Uncertainty Aversion and Business Condition

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Abstract

This paper focuses on uncertainty aversion rather than risk aversion. First we introduce an empirical uncertainty aversion. We find that empirical uncertainty aversion tends to move together with stock index such as FTSE100 and S&P500. Second, applying VECM regression and Granger causality test, we present a relationship between empirical uncertainty aversion and business condition. Using credit spread and term spread as indicators of business condition, we find interesting results: (1) the change of empirical uncertainty aversion has significant positive relationship with credit spreads in UK and US. (2) the change of empirical uncertainty aversion has no significant relationship with term spread. (3) the change of empirical uncertainty aversion granger causes both credit spreads and term spreads. This implies that empirical uncertainty aversion can be the source of the credit spread as well as uncertainty aversion can predict future business condition. If today's uncertainty aversion increases, tomorrow's business condition will be worse, and if today's uncertainty aversion decreases or is resolved, tomorrow's business condition will be better.

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1. Introduction

Investors fear unexpected shocks such as Black Monday and 9.11 terror[1]. Economists have tried to measure the aversive attitude about these unexpected shocks. Risk aversion has been used to represent this kind of aversive attitude. However, Risk aversion alone can not explain it. For example, too high risk aversion is required to explain equity premium puzzle. Economists introduce the concept of the uncertainty aversion or ambiguity aversion. The uncertainty aversion is the aversive attitude about the unknown distribution, but the risk aversion is about known distribution. We focus on model uncertainty, which is based on the Knightian approach. The Ellsberg (1961) paradox is an example of Knightian uncertainty, in which investor's choice violates the Von-Neumann expected utility hypothesis.

According to recent papers about model uncertainty, uncertainty aversion can be measured by robust control theory[2], developed by Anderson Hansen Sargent (2000). Recently Maenhout (2004, 2006) presented a new method of the dynamic portfolio[3] and consumption rules based on Anderson Hansen Sargent (2000). Assuming the uncertainty about the return process, they found a closed form solution of the optimal portfolio rules and estimated constant uncertainty aversion. Maenhout showed that robustness dramatically decreases the demand for risky assets and is equivalent to recursive[4] preferences. This means that equity premium puzzle and risk-free rate puzzle can be explained by robustness. Cagetti Hansen Sargent Williams (2002) study the effect of decision maker's concerns about robustness in stochastic growth model. Liu Pan Wang (2005) includes uncertainty about jump process in option pricing model and suggests the reason of the option smirk with robustness. Cao Wang Zhang (2005) shows

[1] Black Monday happens on Oct 19, 1987. 9.11 terror happens on Sep 11, 2001.
[2] With the concept of relative entropy, which is defined an expected log Radon-Nikodym derivative, robust control theory assumes that investors have alternative models besides a reference model. Investor's uncertainty aversion is related with the distance between the reference model and the worst case alternative model.
[3] Merton (1969, 1971) pioneered dynamic portfolio selection problem with Bellman principle.
[4] Duffie and Epstein (1992a, 1992b) introduce investor's continuous time recursive preferences.

that equity premium can be decomposed into both the risk premium and uncertainty premium. Under the mean-variance framework, they show that investors with high uncertainty about mean return of a stock avoids participating stock market. These works do not assume the change of uncertainty aversive attitude.

This paper provides an empirical uncertainty aversion instead of constant uncertainty aversion. Aversive attitude about unexpected shocks can be different at a time. Sometimes unexpected shocks like 9.11 terror, Black-Monday happened and small shocks in a year happened even now. To capture this premium of unexpected shocks, we set up a basic model of an empirical uncertainty aversion. Extending Maenhout (2004)'s work, we estimate empirical uncertainty aversion both in UK and US. With this empirical uncertainty aversion, we find that uncertainty aversion is increasing before the crash and is resolved after the crash, and tends to move together stock return.

Second we suggest a relationship between uncertainty aversion and business condition. Engle and Rosenberg (2002) showed the relationship between risk aversion and business condition. They find a significant positive relationship between credit spread change and risk aversion. They say that risk aversion is counter cyclical. We construct a regression of empirical uncertainty aversion and indicators of business cycle. As indicators of explanatory variables, we use both credit spreads and term spreads that were used in Fama and French (1989). Applying VECM models and Granger causality test, we find interesting results: uncertainty aversion has statistically significant positive relationship with credit spreads, and uncertainty aversion has no significant relationship with term-spreads. Finally in UK and US, we find that uncertainty aversion granger causes both credit spreads and term spreads. This implies that we can explain the credit spread puzzle with uncertainty aversion as well as we can predict business condition with uncertainty aversion,

The organization of this paper is as follows. Chapter2, we introduce an empirical uncertainty aversion. Chapter3, we explain the data and regression methodology about empirical uncertainty aversion. Chapter4, we have empirical results about uncertainty aversion and business condition. Finally chapter5, we give a conclusion.

