significantly negative. In Model 3 the point estimate for the GDP growth rate is also negative although it is not statistically significant. Overall, the results seem to suggest that the expected return is counter-cyclical. Interestingly this finding is partly consistent with the implication of the habit formation model of Campbell and Cochrane (1999): as the economy is booming the effective risk aversion declines, the asset price increases and the expected return decreases as a result; as the recession deepens, the effective risk aversion increases, asset price fall and the expected return increases. However, we do note that since only correlation can be established in the type of regression exercise we do here the causality could also go in the opposite direction. We also regress the expected returns onto the yield spread variable but find it not much insignificant and amount of increase of the adjusted R^2 in Model 4 is very minimal compared with the benchmark Model 1.

Besides trying to link the expected returns with the macroeconomic fundamentals in the above analysis we also attempt to provide a couple of cases studies as a piece of evidence supporting the notion that the Chinese equity market has also been heavily influenced by the government policies. To facilitate the illustration we plot the expected return series in Figure 6. For example, near the end of 2001Q2 the government announced the Interim Measures of the

State Council on the Management of Reducing Held State Shares and Raising Social Security Funds that conveys to the public the government's intention to sell the state-owned shares to the general public. This generated a great of uncertainty among the investors and as a result the equity prices fell and the expected return went up. Another example is more gradual and related with the biggest rally of the Chinese stock market beginning at the end of 2004 and the beginning of 2005. Near the end of 2002 the Chinese government launched the so-called Qualified Foreign Institutional Investor (QFII) program and over the next 3 years gradually allowed more and more foreign institutional investors to invest in the *A*-share market. The success of this program clearly has elevated the market participants' confidence and contributed to the biggest rally of the Chinese stock market beginning in 2005 that would end in 2007 due to the global financial crisis.

7. Conclusion

In this paper we employ a state space modeling approach so as to examine the relative contribution of expected stock returns and expected dividend growth to movements in Chinese stock price dividend ratio. There has been a large body of research devoted to the stock price decomposition of more developed countries, but to our knowledge our study marks the first one to apply a latent factor based stock price decomposition technique to the Chinese stock markets. We argue that such a study is not only interesting in its own right because it sheds light on the formation mechanism of stock prices in the Chinese equity markets, but also provides additional evidence with regards to the classical finance topic about whether it is cash flows or discount rate that explains the bulk of stock price variations.

To decompose the stock price we adopt a latent factor approach based on the state-space model, employing quarterly data from 1995Q3-2011Q1, and integrate this into the Campbell-Shiller stock price variance decomposition framework. Our estimation results suggest that the stock price fluctuations in the Chinese stock markets in the past twenty years have been largely dominated by the time-varying expected future returns of investors rather than expected future dividends growth. To further understand the linkage of such results with various economic models we relate the estimated expected returns to the economic fundamentals. We find that the time-varying expected returns appear counter-cyclical which seems to suggest that the habit-formation model of Campbell and Cochrane (1999) is quite relevant in explaining the Chinese equity price fluctuations. We also offer some cases studies to support the general notion that various policies proposed by the Chinese government have greatly affected Chinese investors in stock markets and in turn have heavily influenced stock price fluctuations in Chinese stock markets. However, we also find that in the estimated state-space model the signal-to-noise ratio is small and as a result of this, valid inference of the estimates reveal that there is a great deal of uncertainty with respect to the above stock price variance decomposition. This result implies that further studies, possibly using more disaggregated data, are needed to provide more insights along these lines.

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Notes

1. Latent factors are unobservable variables (expectations) that we must extract using a Kalman filter.
2. The aggregate market return that they use is the value-weighted return covering the period from 1996:07 to 2009:06.
3. See, for example, Cochrane (2008a) for a derivation.
4. Balke and Wohar (2002) and Binsbergen and Koijen (2010) have provided excellent examples and have successfully adopted the state-space model to decompose the stock price variation using the US equity market data.
5. We follow Binsbergen and Koijen (2010) and choose lag 1. It is also important to note that the setting-up as laid out in (3.1) and (3.2) does not allow g and μ to depend on lags of each other, which is different from VAR.
6. In the online appendix to this paper we conduct robustness analysis whereby we employ alternative observation variables of, returns and price-dividend ratio, in contrast to the pair, dividend growth and price-dividend ratio as used in the text. The results for these can be found in Tables B1 and B2 of the appendix B. These online appendices can be found on the author's website: http://cba.ua.edu/~jma/research.
7. In the online appendix we conduct robustness analysis by applying the alternative identifying restriction $\rho_{dg} = 0$ to that found in Table 2, however, we still use the system of variables dividend growth and price-dividend used in Table 2. These results are reported in Tables C1 and C2 in the appendix C. These online appendices can be found on the author's website: http://cba.ua.edu/~jma/research.

