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Examining Systematic Risk with Principal Component Analysis: An Empirical Analysis in Hong Kong Stock Market

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This paper proposes a two-step approach to examine the macroeconomic determinants of systematic risk. The first step takes as systematic risk the first principal component in a portfolio that explains the largest variance from a Principal Component Analysis (PCA). The second step examines the macroeconomic determinants that constitute systematic risk. Applying the approach to monthly data of 189 stocks in 11 sector portfolios in Hong Kong, the findings show that the unemployment rate and trade balance are the significant factors constituting systematic risk. Further, systematic risk is autoregressive and has a non-zero mean. The error correction force of the long-run equilibrium between the co-integrated series unemployment rate and trade balance significantly contributes to the systematic risk.

JEL Codes: G12 and F62

1. Introduction

In the Capital Asset Pricing Model (CAPM), beta as the amount of systematic risk is the only factor that explains an asset's expected returns; however, CAPM provides no clear framework on determining macroeconomic constituents of the systematic risk. The literature in the last few decades has focused on using macroeconomic variables to explain stock returns but not the systematic risk, commonly using the Ross (1976) Arbitrage Pricing Theory (APT). Unlike CAPM, APT defines a relationship between the stock's expected return and the covariance with other random factors. Clare and Thomas (1994) applied the APT to the UK stock market to demonstrate that the macroeconomic variables oil price, retail price index, bank lending, and corporate default risk influenced stock returns significantly. Günsel and Çukur (2007) applied the APT to study the relationship between seven macroeconomic variables (interest rate, exchange rate, inflation, industrial production, risk premium, money supply, and unanticipated sectoral dividend yield) and stock returns in the UK finding that some macroeconomic variables significantly influence stock returns, but vary by industry portfolios. Saeed (2012) and Zhu (2012) applied the APT to stock returns in the Pakistan Karachi Stock Exchange and China Shanghai Stock Exchange respectively, both finding that macroeconomic variables do have significant effects on stock returns. Apart from the application of the APT, Humpe and Macmillan (2009) performed co-integration tests between stock returns and macroeconomic variables in the US and Japanese stock market. The results show that the US stock returns are influenced by industrial production, inflation, and long-term interest rates, while the Japanese stock returns are influenced by industrial production and the money supply. Sariannidis et al. (2010) examined the influence of macroeconomic variables on the US stock market using a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model showing that stock returns are significantly affected by crude oil returns and interest rates. Ladrón de Guevara and Torra (2014) use APT to study the stock returns in Mexican stock market. Unlike previous studies have been based on a

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prior selection of macroeconomic variables to identify potential factors, they apply the PCA to estimate the potential factors statistically. They studied 22 shares in the Mexican market, and the result shows that the APT statistical approach is unstable and it is sensitive to the techniques used in extracting the risk factors.

This study takes a statistical approach to study the systematic risk. It is assumed that the systematic risk is unobservable, and which should be extracted statistically. Unlike Ladrón de Guevara and Torra (2014) apply the PCA and consider the principle components as potential factors, the first principle component is considered to explain the largest variance of the portfolio returns represents the systematic risk. This study takes two stages to study the systematic risk: (1) by performing PCA on portfolio returns and then extracting the first principal component that explains the greatest variance of the portfolio return as the representation of systematic risk. (2) by performing a regression analysis on the first principal component series with macroeconomic variables as the independent variables. This study takes a different approach from the traditional APT and factor models; it use a two-step procedure to statistically extract the systematic risk that suffers no model risks inherent in a factor model, followed by identifying the underlying macroeconomic determinants of it. This paper proceeds as follows: In Section 2, the methods of identifying the relationship between macroeconomic factors and systematic risk are reviewed. Section 3 introduces the data that used throughout this study and performs stationary checks for cointegration tests. It also explains the statistical methodology and outlines the implementation procedures by considering the stocks in Hong Kong stock market as an empirical example. Section 4 provides the empirical findings and section 5 concludes.