2. Empirical Uncertainty Aversion

2.1 Updating the reference model

To incorporate the dynamics of discrepancy between reference model and alternative models, we present an empirical uncertainty aversion, i.e. a kind of uncertainty aversion time series. Based on model uncertainty, we assume that investors consider both reference model and alternative model, and each reference model and alternative models evolve as time passes. Similar to Anderson, Hansen, Sargent (2000), Hansen and Sargent (2001), Maenhout (2004, 2006), in our framework, investors worry about the pessimistic situation due to a sudden shock and investors consider alternative models that have drift distortions away from reference model. Our agents update the reference model similar to generalized Bayesian[5] learning of Epstein and Schneider (2005). They assume that using memoryless mechanism, learning can cease without all uncertainty having been resolved. Instead, we don't fix the information set; rather consider information set is expanding as time passes. Our agents can update the reference model through updating, simultaneously having worst case alternative model at each period.

Considering drawing balls in an urn, which contains some known balls and some unknown balls, Epstein & Schneider (2005) suggested the multiple priors' model[6]. They assume uncertainty will be resolved in the long run as the number of draws increases. Since they fix the total number of unknown balls, it is plausible that uncertainty will be

[5] Garlappi, Uppal, Wang (2007) refers that in Bayesian approach, unknown parameters were treated as random variables, and assumed to have only single prior i.e. to be neutral to uncertainty.
[6] Gilboa and Schmeidler (1989) study maxmin expected utility with nonunique prior.

resolved in the long run. In contrast, we don't fix the total number of unknown balls, rather assumes the number of balls are increasing as time passes. This scenario is associated with the information set is expanding as time passes. Like this, in each drawing our agent updates the reference model, simultaneously having another worst case alternative model.

2.2 Model Setup

We consider one risky asset with two models[7] and one risk free asset with constant interest rate. Let $\{B_t\}$ be a standard Brownian motion on a probability space (Ω, F, P) and F_t is a filtration generated by this Brownian motion.

Given risky asset process is

$$dS_t = \mu S_t dt + \sigma S_t dB_t \tag{1}$$

The reference model of state (or wealth) dynamics is

$$dW_t = \mu(W_t)dt + \sigma(W_t)dB_t = \left[W_t(r + \alpha_t(\mu - r) - C_t\right]dt + \alpha_t \sigma W_t dB_t \qquad (2)^8$$

And alternative model of state (or wealth) dynamics is

$$dW_t = \mu(W_t)dt + \sigma(W_t)\left[\sigma(W_t)u(W_t) + dB_t\right] \tag{3}$$

[7] Reference model model and worst case alternative model.

[8] α_t: portfolio weight of risk asset, C_t : consumption

Also, our agent updates the reference model with maximizing her log likelihood at each period.

$$L_t\left(\hat{\mu}_t,\hat{\sigma}_t\right)=\prod_{i=1}^{t} f(\mu_1,\mu_2,...,\mu_t\left|\hat{\mu}_t,\hat{\sigma}_t\right.)=\left(\frac{1}{2\pi\hat{\sigma}_t^{\,2}}\right)^{t/2}\exp\left(-\frac{\sum_{i=1}^{t}\left(\mu_i-\hat{\mu}_t\right)^2}{2\hat{\sigma}_t^{\,2}}\right) \tag{4}$$

Where μ_i is an observed risky asset return on i-period, $\hat{\mu}_t$ is an updated drift of risky asset on t-period, $\hat{\sigma}_t$ is an updated standard deviation of risk asset on t-period. With estimated reference model, our agent worries about pessimistic situation considering worst case alternative model. Hence, updating the reference model, we can derive the time varying discrepancy between the reference model and the worst case alternative model. We relate this time varying discrepancy to an empirical uncertainty aversion.