8. For comparison purpose we present summary statistics of the monthly observations in Table A.1 in the online Appendix A. These online appendices can be found on the author's website: http://cba.ua.edu/~jma/research. The monthly dividends growth is about eight times more volatile than the quarterly observations as measured by the standard deviations, and the monthly returns is about twice as volatile as the quarterly observations. Furthermore, we also estimate the model using monthly data and report the estimation results in the Appendix A. The results are very similar to those using the quarterly data but there is an important difference that suggests the usage of the quarterly data. The signal-to-noise ratios for both the expected returns and expected dividend growth (corresponding to the ZILC indication σ_μ / σ_r and σ_g / σ_d) using the monthly data are much smaller than these using the quarterly data, indicating that the monthly data is too noisy and tends to be very uninformative.
9. Note that we work with nominal variables but studies such as by Campbell and Ammer (1993) use real variables.
10. Please refer to (3.1) and (3.3) for the definition of the expectation shock and news shock.
11. The off-diagonal elements in the matrix of moving average parameters are restricted to zero to facilitate estimation.

Table 1. Summary Statistics of the Chinese Stock Market

	Dividends Growth	Price-Dividend Ratio	Total Returns
Mean	0.08	4.41	0.11
Standard Deviation	0.19	0.34	0.74
1st Order Autocorrelation	0.634	0.842	0.139

Notes: Data frequency is quarterly and the sample period is from 1995Q3 to 2011Q1; all data are annualized.

Table 2. State-Space Estimation Results

(Variables: dividends growth and price-dividend, lag = 1)

(Restriction: $\rho_{\mu g} = 0$)

Parameters	Estimates	Standard Errors
a_g	0.0802	0.0253
ϕ_g	-0.3652	0.1310
a_μ	0.0919	0.0253
ϕ_μ	0.8280	0.0723
σ_d	0.1395	0.0142
σ_μ	0.0349	0.0142
σ_g	0.0823	0.0142
$\rho_{d\mu}$	0.0271	0.1182
ρ_{dg}	0.9996	0.0032
Log-Likelihood Value	46.9232	
	Implied Parameters Estimates	
σ_r	0.2726	0.0262
ρ_{dr}	0.7121	0.0757
$\rho_{\mu r}$	-0.6825	0.0526
ρ_{gr}	0.7309	0.0491
	Model Constants	
κ	0.0646	--
ρ	0.9881	--
	ZILC Indication	
σ_μ / σ_r	0.1282	--
σ_g / σ_d	0.5896	--

Notes: data are annualized quarterly observations from 1995Q3 to 2011Q1. The model is estimated by imposing the restriction $\rho_{\mu g} = 0$. a_g is the average dividend growth rate; ϕ_g is the

AR(1) parameter in the expected dividend growth process; a_μ is the average return; ϕ_μ is the AR(1) parameter in the expected return process; σ_d is the size of the news shock to the realized dividend growth; σ_μ is the size of the shock to the expected return; σ_g is the size of the shock to the expected dividend growth; $\rho_{d\mu}$ is the correlation between the news shock to realized dividend growth and the shock to the expected return; ρ_{dg} is the correlation between the news shock to the realized dividend growth and the shock to the expected dividend growth. Implied parameters estimates are calculated from the implicit restriction (3.9) and their standard errors are computed using the Delta method. σ_r is the size of the news shock to the realized returns; ρ_{dr} is the correlation between the news shock to realized dividend growth and the news shock to realized returns; $\rho_{\mu r}$ is the correlation between the shock to the expected returns and the news shock to the realized returns; ρ_{gr} is the correlation between the shock to the expected dividend growth and the news shock to the realized returns.

