Journal of Banking & Finance 36 (2012) 2575–2592

Contents lists available at SciVerse ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

State uncertainty in stock markets: How big is the impact on the cost of equity?

Yufeng Han *

University of Colorado Denver, Business School, PO Box 173364, Campus Box 165, Denver, CO 80217-3364, United States

ARTICLE INFO

Article history:
Received 2 October 2009
Accepted 29 May 2012
Available online 7 June 2012

JEL classification:
G12
G31
C11

Keywords:
Cost of capital
Time-varying parameters
State uncertainty
Dirichlet process
Bayesian analysis

ABSTRACT

We propose a novel Bayesian framework to incorporate uncertainty about the state of the market. Among others, one advantage of the framework is the ability to model a large collection of time-varying parameters simultaneously. When we apply the framework to estimate the cost of equity we find economically significant effects of state uncertainty. A state-independent pricing model overestimates the cost of equity by about 4% per annum for a utility firm and by as much as 3% for industries. We also observe that the expected return, volatility, risk loading, and pricing error all display state-dependent dynamics that coincide with the business cycle. More interestingly, the forecasted market and Fama–French factor risk premiums can predict the future real GDP growth rate even though the model does not use any macroeconomic variables, which suggests that the proposed Bayesian framework captures the state-dependent dynamics well.

1. Introduction

In a CAPM world, returns are assumed to be normally distributed with constant expected returns and volatilities, and the expected returns are a function of the market betas, the market risk premium, and potential pricing errors. All the parameters are assumed to be constant. However, extensive empirical evidence suggests that the assumption of constant parameters is far from reality. For example, a large body of literature on return predictability suggests that the expected return varies over time.[1] There is also a huge amount of research in modeling time-varying volatility.[2] Time-varying market risk (beta) is also widely documented.[3] In fact, just about every parameter is shown to change over time. One approach to deal with time-varying parameters is to use conditional versions of the pricing model. For example, Ferson and Locke (1998) use the conditional CAPM to investigate the sources of errors in estimating the cost of equity.[4] The difficulty, however, lies in the fact that these time-varying parameters are unobserved, and thus the problem with the conditional approach is that it requires specifying the dynamics of the time-varying parameters in ad hoc manners. Ghysels (1998) finds that the usual specifications of the conditional pricing models often perform worse than the unconditional pricing models. Other studies also find the lack of support for the conditional models by the data.[5] More importantly, the conditional approach is difficult to implement when more time-varying parameters need to be modeled.[6]

In this paper, we propose a novel Bayesian framework that can easily incorporate a large number of unobserved time-varying parameters. Instead of modeling these time-varying parameters separately, we model them collectively and assume that their values depend on a latent state variable. Whenever the state of the market changes, the values of these parameters change as well. With a Bayesian approach, any ad hoc assumptions about the states are unnecessary, and instead we will learn about the states of the market from the data.

* Tel.: +1 303 315 8458; fax: +1 303 315 8084.
E-mail address: yufeng.han@ucdenver.edu

[1] See, e.g., Ferson (1989), Avramov (2003), Guo (2006), and Han (2010) to name a few.

[2] For the (G)ARCH model, see the review by Bollerslev et al. (1994) and references therein; for the stochastic volatility model, see Kim et al. (1998), the review by Ghysels et al. (1995) and references therein.

[3] See Kothari et al. (1995), Harvey (2001), Campbell and Vuolteenaho (2004), Adrian and Franzoni (2005), ?, Lewellen and Nagel (2006), Andersen, Bollerslev, Diebold and Wu (2006), Basu and Stremme (2007), and Ang and Chen (2007) to name a few.

[4] Other studies include Fama (1996), Brennan (1997), Bakshi and Chen (2001), Ang and Liu (2002), etc.

[5] Examples are He et al. (1996), Ferson and Siegel (1999), and Ferson and Harvey (1999).

[6] Avramov and Chordia (2006) model time-varying alpha, beta, and factor premiums, but do not model time-varying volatility.

0378-4266/$ - see front matter © 2012 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.jbankfin.2012.05.016

As the key component of our Bayesian framework, the dynamics of the state and the state-dependent parameters are described by a mixture of Dirichlet process (MDP). Because of the discreteness of the Dirichlet process (due to Dirichlet distribution), all the state-dependent parameters evolve in a discrete fashion and are clustered into distinct values. These distinct clusters represent the distinct states of the market.

One major advantage of this framework is that it allows for the arrival of new states in future – the market in the future can fall into one of the existing states or emerge as a completely new state, and thus a financial decision maker faces state uncertainty. For example, let's assume that there have been three distinct states in the market, say Bear (a bear state), Norm (a normal calm state), and Bull (a bull state). If the current state is Bear, the uncertainty a financial decision maker faces is whether the market next period would be still in Bear, or change to Norm, or change to Bull, or change to a completely new state (say, a even deeper bear state). With our Bayesian framework, a financial decision maker is able to not only learn about the past states from the data but also to forecast future states of the market.