2.3 Estimation of Empirical Uncertainty Aversion

Maenhout (2004) derived robust Hamilton-Jacobi-Bellman equation, which contains both drift distortion and entropy penalty. He shows that the excess return on the risky asset is

$$\frac{dS_t+D_t dt}{S_t}-rdt=[\gamma+\theta]\sigma_{cs}dt+\sigma_s dB_t \qquad (5)^9$$

[9] Proof : see the appendix of Maenhout (2004), and $\sigma_{cs}=\rho\sigma_c\sigma_s$

Substituting θ in equation (5) into θ_t, we can rewrite equation (5) as following equation (6).

$$\frac{dS_t + D_t dt}{S_t} - rdt = [\gamma + \theta_t]\rho\sigma_{cs}dt + \sigma_s dB_t \tag{6}$$

Let the i-period's excess return on risk asset be ζ_i, and the drift of excess return on risky asset be $\hat{\zeta}_t$. If we assume $S_t = a^{-1}D_t$, then $\hat{\zeta}_t = \hat{\mu}_t + \frac{1}{a}\hat{\mu}_t - r$.

So, we can induce a simplified equation (7).

$$\hat{\zeta}_t = [\gamma + \theta_t]\sigma_{cs} \tag{7}$$

Finally, using equation (7), we can measure the empirical uncertainty aversion θ_t with assuming time varying standard deviation of consumption increase and stock return.

$$\theta_t = \frac{\hat{\zeta}_t}{\sigma_{cs}} - \gamma = \frac{\hat{\zeta}_t}{\rho\hat{\sigma}_{c,t}\hat{\sigma}_{s,t}} - \gamma \tag{8}$$

Where $\hat{\zeta}_t, \hat{\sigma}_{c,t}, \hat{\sigma}_{s,t}$ [10] can be estimated by updating log likelihood maximization of similar approach to equation (4).

[10] $\hat{\sigma}_{c,t}$ is estimated standard deviation of consumption increase on t-period, $\hat{\sigma}_{s,t}$ is estimated standard deviation of stock return on t-period.

3. Data and Methodology

3.1 Data

We have empirical tests on UK and US. To measure empirical uncertainty aversion, we used equation (8) which contains the drift of excess return on risky asset and its standard deviation, standard deviation of consumption increase, correlation between consumption increase and return on risky asset, and finally risk aversion.

For US, sample is quarterly based from 1954:1[11] to 2006:2. We construct equity returns from CRSP database. We use S&P500 index, its dividend yield and use 10 yr government benchmark bond yield as a risk free rate. As a proxy of consumption data, we used the seasonal adjusted quarterly gross domestic product in US and we estimated standard deviation of consumption data. We assume that constant correlation between consumption increase and return on risky asset is 0.2[12]. Since risk aversion parameter is usually estimated between 0~10 in other empirical papers, we assume that pure risk aversion is constant[13]. As indicators of business condition, we used both credit spread and term spread. Fama and French (1989) used credit spread, term spread, risk free rate and dividend yield as indicators of business condition. To avoid multi collinearity we don't include risk free rate and dividend yield as indicators of business condition in measuring the relation between uncertainty aversion and business condition, because both risk free rate and dividend yield were already used in measuring empirical uncertainty aversion. We define CS a credit spread between 10yr government bond yield and 10yr corporate bond yield and define TERM as a term spread between 10yr

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[11] Note the quarterly based time convention: for example 1954:1 refers to first quarter of 1954, i.e 1/1/1954 through 1954/3/31. Also, 1954:3 means third quarter of 1954, i.e 6/1/1954 through 1954/9/30.

[12] Campbell (1999) calculates correlation between consumption and excess return is 0.095 in UK, 0.248 in US. We assume that correlation is 0.1 in UK and 0.2 in US.

[13] Kim and Kang (2006) shows that implied risk aversion parameter is around 4 in US, and around 3 in UK. Since we focus the empirical uncertainty aversion increase, risk aversion parameter does not effect on empirical results. We assume that risk aversion is 4 in US, 3 in UK.

government bond yield and 3yr government bond yield.

For UK, sample is quarterly based from 1970:1 to 2006:2. We construct equity returns from Reuters Ecowin database. We use FTSE100 index, its dividend yield and use 10yr government benchmark bond yield as a risk free rate. As a proxy of consumption data, we used the seasonal adjusted quarterly gross domestic product in UK and we estimated standard deviation of consumption data. Similarly, we assume that constant correlation between consumption increase and return on risky asset. We assume that pure risk aversion is constant 3. We define CS a credit spread between 10yr government bond yield and 10yr corporate composite bond yield and define TERM as a term spread between 10yr government bond yield and 2yr government bond yield.

