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IS TIME-VARYING INDUSTRY BETA RISK BROKEN STATIONARY? PANEL UNIT ROOT TEST WITH MULTIPLE STRUCTURAL BREAKS

Abstract*. Dynamics and the instability beta risk have been recognized in previous studies, but as to whether or not there exist structural breaks in time-varying risk there is little known in spite of the issue being addressed in various empirical studies. Therefore, this paper aims to empirically investigate the stability of industry beta risk over time and identify potential and unkown mean revision using the panel data unit root test with multiple structural breaks approach developed by Carrion-i-Silvestre et al. (2005). Time-varying beta is generated by utilizing the Kalman filtering approach for eight main monthly industry portfolio indexes over the period from January 1981 to October 2007, covering several sectors of banking, cement, construction, electrical machinery, food, plastics, pulp and paper, and textiles. The results differ from previous findings in that industry beta risk is found to exhibit time-varying characteristics as well as stationarity based upon the panel unit root test for beta series. Besides the pulp and paper, plastics, and textiles sectors, the empirical evidence reveals three distinct regime changes for the months July 1988, December 1996, and April 2000 in the case of the electrical machinery sector, as well as three distinct regime changes for the months of July 1988 and March 2001 in the case of the food sector.*

Keywords: *Time-Varying Beta Risk, Panel Data Unit Root test, Multiple Structural Breaks, Kalman Filtering Approach*.

JEL Classification: **G10; G14 ; C15 ; C1**

I. Introduction

The properties of dynamics and the instability of beta values have been recognized in previous studies, but as to whether or not there are structural breaks in beta risk there is still very little evidence in spite of the issue being addressed in various empirical studies. However, identifying the mean revision in industry beta risk is a crucial component of corporate strategy in response to environmental change. In addition, this stock market-based information is also of importance to fund managers and industry analysts in appraising the industrial transformation. Therefore, this paper empirically investigates the stochastic properties of industry beta risk over time and identifies regime changes using the panel unit root test with the multiple structural breaks approach developed by Carrion-i-Silvestre et al. (2005). Moreover, the Kalman filtering approach is applied to estimate time-varying industry beta for eight main industry portfolio indexes on a monthly basis over the period from January 1981 to October 2007, covering the banking, cement, construction, electrical machinery, food, plastics, pulp and paper, and textile sectors.

The major contribution of this study to the literature is that it enhances statistical power by exploiting the cross-sectional variability of the panel data for industry beta risk in Taiwan. This setting mainly considers not only the common influences caused by the stock market environment but also the potential relationship within industry interaction. Unlike previous studies that directly test the beta coefficient in the market model, this study initially estimates the time-varying beta series. It then examines the stability of the beta series using panel unit root tests, through which we are able to jointly use the cross-sectional information in the dataset and thereby control for multiple breaks.

The systematic risk described in the Capital Asset Pricing Model (CAPM) is generally estimated for a sizeable number of studies on empirical finance using the market model, where the return on the individual portfolio is regressed against the market return. The coefficient of the beta obtained from the regression thus serves as an estimate of the systematic or market risk. In practice, beta estimates of portfolios at the industry level are particularly valuable to portfolio management and helpful in facilitating the risk management of enterprises. In addition, the information on beta risk for different sectors is crucial in portfolio analysis and in assisting portfolio managers with their investment strategy.

The estimation of beta risk and the testing of asset pricing models on stock market data have a long and well-established development in academic finance. There have been a good number of studies that have investigated the characteristics of time-varying and unstable beta, for instance, Blume (1971 and 1975), Garbade (1977), Garbade and Rentzler (1981), Brenner and Smidt (1977), Kon and Jen (1978), Francis (1979), Ohlson and Rosenberg (1982), Ferson et al. (1987), Bollerslev et al. (1988), Mark (1988), Harvey (1989), Bodurtha and Mark (1991), Ng (1991), Gregory-Allen et al. (1994), Kim (1993), and Evans (1994). Furthermore, there have also been a considerable number of empirical studies that have focused on the international stock markets of many countries, for example, the United States (Levy, 1971; Fabozzi and Francis, 1978; Roenfeldt et al., 1978; Sunder, 1980; Alexander and Benson, 1982; Bos and Newbold, 1984; Simonds et al., 1986; Collins et al., 1987; Kim, 1993; Bos and Fetherston, 1995), Australia (Bos and Newbold, 1984; Faff et al., 1992; Brooks et al., 1992 and 1994; Pope and Warrington, 1996; Faff and Brooks, 1997; Brooks et al., 1998), the United Kingdom (Black et al., 1992; Reyes, 1999), Sweden (Well, 1994), Finland (Bos et al., 1995), Hong Kong (Mok et al., 1990; Cheng, 1997), Singapore (Brooks et al., 1998), and Korea (Bos and Fetherston, 1995), and Malaysia (Kok, 1992 and 1994; Brooks and Faff, 1997; Brooks et al., 1997). However, few of those have concentrated on the industrial beta's time-varying property (see Faff et al., 1992; Faff and Brooks, 1998; Groenewold and Fraser, 1999; Gangemi et al., 2001; Josev et al., 2001; Yao and Gao, 2004). However, previous researchers have paid little attention to the empirical evidence on structural changes in time-varying beta.