Table 3. State-Space Variance Decomposition

(Variables: dividend growth and price-dividend, lag = 1)

Variance Decomposition of Price-Dividend Ratio (%)	
Contribution of expected return μ_t	103.24% (13.20%)
Contribution of expected dividend growth g_t	3.71% (1.56%)
Covariance contribution	0% (NA)
Approximation error (1 minus the above three)	-6.95% (13.20%)

Notes: data are annualized quarterly observations from 1995Q3 to 2011Q1. Numbers in parenthesis are standard deviations based on the Monte Carlo simulations of 500 replications using the parameters estimates and their estimated variance covariance matrix of the state-space model in Table 2. The covariance contribution is by construction 0% since the model is estimated by imposing $\rho_{\mu g} = 0$ and the covariance contribution can be shown to be equal to $-\frac{2}{(1-\rho\phi_g)(1-\rho\phi_\mu)} \cdot \sigma_\mu \cdot \sigma_g \cdot \rho_{\mu g}$. The last line reports the approximation error of the Campbell-Shiller linearization which is defined to be 100% minus the above three lines.

Table 4. Regression of the Expected Returns (demeaned) onto the Macroeconomic Indicators

Explanatory Variables	Model 1	Model 2	Model 3	Model 4
Constant	-0.0003 (0.0045)	-0.0002 (0.0043)	0.0355 (0.0251)	0.0067 (0.0077)
Expected Return-Lag One Period	**0.8355** **(0.0693)**	**0.8712** **(0.0674)**	**0.8460** **(0.0690)**	**0.8436** **(0.0695)**
Industrial Production Growth Rates	--	**-0.1577** **(0.0597)**	--	--
GDP Growth Rates	--	--	-0.3589 (0.2468)	--
Yield Spread	--	--	--	-0.2943 (0.2604)
Adjusted R^2	70.67%	73.37%	71.20%	70.80%

Notes: data are annualized quarterly observations from 1995Q3 to 2011Q1. Numbers in parenthesis are standard errors. Bold estimates indicate 5% significance.