3.2 Long memory mechanism and memoryless mechanism

Our agents take part in drawing balls in an urn and each ball has a number representing the excess return of risky asset. They don't know the distribution of balls. We measure the empirical uncertainty aversion in two methods: memoryless mechanism and long memory mechanism.

In memoryless mechanism, we assume that total number of balls is fixed and one unknown ball in an urn is changing at every period. This case is similar to the scenario of Epstein and Schneider (2005). They presented memoryless mechanism and assume that learning may cease without all uncertainty having been resolved. Using the data between 1954:1 and 1978:4[14], we estimated the drift of excess return of the model and measured the empirical uncertainty aversion at 1978:4 in US. Next, using the data between 1954:2 and 1979:1[15], we estimated the drift of excess return of the model and measured the uncertainty aversion at 1979:1. Lastly, using the data between 1981:3 and

[14] The number of observation between 1954:1 and 1978:4 is 100.
[15] The number of observation between 1954:2 and 1979:1 is 100.

2006:2, we estimated the drift of excess return of the model and measured the empirical uncertainty aversion at 2006:2. Following this step, we extracted the memoryless empirical uncertainty aversion time series from 1978:4 to 2006:2 in US. Similarly in UK, using the sample data from 1970:3 to 2006:2, we extracted memoryless empirical uncertainty aversion time series from 1994:3 to 2006:2.

In long memory mechanism, we assume that the total number of balls is increasing by one at each period. Using the data between 1954:1 and 1978:4, we estimated the drift of excess return of the model and measured the empirical uncertainty aversion at 1978:4 in US. Next, using the data between 1954:1 and 1979:1[16], we estimated the drift of excess return of the model and measured the empirical uncertainty aversion at 1979:1. Lastly, using the data between 1954:1 and 2006:2 we estimated the drift of excess return of the model and measured the empirical uncertainty aversion at 2006:2. Following this step, we extracted the empirical uncertainty aversion time series from 1978:4 to 2006:2[17]. And in UK, we extracted long memory empirical uncertainty aversion time series from 1994:3 to 2006:2.

3.3 VECM regression model

The empirical uncertainty aversion can be a proxy of an aversive attitude about worst case pessimistic situation such as a Black Monday, a 9.11 terror. It's natural to relate business condition and uncertainty aversion. As an indicator of business cycle, many papers used credit spread, term spread, dividend yield, and risk free rate. Fama and French (1989) show that risk premia are lower when business condition are strong and higher when business condition are weak. Rosenberg and Engle (2002) measure the relation between the empirical risk aversion and business cycle supporting Fama and

[16] The number of observation between 1954:1 and 1979:1 is 101.
[17] Extracted empirical uncertainty aversion time series have 111 observations in US and 48 observations in UK.

French (1989). Along the lines of this research, we extend the empirical risk aversion into empirical uncertainty aversion based on knightian uncertainty.

We focus on the relationship between empirical uncertainty aversion increase and business condition. As indicators of business condition, we used both credit spread and term spread. To avoid multi collinearity we didn't include risk free rate and dividend yield as indicators of business condition in measuring the relation between uncertainty aversion and business condition, because both risk free rate and dividend yield were already used in measuring empirical uncertainty aversion. Considering cointegration and relationships among the variables, we used vector error correction model (VECM)[18] instead of vector autoregressive model (VAR). We construct two VECM models: one is to relate uncertainty aversion and credit spread, the other is to relate uncertainty aversion and term spread.

$$\begin{aligned} d(dUnc) &= \beta_{11} \cdot d(dUnc(-1)) + \beta_{12} \cdot d(dUnc(-2)) + \beta_{13} \cdot d(CS(-1)) + \beta_{14} \cdot d(CS(-2)) \\ d(CS) &= \beta_{15} \cdot d(dUnc(-1)) + \beta_{16} \cdot d(dUnc(-2)) + \beta_{17} \cdot d(CS(-1)) + \beta_{18} \cdot d(CS(-2)) \end{aligned} \tag{9}$$

$$\begin{aligned} d(dUnc) &= \beta_{21} \cdot d(dUnc(-1)) + \beta_{22} \cdot d(dUnc(-2)) + \beta_{23} \cdot d(TERM(-1)) + \beta_{24} \cdot d(TERM(-2)) \\ d(TERM) &= \beta_{25} \cdot d(dUnc(-1)) + \beta_{26} \cdot d(dUnc(-2)) + \beta_{27} \cdot d(TERM(-1)) + \beta_{28} \cdot d(TERM(-2)) \end{aligned} \tag{10}$$

Where $dUnc$ is a 1st differentiated empirical uncertainty aversion, CS is a credit spread, $TERM$ is a term spread.