2. Literature Review

Early literature of Abell and Krueger (1989) proposed a variable beta model (VBM) to study the influence of macroeconomic activity on portfolio beta change. The results show that interest rates, budget deficits, trade deficits, inflation, and oil prices significantly influent the change of beta. They identify the relationship between macroeconomic factors and systematic risk based on the assumption of the validity of the single-factor model.

$$R_t = a + B_t(MRP_t) + e_t \tag{1}$$

$$B_t = b_0 + \sum_{i=1}^{p} b_i F_i + w_t \tag{2}$$

Where R_t is the portfolio return at time t, a and b_0 are constants, e_t and w_t are random errors, MRP_t is the market risk premium and $F_{i,t}$ values are the macroeconomic variables that explain the time-varying beta B_t. By substituting equation (2) into equation (1), one can estimate the macroeconomic determinants of beta in one equation. One weakness in this approach is that if equation (1) is misspecified, as suggested by Fama and French (1992), the results may be biased, a risk inherent in this model.

Groenewold and Fraser (1997) studied the relationship between macroeconomic factors and systematic risk by identifying time-varying betas, then examining their relationship with macroeconomic factors. Their work suffered from the same problem of Abell and Krueger (1989), which assumes the one-factor approach in the CAPM is valid, and the systematic risk can fully explain the portfolio expected returns. The validity of the assumption started to be questioned after the seminal work from Fama and French (1992), which suggests a three-factor model for asset returns. Patro et al. (2002) estimated a time-varying two-factor

model for 16 OECD countries and then explained the beta using a number of macroeconomic factors with a panel approach. Guo et al. (2015) found that the time-varying beta comoves strongly with the unemployment rate. Overall, the relationship between macroeconomic variables and stock returns is well-documented while the seminal works from Sharpe (1964); Lintner (1965); Black (1972) suggest that the systematic risk explains the expected returns. There is evidence that macroeconomic factors constitute the systematic risk (beta), but not with a consensus about the nature of factors.

This study takes a different approach without the assumption of the single-factor model will hold. It follows the arguments presented by from Sharpe (1964); Lintner (1965); Black (1972) that systematic risk explains the portfolio's expected return. Therefore, the PCA is applied to the portfolio return to extract its first principal component that explains the greatest variance. If first principal component can explain a large extent of variance in the stock returns, it is a representation of systematic risk. The first principal component is considered as the systematic risk without the use of any single-factor model.

3. Data and Methodology

This study uses the monthly data of 189 stocks listed on the Hong Kong Stock Exchange for the period between May 2005 and April 2014. Following the method used in the Hang Seng Composite Industry Indexes, the 189 stocks are classified into 11 sector portfolios: Energy, Materials, Industrial, Consumer Goods, Consumer Services, Telecommunications, Utilities, Financial, Real Estate and Construction, Information Technology, and Conglomerates. The monthly stock data are collected from Datastream. The macroeconomic variables include the overall unemployment rate, U; unemployment rate of the service sector, $U_{service}$; unemployment rate of the finance and real estate sector, $U_{fin,prop}$; total imports, Imp_t; total exports, Exp_t; consumer price index, CPI_t; and the Hong Kong interbank offered rate, $HIBOR_t$. The macroeconomic variables are well studied in literatures to explain stock returns (see Clare and Thomas, 1994; Patro et al., 2002; Günsel and Çukur, 2007; Guo et al., 2015). These data are obtained from the Census and Statistics Department for the Government of Hong Kong Special Administrative Region. The monthly continuously compounded returns r_i are computed with $r_t = 100 \times \ln(P_t/P_{t-1})$, where P_t is the monthly stock price at the time t. Inflation I_t is calculated using $I_t = (CPI_t - CPI_{t-1})/CPI_{t-1}$. The trade balance TB_t is obtained from $TB_t = Exp_t - Imp_t$.

The macroeconomic factors are first tested by Dickey and Fuller (1979) augmented ADF stationary tests with the null hypothesis of a unit root against ($\phi = 0$), the alternative hypothesis of an explosive root ($\phi < 0$).