Figure 1. DataStream China A Share Index and Shanghai SE A Share Index

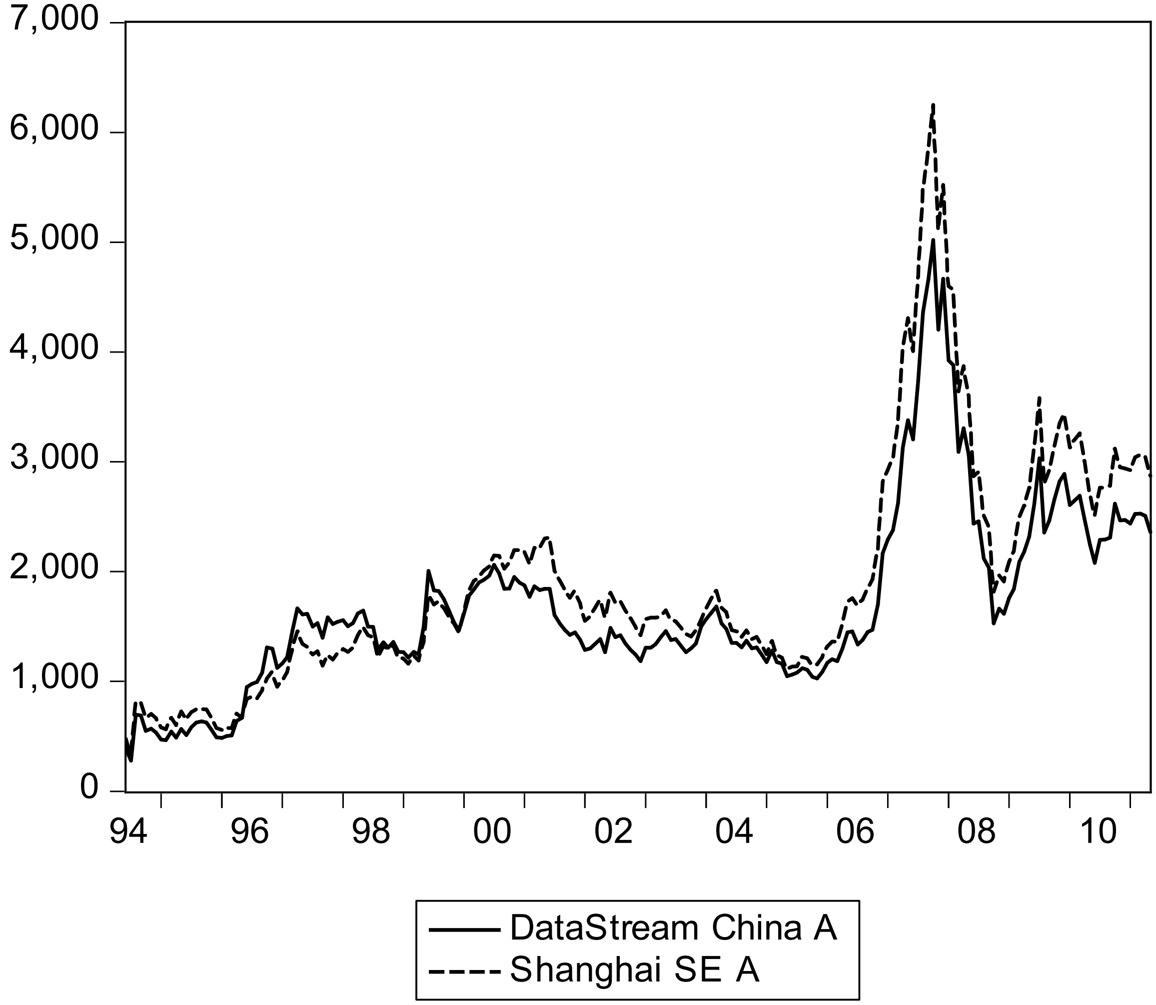