3.4 Granger causality test

Granger causality test determines that one time series is useful in predicting another

[18] After applying ADF Unit Root test, we found that uncertainty aversion time series is non-stationary, so we made stationary time series by log differentiation.

time series. Finding risk source of credit spread has been one of the biggest problems in finance. We suggest that today's aversive attitude about worst case scenario affects the tomorrow's default probability of a company. We have two hypotheses. One is that knowing the change of today's empirical uncertainty aversion is sufficient to predict tomorrow's credit spread. Second is that knowing the change of today's empirical uncertainty aversion is sufficient to predict tomorrow's term spread. These hypotheses imply that when the change of empirical uncertainty aversion is sufficient to predict tomorrow's business condition.

4. Empirical Results

4.1 Empirical Uncertainty Aversion

[Figure 1]

We provide memoryless empirical uncertainty aversion and long memory empirical uncertainty aversion in UK and US. Figure 1 shows that empirical uncertainty aversion moves together with stock return in both UK and US. Figure 1's <Panel A> shows memoryless empirical uncertainty aversion and FTSE100 index and <Panel C> shows memoryless empirical uncertainty aversion and S&P500 index. The correlation between empirical uncertainty aversion and FTSE100 is 0.8090 and the correlation between empirical uncertainty aversion and S&P500 is 0.9088. In UK, average empirical uncertainty aversion is 85.7 and ranges from 72.21 (2003:2) to 114.42 (1999:4). In US, average empirical uncertainty aversion is 85.7 and ranges from 57.02 (1982:2) to 115.272 (2000:1). Interestingly, empirical uncertainty aversion has increased before Black Monday at 1987:4, but after 1987:4 it fell down. Also when S&P500 and

FTSE100 are peaked at 1999:4, empirical uncertainty aversion is highest at that time. This implies that when a sudden shock happens, investor's aversive attitude about worst case scenario decreased; i.e investor's uncertainty can be resolved partly. <Panel B> and <Panel D> shows long memory empirical uncertainty aversion in UK and US. The correlation between empirical uncertainty aversion and FTSE100 is 0.7949 and between empirical uncertainty aversion and FTSE100 is 0.9466. The tendency of empirical uncertainty aversion to move together with stock index is higher in US than in UK. Figure 2 compares the empirical uncertainty aversion between UK and US. <Panel A> compares memoryless empirical uncertainty aversion and <Panel B> compares long memory empirical uncertainty aversion. <Panel A> and <Panel B> of Figure 2 shows that UK's empirical uncertainty aversion is similar to US's.

[Figure 2]

4.2 Empirical Uncertainty Aversion and Business Condition

[Table 1]

Applying VECM regression on equation (9) and (10), we found interesting results. <Panel A> ~ <Panel D> of Table 1 show that time t period's change of empirical uncertainty aversion has statistically significant positive relationship with time t+1 period's credit spread in both long memory and memoryless in UK, long memory in US. This implies that the more worrying about pessimistic situation, the more credit spreads induces. In other words, business condition will be poor when the change of empirical uncertainty aversion is positive and business condition will be better when the change of empirical uncertainty aversion decreases. This result supports the Fama and French

(1989), and Rosenberg and Engle (2002). Also this result can give an idea of solving credit spread puzzle. Many studies have tried to find the source of credit spread including liquidity risk, jump risk, and so on. Besides those factors, we present the uncertainty aversion as a source of credit spread.

[Table 2]

In contrast, with regard to term spread, the relationship between empirical uncertainty aversion and term spread is not exact. Table 2 shows no significant relationship between empirical uncertainty aversion and term spread both in UK and US.