The industry environment might shift permanently over time with unexpected economic shocks or specific policy interventions such as financial crises or financial market deregulations (Brown et al., 1975). Whether or not there are structural changes in industry beta risk is of importance to fund managers when adjusting their portfolios as well as to policy-makers when evaluating the effectiveness of policy implementation. However, this empirical issue is yet to be tackled comprehensively and has rarely been addressed quantitatively in previous studies. Therefore, this paper provides some empirical evidence that helps identify the potential regime changes in industry beta risk over time using data on the Taiwan industry weighted portfolios index that spans the period from 1980 to 2007. Time-varying beta risk is specifically estimated by utilizing the Kalman filtering approach and its dynamic characteristics are also examined in this study.

An alternative approach is directly employed to model time-varying beta in terms of different macroeconomic variables (Rosenberg and McKibben, 1973; Rosenberg and Marathe, 1975; Abell and Krueger, 1989; Shanken, 1990), and market risk premium is found to be highly correlated with the business cycle (Fama and French, 1989; Chen, 1991; Ferson and Harvey, 1991; Ragunathan et al., 1999). In particular, Grinold et al. (1989) and Jagannathan and Wang (1996) also indicate that the phase of the business cycle itself captures the net effect of the major macroeconomic forces, and the business cycle in turn influences the returns on the stock and its beta. Moreover, Ragunathan et al. (2000) clearly demonstrate that business cycles are important and that, in particular, the US business cycle has a much larger impact on the equity betas of industry portfolios than the Australian business cycle. They all find that interactions between the business cycles of Australia and the US have an impact on the beta risk of many industries.

Although the Taiwan stock market has encountered many rapid changes during the past decade and industrial betas are now calculated by virtually all financial practitioners and industry analysts, indeed, follow-up studies investigating how the systematic risk of industry portfolios has evolved over time are very few in number in the econometrics literature. Hence, identifying industry systematic risk is of particular importance and specifically involves recognizing the shift in the mean over time that pertains to both macro- and micro-economic factors. The remainder of this paper is organized as follows. Section 2 briefly describes the econometric methodology of the Kalman filtering approach in order to estimate the time-varying beta as well as the panel procedures employed in the analysis. Section 3 reports the data and empirical results from the time-varying beta risk and the implementation of the testing procedures. Section 4 concludes the paper.

II. Methodology

A number of techniques that have been alternatively applied through time-varying betas may be estimated in a variety of contexts as follows: (1) the multivariate generalized ARCH (M-GARCH) model, first introduced by Bollerslev (1990) and empirically applied by Reyes (1999); (2) a time-varying beta market model, initially suggested by Schwert and Seguin (1990); and (3) the Kalman filtering approach, applied successfully by Black et al. (1992) and Wells (1994). This last approach was originally developed by Kalman (1960) within the context of linear systems, and the method now serves as the basic tool for dealing with the standard state-space model. Due to the ease of implementation of its related algorithms, the Kalman filter is now widely applied in many areas of empirical finance, most notably in the state-space form of stochastic parameter regression.

II.1 Estimating Time-Varying Industry Beta Risk

The state-space representation of a system is a fundamental technique in modern control theory. It is now commonly used for expressing dynamic systems. A state-space system consists of two equations: a transition equation (or state equation) and a measurement equation. The transition equation describes the dynamics of the state variables based on a minimum set of information from the present and past such that the future behavior of the system can be completely described by the knowledge of the present state and the future input. Furthermore, the measurement equation represents the relationship between observed variables and unobserved state variables. Therefore, the time-varying market model may be expressed as follows:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t} RM_t + \psi_t \,, \quad \mu_t \sim N \;\; 0, \sigma^2 \tag{1}$$

where i=industry and t=time; $R_{i,t}$ is the log-return of the industry index portfolio; and RM_t is the log- return of the market portfolio.