The regression model used in the ADF test is:

$$\Delta y_t = \alpha + \phi y_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{t-j} + e_t \tag{3}$$

Where y_t is the macroeconomic variable tested, k is the lag order, and e_t is the random error. Table 1 shows the results of the stationary analysis of the macroeconomic variables. All variables are considered stationary except the unemployment rates and trade balance. The critical value of the ADF test at the 1% significance level is -2.58.

Table 1: Augmented Dickey-Fuller Unit Root Test Results

	ADF test statistic	Stationary	Integrated Order
Macroeconomic Variables			
Unemployment Rate (Total)	-1.74	No	I(1)
Δ Unemployment Rate (Total)	-8.58	Yes	
Unemployment Rate (Service Sector)	-0.72	No	I(1)
Δ Unemployment Rate (Service Sector)	-8.62	Yes	
Unemployment Rate (Real Estate and Finance Sector)	-0.95	No	I(1)
Δ Unemployment Rate (Real Estate and Finance Sector)	-11.01	Yes	
Inflation	-9.64	Yes	I(0)
Trade Balance	-1.80	No	I(1)
Δ Trade Balance	-17.97	Yes	
Continuous Compound Changes in Trade Balances	-10.27	Yes	I(0)
Changes in Interest Rates (3-m HIBOR)	-12.63	Yes	I(0)

As both the unemployment rate and trade balance are used in the regression analysis below, to ensure that the results do not contain a false regression, this study follows Granger and Engle (1987) to perform a co-integration test on the unemployment rate and trade balance variables. If both the unemployment rate and trade balance are I(1) and have a long run relationship, there must be some force to pull the equilibrium error back to zero. Equation (4) shows the traditional long-run equilibrium equation used in the Granger and Engle (1987) two-step co-integration test.

$$UR_t = \theta_0 + \delta_0 TB_t + u_t \tag{4}$$

Where u_t is a stationary random error. The estimated coefficient in equation (4) can be biased in a small sample because of serial correlation in the regressed residuals $\widehat{u_t}$. To address this issue, this study models the long-run equilibrium equation in equation (5) in an autoregressive distributed lag (ARDL) form.

$$UR_t = \theta_0 + \sum_{i=1}^{p} \theta_i UR_{t-i} + \sum_{j=0}^{q} \delta_j TB_{t-j} + u_t \tag{5}$$

Table 2 shows the regression results of the long-run equilibrium equation (5) calculations. The ADF test demonstrates that the residual series $\hat{u}$ is stationary. From the results in Table 2, equation (6) is obtained, where $r_t = \widehat{u_t}$, which describes deviations from the long-run equilibrium relationship between unemployment rate and trade balance.

$$r_t = \hat{u}_t = -\theta_0 + UR_t - \theta_1 UR_{t-1} - \theta_2 UR_{t-2} - \delta_1 TB_{t-1} \tag{6}$$

Table 2: Regression Results of the Long-run Equilibrium Function: Unemployment Rate and Trade Balance

Variable	Coefficients	
Intercept	θ_0	0.257 (0.082)***
UR_{t-1}	θ_1	1.098 (0.096)***
UR_{t-2}	θ_2	-0.207 (0.095)**
TB_{t-1}	δ_1	2.144×10^{-6} (8.560×10^{-7})**
	R^2	0.949
	DW stats	2.003
	ADF stats of $\hat{u}$	-10.232

Note: Numbers in parentheses are standard errors. *** represents significance at the 1% level, ** represents significance at the 5% level.

The following error correction model in equations (7) and (8) are estimated.

$$\Delta UR_t = \phi_{1,0} + \sum_{i=1}^{p} \phi_{1,i} \Delta UR_{t-i} + \sum_{j=0}^{q} \gamma_{1,j} \Delta TB_{t-j} + \alpha_1 r_{t-1} + e_{1,t} \tag{7}$$

$$\Delta TB_t = \phi_{2,0} + \sum_{i=1}^{p} \phi_{2,i} \Delta TB_{t-i} + \sum_{j=0}^{q} \gamma_{2,j} \Delta UR_{t-j} + \alpha_2 r_{t-1} + e_{2,t} \tag{8}$$