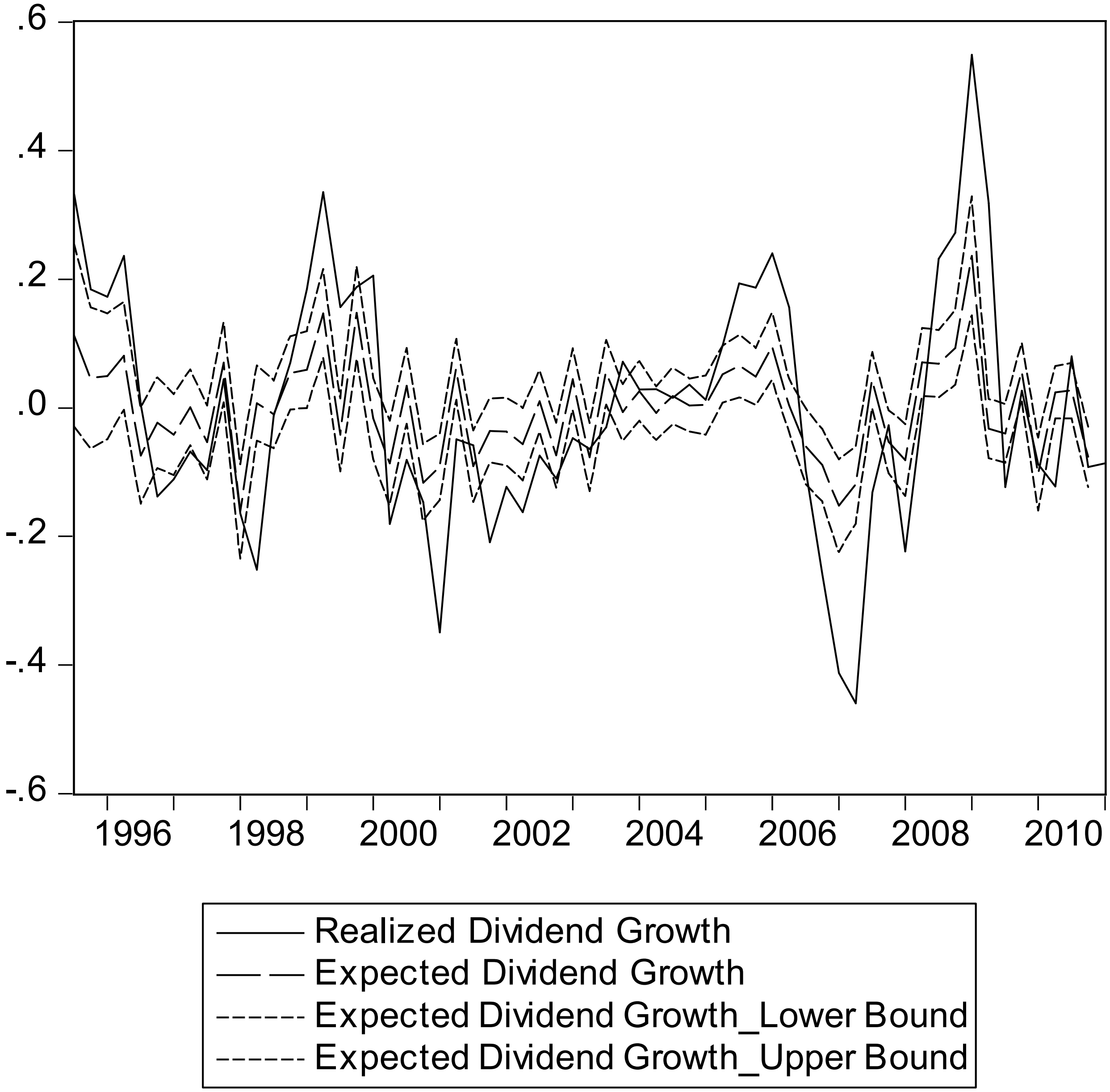
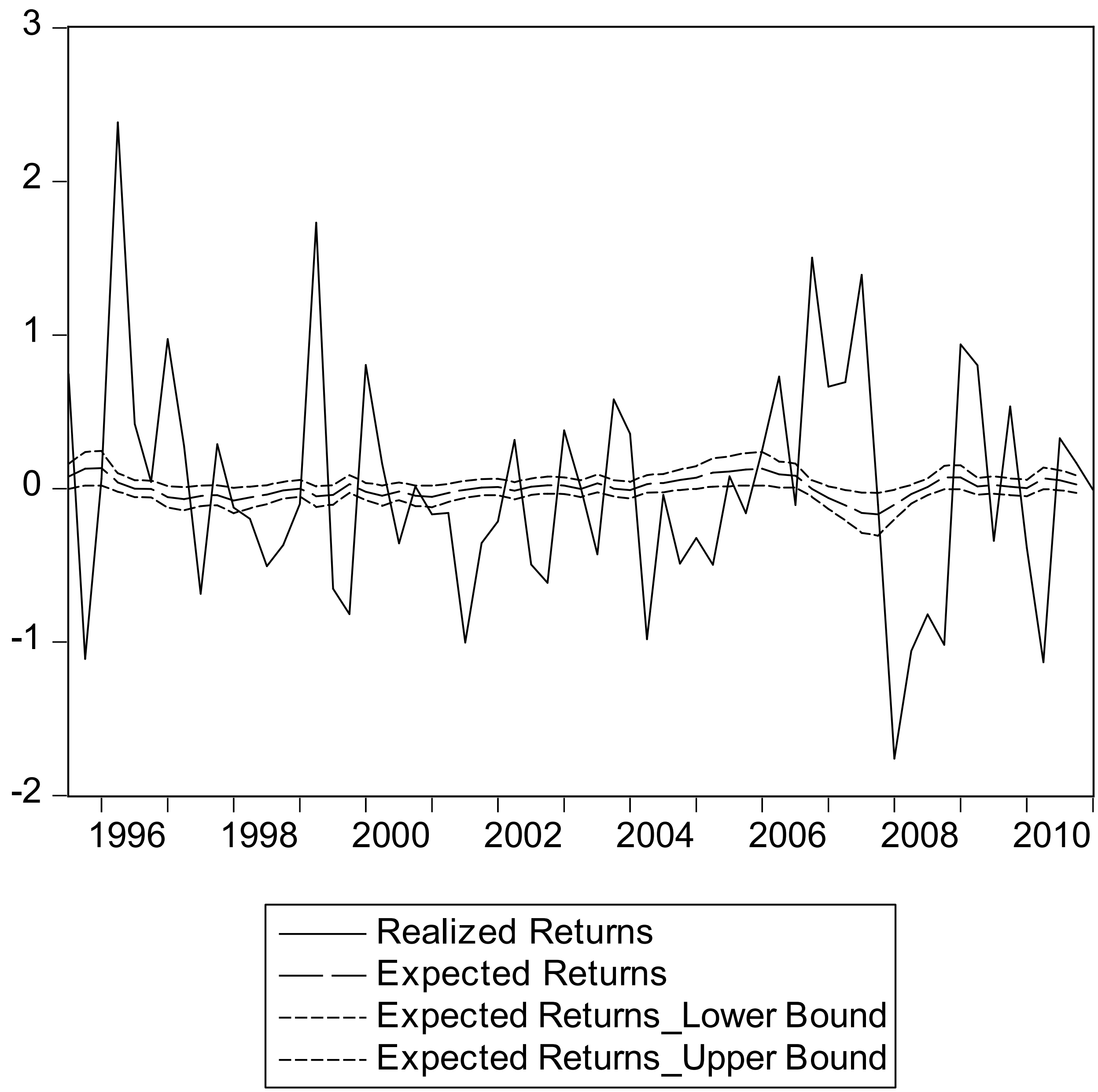