As this paper considers only the case where the industrial indices are mutually independent, we estimate the parameters individually for each industry. Therefore, $R_{i,t}$ can be denoted by RM_t, $\alpha_{i,t}$ by α_t and $\beta_{i,t}$ by β_t for each discussed index. If both the risk-free rate α and the regression coefficient β are assumed to be constant, the model can be estimated using ordinary least squares. The state-space form of the time-varying market model above can be rewritten as follows:

Measurement equation: $R_{i,t} = \Gamma_{i,t} B_{i,t} + \phi_{i,t}$, $\phi_{i,t} \sim N(0, \sigma^2)$ (2)

Transition equation: $B_{i,t} = \Omega B_{i,t-1} + \lambda_{i,t}$, $\lambda_{i,t} \sim N(0, \Psi)$ (3)

where each $\Omega_{i,t} = (1, RM_t)^{\tau}$ is a vector; $R_{i,t}$ is the asset return and RM_t is the market portfolio return at time t, each $B_{j,t} = (\alpha_t z, \beta_t)^{\tau}$ is also a parameter vector, and both ϕ_t and λ_t are Gaussian and mutually independent. By setting different values to Γ, we can derive random walk, random coefficient or mean reverting processes. The covariance matrix Ω and any components of the transition matrix Γ are known as the **hyperparameters** of the system. Although a sequence of generalized least squares (GLS) regressions can achieve the inferences regarding the state vector that are conditional upon information available up to time *t*, it is exceedingly inefficient in terms of the computational burden (see Kim and Nelson, 1999, p. 20).

Using the Kalman filter to estimate the time-varying parameters has two major advantages. First, the calculation is repeatedly recursive. Although the current estimates are based on the whole past history of measurement, there is no need to expand memory and the extra observations available for the regression; second, the Kalman filter converges quickly, regardless of the underlying model. Meinhold and Singpurwalla (1983) suggested that the Kalman filter could actually be viewed as an updating procedure, which consists of forming a preliminary guess regarding the state of nature and then adding a correction to that which is determined by how well the guess has performed in predicting the next observation.

II.2 Panel Stationarity Test with Multiple Structural Breaks

Carrion-i-Silvestre et al. (2005) initially introduced the panel data stationarity test (CBL, hereafter). This approach simultaneously conducts panel and individual data stationarity tests with multiple structural breaks and is applied in this study. Hadri (2000) modified the stationarity test to allow for multiple structural breaks by incorporating dummy variables as the deterministic specification in the model. In this case, under the null hypothesis the data generation process for the time-varying beta is assumed to be as follows:

$$\beta_{i,t} = \alpha_i + \sum_{k=1}^{m_i} \theta_{i,k} DU_{i,k,t} + \delta_i t + \sum_{k=1}^{m_i} \gamma_{i,k} DT^{*}_{i,k,t} + \zeta_{i,t} \tag{4}$$

where $\beta_{i,t}$ is a time-varying beta series in industry i at time t and is initially estimated by the Kalman Filtering approach; $t = 1,...,T$ time periods; $i = 1,...,N$ represents members of the sector; and $\zeta_{i,t}$ is the error term. The dummy variables $DU_{i,k,t}$ and $DT^{*}_{i,k,t}$ are defined as $DU_{i,k,t} = 1$ for $t > T^{i}_{b,k}$ and 0 otherwise, and $DT^{*}_{i,k,t} = t - T^{i}_{b,k}$ for $t > T^{i}_{b,k}$ and 0 otherwise; and $T^{i}_{b,k}$ denotes the k^{th} date of the break for the i^{th} sector, $k = 1,...,m_i$, $m_i \geq 1$.

The specification in (4) generally allows for unit-specific intercepts and time trends in addition to unit-specific mean and slope shifts. CBL computes the panel stationarity test as the average of the univariate KPSS tests:

$$LM(\lambda) = N^{-1} \sum_{i=1}^{N} \left(\hat{\omega}_i^{-2} T^{-2} \sum_{t=1}^{T} S^{2}_{i,t} \right) \tag{5}$$

where $S_{i,t} = \sum_{j=1}^{t} \hat{\varepsilon}_{i,j}$ denotes the partial sum process obtained by using the estimated OLS residuals of (4). $\hat{w}_i^{2}$ is a consistent estimate of the long-run variance of $\zeta_{i,t}$.