[Table 3]

Table 3 examines more specific relationship between empirical uncertainty aversion and business cycle using granger causality tests. Applying granger causality test on three time series of empirical uncertainty aversion increase, credit spread, and term spread, we find interesting results. First we reject the null hypothesis that the change of empirical uncertainty aversion does not granger cause credit spread in both memoryless and long memory in UK, and long memory in US. We can say that the change of empirical uncertainty aversion is useful in predicting credit spread. Secondly we reject the null hypothesis that the change uncertainty aversion does not granger cause term spread in memoryless in UK and long memory in US. Similarly, we can say that the change of empirical uncertainty aversion is useful in predicting term spread. Considering these two results, we can conclude that the change of empirical uncertainty aversion is effective in predicting future business condition, which can be represented by indicators of credit spread and term spread. More specifically, we can say if today's uncertainty increase, tomorrow's business condition will be weak, and if today's uncertainty decrease or resolved, tomorrow's business condition will be better. This supports Fama and French (1989).

5. Conclusion

In conclusion, this paper focuses on empirical uncertainty aversion in UK and US. With robust control theory, originally developed by Anderson, Hansen, Sargent (2000), we extend the concept of Maenhout (2004, 2006) framework which assumes constant uncertainty. With the example of drawing balls in an urn, we simplified the model and measured empirical uncertainty aversion time series in two ways: memoryless empirical uncertainty aversion and long memory empirical uncertainty aversion. Using VECM model and granger causality test, we found interesting results. First, in both UK and US, the empirical uncertainty aversion tends to move together with stock index such as FTSE100, S&P500. As stock index increases, empirical uncertainty aversion also increases, and vice versa. Second, we found the relationship between empirical uncertainty aversion and business cycle. Using credit spread and term spread as indicators of business cycle, we found that credit spread is highly associated with the change of empirical uncertainty aversion. When the change of empirical uncertainty aversion is positive, the business condition is weak, and when the change of empirical uncertainty aversion is low, the business condition is better. Lastly, the change of empirical uncertainty aversion granger causes both credit spread and term spread. This implies that the empirical uncertainty aversion can be the source of credit spread as well as we can predict business condition with empirical uncertainty aversion.

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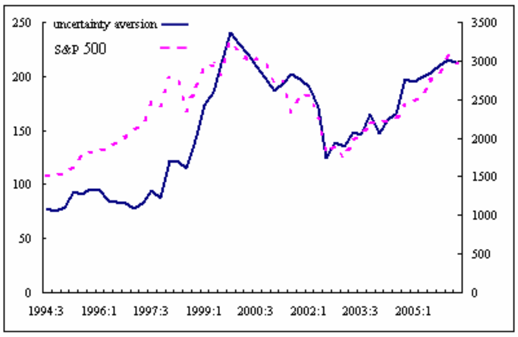
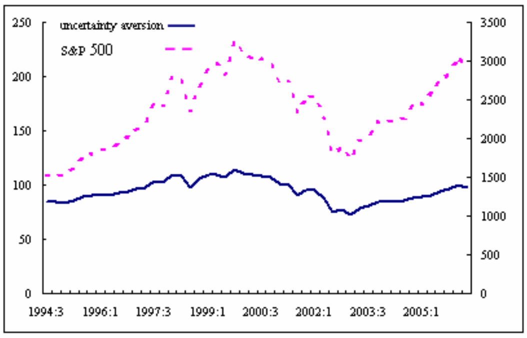
Figure 1. Empirical Uncertainty Aversion

<Panel A> and <Panel B> shows memoryless empirical uncertainty aversion and long memory empirical uncertainty aversion with FTSE100 in UK from 1994:3 through 2006.2. <Panel C> and <Panel D> shows memoryless and long memory empirical uncertainty aversion with S&P500 from 1978:4 through 2006:2. Empirical uncertainty aversion tends to move together both in UK and US.

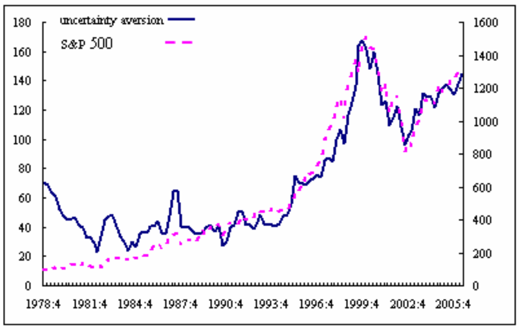
<Panel A> Memoryless empirical uncertainty aversion in UK