Figure 2. Realized Dividend Growth and Expected Dividend Growth (both demeaned)



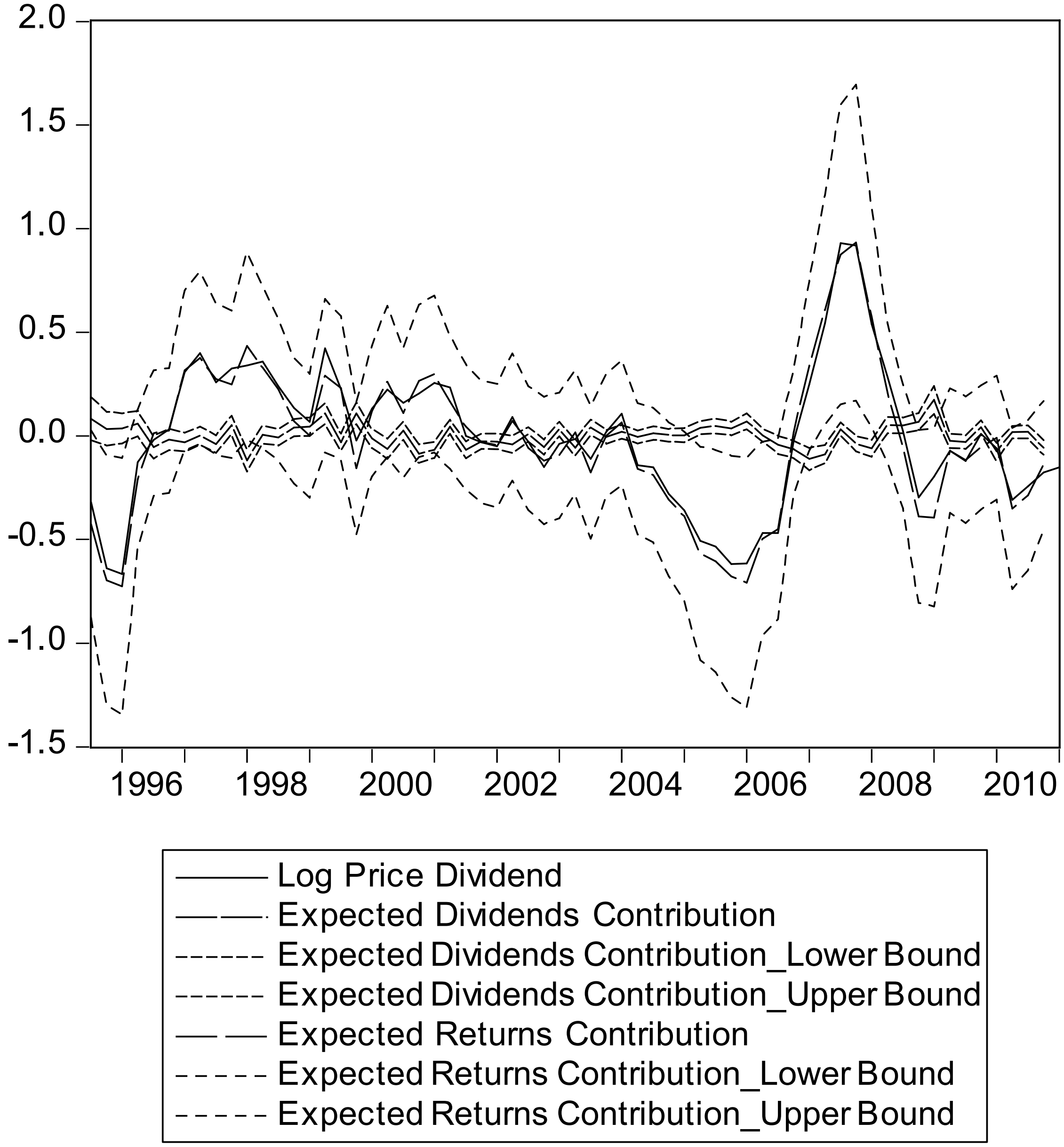
Notes: data is quarterly from 1995Q3 to 2011Q1; the lower and upper bounds are 95% confidence intervals based on Monte Carlo simulations.