Since the test is dependent upon $\lambda_i = (\lambda_{i,1},\ldots,\lambda_{i,m_i})' = (T^{i}_{b,1}/T,\ldots,T^{i}_{b,m_i}/T)'$ which indicates the location of the breaks relative to the whole period T, we estimate the vector λ_i for each unit using the procedure of Bai and Perron (1998) which is based upon the global minimization of the sum of squared residuals (SSR). This procedure chooses as the estimate of the breaks location with argument minimizes sequence of unit-specific $SSR(T^{i}_{b,1},\ldots,T^{i}_{b,m_i})$ obtained from (4) such that:

$$(\hat{T}^{i}_{b,1},\ldots,\hat{T}^{i}_{b,m_i}) = \arg\min SSR(T^{i}_{b,1},\ldots,T^{i}_{b,m_i}) \tag{6}$$

Once the dates for all possible $m_i \leq m^{\max}$ for each i are estimated, where $m^{\max}$ is the maximum number of breaks, we select the appropriate number of structural breaks using the modified Schwarz information criterion of Liu et al. (1997), which is designed for the case where there are trending variables. Once the vector $\hat{\lambda}_i$ is determined, we compute the normalized test statistic as follows:

$$Z(\lambda) = \frac{\sqrt{N}(LM(\lambda) - \bar{\xi})}{\bar{\zeta}} \rightarrow N \;\; 0,1 \tag{7}$$

where $\bar{\xi}$ and $\bar{\zeta}$ are computed as averages of individual means and variances of $LM_i \;\; \lambda_i$. The computation of the $Z(\lambda)$ statistic requires that the individual series be cross-sectionally independent along with asymptotic normality. Since these assumptions may be overly strong, we will compute the bootstrap distribution of the panel stationarity test with multiple breaks following Maddala and Wu (1999) in order to allow for any kind of cross-sectional dependence, thereby correcting for finite-sample bias.

III. Data and Empirical results

Our sample data are monthly-adjusted price relative information for Taiwan Stock Exchange (TSE) indices provided by the Taiwan Economic Journal (TEJ) database, covering eight industry portfolios indexes in Taiwan (the banking, cement, construction, electrical machinery, food, plastics, pulp and paper, and textile sectors), and the market stock return (the TSE Weighted Price Index). The sample period covers the period from 10 January 1981 to 12 October 2007. A total of 1,358 observations are finally used in the empirical analysis.

As Table 1 shows, the results of the panel unit root tests without a trend, as proposed by Breitung (2000), Im et al. (2003), Levin et al. (2002) and Maddala and Wu (1999) as well as the panel stationarity test proposed by Hadri (2000), are jointly stationary in eight time-varying beta series. This result is obtained under the assumption that there are no structural breaks in the series.

Since it is well documented that unit root tests that fail to control for structural breaks are biased towards the non-rejection of the nonstationarity null, we employ the panel stationarity test recently developed by Carrion-i-Silvestre et al. (2005) which allows for an unknown number of multiple breaks. The empirical results are reported in Table 2 with their 90%, 95%, 97.5%, and 99% confidence intervals, for each of the break dates. Panel A reports the results of the individual KPSS tests allowing for a maximum of five breaks, that are used in the panel tests. Finite-sample critical values for univariate KPSS tests are computed by means of Monte Carlo simulations using 20,000 replications. Panel B shows the panel stationarity test for the case of cross-sectional independence and asymptotic normality, and Panel C reports the bootstrap distribution which allows for cross-sectional dependence in addition to correcting for small-sample bias. The results from the CBL panel stationarity test for the specification with industry-specific intercepts and mean shifts are also presented.

As observed in Panel B in Table 2, we can not reject the null of regime-wise mean stationarity for eight industry beta at the 1% level. This indicates that the panel datasets for the eight sector-based panels for time-varying beta are joint stationary; otherwise, the results mean that any shock may have a permanent effect on beta risk. After introducing the structural breaks and cross-sectional correlations into the model, our results supplement the traditional panel unit root test results to confirm the stability of the time-varying beta.

Even though the panel unit root test results are indicative of the stability of the time-varying beta, some of the sector beta were found to encounter significant structural breaks over time, such as in the electrical machinery, banking, food, plastics, and construction sectors. The average (mean) value of the time-varying beta is reported for each regime. For the full sample period (January 1981 to October 2007) of the electrical machinery sector, we find three break dates: July 1988, December 1996, and April 2000. There are two break dates in July 1988 and March 2001 for the food sector beta. We also find one break date for each of the banking, cement, and construction sectors, with these being November 1996, July 2002 and January 2002, respectively.

It is noted that the Asian financial crisis has a significant influence on the electrical machinery and banking industries, signifying that their beta risk is responding to the systematic risk. However, there are no structural breaks in the time-varying beta for the pulp and paper, plastics, and textile sectors. This implies that the systematic risk in those sectors is comparative stationary under the same stock market conditions while the electrical machinery and banking sectors encounter a spillover effect from the financial crises. This finding also indicates that the electrical machinery and banking sectors are more sensitive to stock market changes and their beta means exceed one as in their reaction to the stock market.