Compared to the conditional model, an important advantage of the framework is that no ad hoc specifications and auxiliary instrumental variables are required, hence overcoming the mis-specification problem described by Ghysels (1998). Instead, the parameters evolve to different values according to a latent state indicator. This parsimonious specification can easily accommodate a large collection of state-dependent parameters. Perhaps, a more closely related model is the regime switching model. However, several important differences are worth noting. First, in the most common specification of the regime switching model, only two states are specified and only the expected return and volatility are modeled. On the one hand, this simple specification captures the common classification of the market into Bull and Bear states. On the other hand, it imposes the strong and unrealistic assumption that every bull market is the same and every bear market is the same. Using the MDP model, however, relaxes this assumption so that, for example, the recession in 1970s characterized by "stagflation" because of "Oil Crisis", can be different from the recession in 2001, the burst of the internet bubble. Second, in the regime switching model, the number of states is exogenously specified, whereas in the MDP model the number of states is endogenously determined by the data. Third, the transition probability is thus different. In the MDP model, the probability of a state occurring in future does not explicitly depend on the current state but depends on the likelihood of that state to fit the data and how frequent that state has occurred in the past.[7] Finally, the uncertainty in the regime switching model is which of the two states will be realized. The MDP model, however, adds another dimension of uncertainty – not only which of the existing states may be realized, but also how likely a new state may be realized.

We apply the Bayesian framework to the estimation of cost of equity focusing on the expected excess rate of return on the firm's stock. We choose to estimate the cost of equity because it is one of the most important inputs for a firm's financial decisions, and a common approach to estimating it is to use a factor asset-pricing model such as CAPM or Fama–French three-factor model.[8] Furthermore, Pástor and Stambaugh (1999) propose a Bayesian framework to estimate the cost of equity with the assumption that the expected excess returns are constant. Thus our Bayesian framework provides a natural extension to their framework.

Consistent with the existing literature, we observe interesting state-dependent dynamics of the expected excess returns and volatilities, which are evidently related to the business cycles identified by the NBER. While volatilities always change counter-cyclically, expected excess returns display both cyclic and counter-cyclic dynamics. For example, the market risk premium displays cyclic dynamics consistent with prior findings, whereas some industries display counter-cyclic dynamics in the expected excess return. In addition, we document for the first time the state-dependent dynamics of the SMB and HML portfolios and of their loadings. We find that the expected returns of SMB and HML portfolios increase during volatile periods (counter-cyclic), which is consistent with the conjecture that the SMB and HML are proxies for "distress risk". However, the risk loadings on the SMB and HML portfolios display different dynamics, suggesting that these two portfolios may mimic different risk factors. We observe higher correlations among the factor portfolios and higher market betas for many industries during volatile periods, suggesting that stocks tend to move more closely in volatile periods. The pricing errors often display dynamics similar to those of volatilities, suggesting increased idiosyncratic abnormal returns during volatile periods.

Finally, we find that the market risk premium forecasted from the MDP model has a Granger causality relation with the real GDP growth rate. Furthermore, the forecasted Fama–French factor risk premiums predict future GDP growth rate with high adjusted R^2s, whereas the realized factor returns fail to predict future GDP growth rate. This is striking given that no GDP growth rate or any other macroeconomic variables are used in the model. This evidence suggests that the MDP model captures the state-dependent dynamics well.

Consistent with the findings of Pástor and Stambaugh (1999), we find that the posterior means of the expected excess returns are relatively insensitive to mispricing uncertainty, more so in the presence of the state uncertainty. In contrast, we find that state uncertainty has economically significant effects on the estimation of the cost of equity. Ignoring state uncertainty results in overestimating the posterior means of the expected excess returns – the average overestimation bias is about 4% per annum for an individual utility stock, and about 1.5% per annum for industry portfolios (as high as 3%). Both the pricing error and risk premium, the two components of the expected excess return, contribute to the overestimation, but one may dominate the other in different cases. In addition, the overestimation is insensitive to different prior beliefs about the number of states in the market and persists regardless of the level of prior mispricing uncertainty. State uncertainty also substantially increases the uncertainties about the pricing error, risk loading, and factor risk premium, and thus increases the overall uncertainty about the expected excess return.

It should be noted that our results are conservative because we only compare the forecasted expected excess returns for the first month, but in practice, to evaluate a project, the decision maker would have to forecast a term structure of future expected excess returns. As we will discuss later, the expected excess returns over longer periods are functions of the monthly expected excess returns, and hence it is likely that the effect of state uncertainty is much greater due to accumulation.

Recently, there emerges a promising literature that uses the discounted Residual Income Valuation (RIV) model to estimate the cost of equity capital. Claus and Thomas (2001) use the residual income model to estimate the market risk premium and conclude that the equity premium is as low as three percent. Gebhardt et al. (2001) use the residual income model to estimate the implied

[7] Thus in the MDP model, it is impossible to have a transition probability matrix; the persistence of the states is determined by the persistence of the data because similar data will have similar likelihood and will thus fall in the same state.

[8] For example, Bower et al. (1984), Bower and Schink (1994), Elton et al. (1994), Fama and French (1997), Ferson and Locke (1998), Koedijk et al. (2001), Barnes and Lopez (2006) have used the CAPM, the Fama–French three-factor model, or the APT model to estimate the cost of equity.