Figure 3. Realized Returns and Expected Returns (both demeaned)



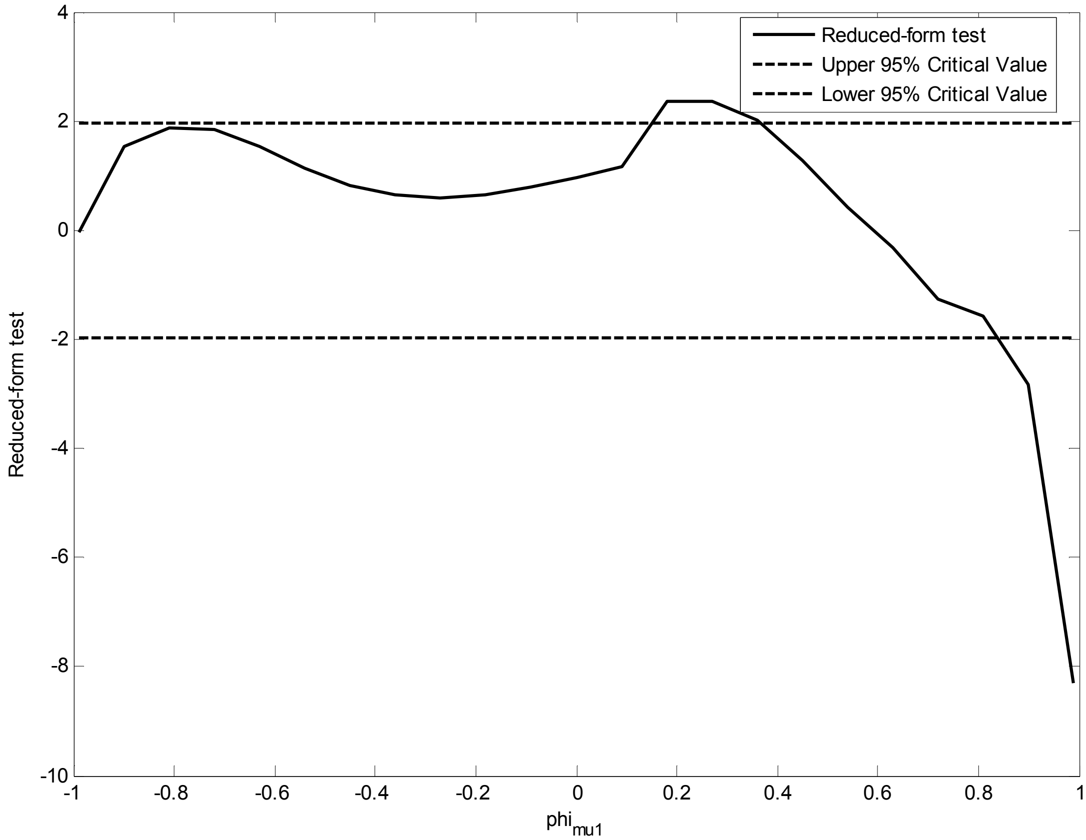
Notes: data is quarterly from 1995Q3 to 2011Q1; the lower and upper bounds are 95% confidence intervals based on Monte Carlo simulations.