<Panel B> Long memory empirical uncertainty aversion in UK



<Panel C> Memoryless empirical uncertainty aversion in US



<Panel D> Long memory empirical uncertainty aversion in US

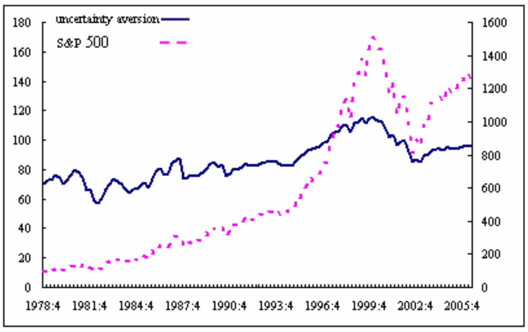


Figure 2. Comparison Empirical Uncertainty Aversion between UK & US

<Panel A> and <Panel B> compares memoryless and long memory empirical uncertainty aversion between UK and US from 1994:3 to 2006:2. The correlation of two time series is 0.9321 and 0.9149 in <Panel A> and <Panel B>. Investor's aversive attitude about worst case scenario seems to be similar in UK and US.

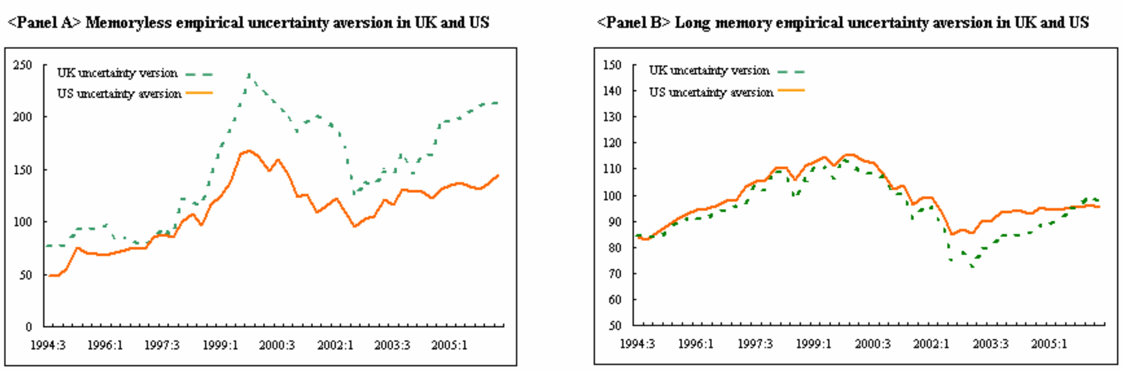


Table 1. Relation between Uncertainty Aversion Increase and Credit Spread

<Panel A> ~ <Panel D> shows VECM regression result of equation (9). We are interested in β_{15}, which means the relationship between yesterday's increase of empirical uncertainty aversion and today's credit spread. Estimated coefficient are statistically significant at 99% (95%) level are indicated by **(*). <Panel A> shows 99% significance and <Panel B> and <Panel D> shows 95% significance.

<Panel A> memoryless mechanism in UK

	β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	β_{16}	β_{17}	β_{18}
estimation	-0.3610	-0.1565	0.0440	0.1126	1.4737**	0.2458	0.1302	0.2824*
t-statistics	-1.4290	-0.8734	0.6543	1.6195	2.9202**	0.6864	0.9695	2.0333*

<Panel B> long memory mechanism in UK

	β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	β_{16}	β_{17}	β_{18}
estimation	-0.3551	-0.0833	0.0667*	0.0060	3.2797*	1.1039	-0.0484	0.1960
t-statistics	-1.2104	-0.4372	2.2052*	0.1855	2.3115*	1.1981	-0.3309	1.2413

<Panel C> memoryless mechanism in US

	β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	β_{16}	β_{17}	β_{18}
estimation	0.1209	0.0295	0.0158	0.0194	0.3292	0.0765	-0.2648**	-0.0875
t-statistics	0.9180	0.2971	0.4928	0.6056	0.8139	0.2503	-2.6877**	-0.8869

<Panel D> long memory mechanism in US

	β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	β_{16}	β_{17}	β_{18}
estimation	0.0583	0.0735	0.0138	0.0152	2.6003*	0.0927	-0.2768**	-0.0939
t-statistics	0.4198	0.7182	1.3612	1.5000	2.0144*	0.0975	-2.9266**	-0.9924

Table 2. Relation between Uncertainty Aversion Increase and Term Spread

<Panel A> ~ <Panel D> shows VECM regression result of equation (10). We are interested in β_{25}, which means the relationship between yesterday's increase of empirical uncertainty aversion and today's term spread. Estimated coefficient are statistically significant at 99% (95%) level are indicated by **(*). Both panel shows no statistically significance.