Moreover, the time-varying beta for pulp and paper and plastics were found to exhibit obvious fluctuations in terms of their trend around one, but no evidence of a structural break was found in the time-varying beta series. This implies that their industry risk resounded sharply to stock market movements. It is noted that the beta means for the four regimes in the electrical machinery sector over the entire sample period are 1.063, 0.973, 1.267, and 1.115, respectively. Besides regime two, the average beta risk in the electrical machinery sector is more than one, showing that the market risk in the electrical machinery sector had higher industry risk in comparison to the stock market risk. This reflects the product competition and fluctuations in firm profitability in this industry. Prior to November 1996, the industry risk exceeded the stock market risk but this declined to less than one, indicating that the overall industry risk in banking was lower after the impact of the 1997 Asian financial crisis had been felt.

IV. Conclusion

This paper investigates the stability of industry beta risk over time and identifies mean revision by using the panel unit root test with multiple structural breaks approach developed by Carrion-i-Silvestre et al. (2005). Time-varying beta are estimated utilizing the Kalman filtering approach for eight main monthly industry portfolio indexes over the period from January 1981 to October 2007, covering the banking, cement, construction, electrical machinery, food, plastics, pulp and paper, and textile sectors.

The industry beta risk was found to exhibit time-varying characteristics but also stationarity based upon panel unit root tests for beta series, which was different from previous findings. In addition, we found the presence of mean revision in time-varying beta, indicating that time-varying industry beta was broken stationary. Besides the pulp and paper, plastics, and textile sectors, the empirical evidence indicates that there were three distinct regime changes for the following months: July 1988, December 1996, and April 2000 in the electrical machinery sector, as well as three distinct regime changes for the following months July 1988 and March 2001 in the food sector.

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Table 1 Panel unit root and stationary tests without structural breaks

Method	Statistic	Probability
LLC	-7.254***	0.000
Breitung	-8.145***	0.000
IPS	-13.399***	0.000
Fisher ADF	202.164***	0.000
Fisher PP	307.134***	0.000
Hadri Z-stat	4.780***	0.000
Heteroscedastic Consistent Z-stat	3.772***	0.000

Note: LLC and IPS represent the panel unit root tests of Levine et al. (2002) and Im et al. (2003), respectively. Fisher-ADF and Fisher-PP represent the Maddala and Wu (1999) Fisher-ADF and Fisher-PP panel unit root tests, respectively. *** indicate statistical significance at the 1% level. Probabilities for Fisher-type tests were computed by using an asymptotic χ^2 distribution. All other tests assume asymptotic normality.

Table 2. Panel data stationary tests and individual tests with structural breaks for time-varying beta

Sectors	KPSS	m	$T_{b,1}$	$T_{b,2}$	$T_{b,3}$	Finite sample critical values (%)			
						90	95	97.5	99
Panel A: Industry-by-industry testing									
Banking	0.031	1	Nov-96	-	-	0.113	0.147	0.177	0.217
Cement	0.040	1	Jul-02	-	-	0.211	0.277	0.342	0.444
Construction	0.033	1	Jan-02	-	-	0.200	0.261	0.324	0.409
Electrical Machinery	0.034*	3	Jul-88	Dec-96	Apr-00	0.033	0.038	0.042	0.048
Food	0.052*	2	Jul-88	Mar-01	-	0.049	0.057	0.067	0.080
Pulp and Paper	0.036	0	-	-	-	0.118	0.147	0.180	0.221
Plastics	0.068	0	-	-	-	0.119	0.147	0.176	0.218
Textile	0.100	0	-	-	-	0.119	0.147	0.175	0.212

Panel B: Panel data stationary test: assuming cross-section independence

	Test statistics	p-Value
Homogeneity	0.185	0.427
Heterogeneity	0.340	0.367

Panel C: Bootstrap distribution

KPSS test	Bootstrap critical values (%)							
	1	2.5	5	10	90	95	97.5	99
Homogeneity	12.751	13.522	14.247	15.121	22.175	23.333	24.398	25.701
Heterogeneity	11.209	11.947	12.649	13.449	20.725	22.088	23.242	24.779

Notes: * indicates significance at the 2.5% level. The number of break points is estimated using the LWZ information criteria allowing for a maximum of five structural breaks (m). The long-run variance is estimated using the Bartlett kernel with automatic spectral window bandwidth selection as in Sul et al. (2005). In addition, all bootstrap critical values allow for cross-sectional dependence.