Figure 4. State-Space Model 1: Price-Dividend Ratio, Contribution of Expected Dividend Growth, and Contribution of Expected Equity Return (all demeaned)



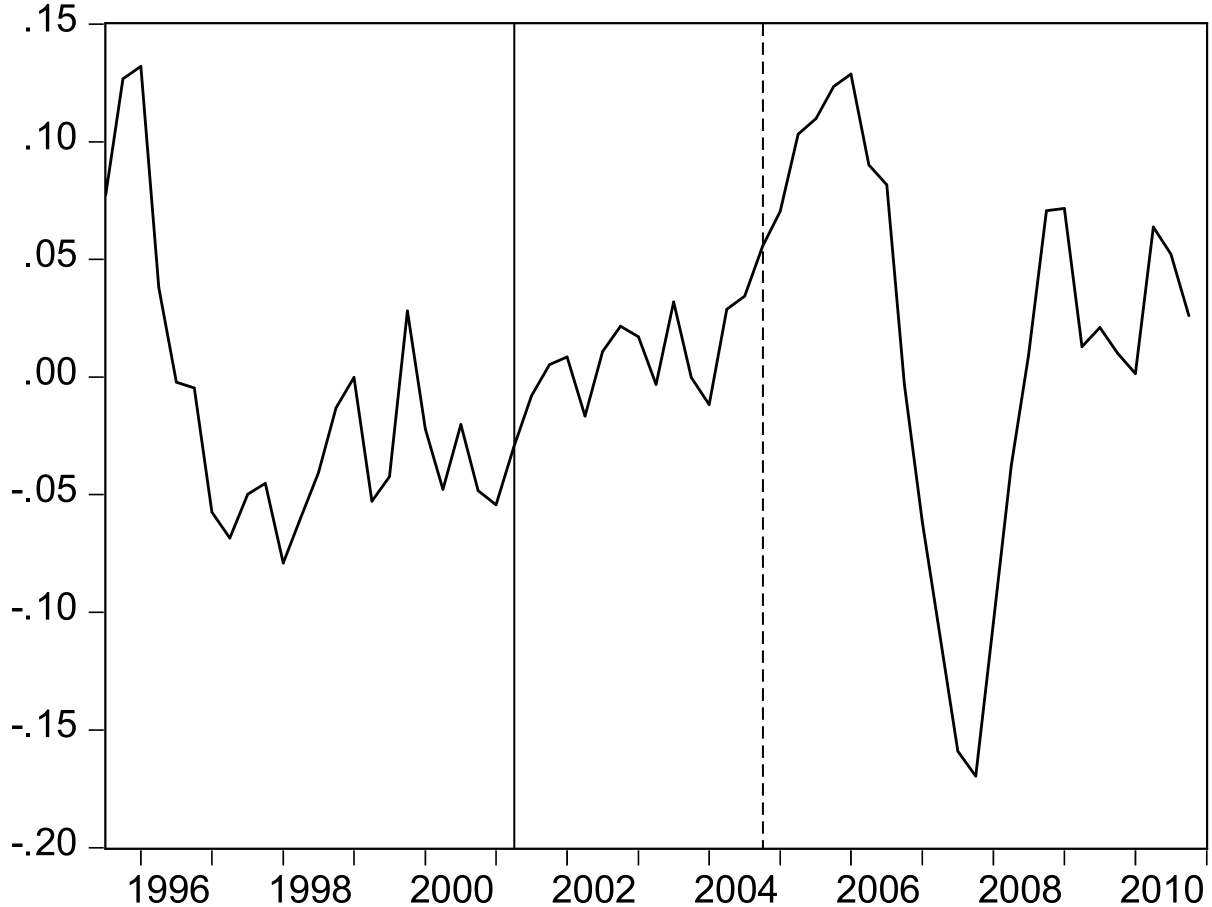
Notes: data is quarterly from 1995Q3 to 2011Q1; the lower and upper bounds are 95% confidence intervals based on Monte Carlo simulations.

Figure 5. 95% Confidence Interval for Expected Return Persistence (ϕ_{μ}) Based on the Reduced-Form Test



Notes: data is quarterly from 1995Q3 to 2011Q1.

Figure 6. Expected Returns (demeaned)



Note: data is quarterly from 1995Q3 to 2011Q1. The solid line is at 2001Q2 and the dotted line is at 2004Q4.

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