<Panel A> Memoryless mechanism in UK

	β_{21}	β_{22}	β_{23}	β_{24}	β_{25}	β_{26}	β_{27}	β_{28}
estimation	-0.2631	-0.0657	-0.0056	-0.0733	0.2345	-0.4617	0.1611	0.2476
t-statistics	-1.0612	-0.3932	-0.0899	-1.1928	0.3972	-1.1598	1.0814	1.6900

<Panel B> Long memory mechanism in UK

	β_{21}	β_{22}	β_{23}	β_{24}	β_{25}	β_{26}	β_{27}	β_{28}
estimation	0.0053	0.0390	0.0450	-0.0424	0.6441	0.6850	0.0405	0.2027
t-statistics	0.0204	0.2437	1.5573	-1.4538	0.3884	0.6733	0.2201	1.0918

<Panel C> Memoryless mechanism in US

	β_{21}	β_{22}	β_{23}	β_{24}	β_{25}	β_{26}	β_{27}	β_{28}
estimation	0.1587	0.0459	0.7385	-1.9522	0.0091	0.0007	-0.2524	-0.2947
t-statistics	1.2100	0.4707	0.5848	-1.5529	0.9096	0.1028	-2.6121	-3.0638

<Panel D> Long memory mechanism in US

	β_{21}	β_{22}	β_{23}	β_{24}	β_{25}	β_{26}	β_{27}	β_{28}
estimation	0.1108	0.1006	-0.0428	-0.1505	0.0152	-0.0159	-0.2625	-0.2300
t-statistics	0.7991	0.9969	-0.1044	-0.4394	0.4835	-0.6968	-2.8206	-2.9604

Table 3. Granger Causality on Uncertainty Aversion Increase, Credit Spread, Term Spread

Each Panel has six null hypotheses. We are interested in 2^{th} and 4^{th} hypothesis. We reject the 2^{th} null hypothesis at 99% (***) in <Panel A>, 95%(**) in <Panel D>, 90%(*) in <Panel B>. We reject the 4^{th} null hypothesis at 99% in <Panel A>, 95% in <Panel D>.

<Panel A> Memoryless mechanism in UK

Null Hypothesis	F-statistics	P-value
Credit spread does not granger cause uncertainty aversion increase.	0.7250	0.4906
Uncertainty aversion increase does not granger cause Credit spread.	5.6271^{***}	0.0070^{***}
Term spread does not granger cause uncertainty aversion increase.	1.0854	0.3475
Uncertainty aversion increase does not granger cause Term spread.	5.2383^{***}	0.0095^{***}
Term spread does not granger cause Credit spread.	0.3658	0.6959
Credit spread does not granger cause Term spread.	1.2897	0.2865

<Panel B> Long memory mechanism in UK

Null Hypothesis	F-statistics	P-value
Credit spread does not granger cause uncertainty aversion increase.	0.8155	0.4496
Uncertainty aversion increase does not granger cause Credit spread.	2.7254^{*}	0.0777^{*}
Term spread does not granger cause uncertainty aversion increase.	1.4685	0.2424
Uncertainty aversion increase does not granger cause Term spread.	0.2292	0.7962
Term spread does not granger cause Credit spread.	0.3658	0.6959
Credit spread does not granger cause Term spread.	1.2897	0.2865

<Panel C> Memoryless mechanism in US

Null Hypothesis	F-statistics	P-value
Credit spread does not granger cause uncertainty aversion increase.	0.0387	0.9620
Uncertainty aversion increase does not granger cause Credit spread.	0.3317	0.7184
Term spread does not granger cause uncertainty aversion increase.	1.5483	0.2175
Uncertainty aversion increase does not granger cause Term spread.	0.4630	0.6306
Term spread does not granger cause Credit spread.	0.6834	0.5701
Credit spread does not granger cause Term spread.	2.1883	0.1172

<Panel D> Long memory mechanism in US

Null Hypothesis	F-statistics	P-value
Credit spread does not granger cause uncertainty aversion increase.	0.1519	0.8593
Uncertainty aversion increase does not granger cause Credit spread.	4.1918**	0.0177**
Term spread does not granger cause uncertainty aversion increase.	0.6277	0.5358
Uncertainty aversion increase does not granger cause Term spread.	4.2004**	0.0176**
Term spread does not granger cause Credit spread.	0.06834	0.5701
Credit spread does not granger cause Term spread.	2.1883	0.1172