Equation (7) and (8) allow a differentiation between the short-run and long-run dynamics. Table 3 and equation (9) show the estimation results of the error correction model with the unemployment rate as the dependent variable. All coefficients $\gamma_{1,j}$ of the lagged first difference in trade balance are statistically insignificant, indicating that the trade balance does not have a contemporaneous effect on the error correction process. By contrast, the coefficient α_1 is significant, which indicates a deviation from the long-run equilibrium between the unemployment rate and trade balance, affecting the movement of unemployment rates. However, as it is not possible to obtain a significant regression result in equation (8), the movement in trade balances is independent of the unemployment rate, and cannot be modelled as an error correction process. The co-integration tests demonstrate that the unemployment rate and trade balance are co-integrated and have a long-run equilibrium relationship. Equation (9) shows the movement of unemployment rates continuously adjusted by a correction force that corrects the deviation from the long-run equilibrium between the two.

$$\Delta UR_t = \phi_{1,1} \Delta UR_{t-1} + \phi_{1,2} \Delta UR_{t-2} + \alpha_1 r_{t-1} + e_t \tag{9}$$

Table 3: Regression Results of the Error Correction Model with Unemployment Rate as the Dependent Variable

Variable	Coefficient	
ΔUR_{t-1}	$\phi_{1,1}$	0.835 (0.300)***
ΔUR_{t-2}	$\phi_{1,2}$	-0.243 (0.109)**
r_{t-1}	α_1	-0.737 (0.315)**
	R^2	0.089
	DW stats	2.090
	ADF stats of $e_{1,t}$	-10.591

Note: Numbers in parentheses are standard errors. *** represents significance at the 1% level, ** represents significance at the 5% level.

3.1 The Principal Component Analysis (PCA)

In recent years, researchers have focused on using PCA to study risks in financial market (see Loretan, 1997; Baek et al., 2015; Giglio et al., 2016; Nucera et al., 2016). Suppose a sector portfolio contains p stocks with n observations, represented by a $n \times p$ data set matrix $X = [X_1, X_2, \cdots, X_p]$, and the covariance matrix of X is Σ_X.

$$\Sigma_X = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1p} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2p} \\ \vdots & & & \vdots \\ \sigma_{p1} & \sigma_{p2} & \cdots & \sigma_{pp} \end{bmatrix} \tag{10}$$

PCA is applied on X to extract its first principal component P_1. PCA considers P_i as a linear combination of X_i, and all P_i values are uncorrelated.

$$\begin{aligned} P_1 &= a_1' X' &= a_{11}X_1 + a_{12}X_2 + \cdots + a_{1p}X_p \\ P_2 &= a_2' X' &= a_{21}X_1 + a_{22}X_2 + \cdots + a_{2p}X_p \\ \vdots & & \vdots \\ P_p &= a_p' X' &= a_{p1}X_1 + a_{p2}X_2 + \cdots + a_{pp}X_p \end{aligned} \tag{11}$$

The variance of $P_i = Var(Y_i) = a_i' \Sigma_X a_i$, and as P_i values are orthogonal, the covariance $Cov(Y_i, Y_k) = a_i' \Sigma_X a_k = 0$.

The first principle component is defined as the P_i (a linear combination of X_is) that has the maximum variance. To obtain P_i, the covariance matrix Σ_X with eigenvalues and eigenvector pairs $(\lambda_1, e_1), (\lambda_2, e_2), \cdots, (\lambda_p, e_p)$ is considered, where $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p$, and therefore P_i is formed by substituting a_i with the eigenvector e_i, thus the variance of P_i is $Var(Y_i) = e_i' \Sigma_X e_i = \lambda_i$, and the covariance is $Cov(Y_i, Y_k) = e_i' \Sigma_X e_k = 0$.

The total variance of X can be written as:

$$\sum_{i=1}^{p} Var(X_i) = \sigma_{11} + \sigma_{22} + \cdots + \sigma_{pp} = tr(\Sigma_X) = tr(W\Lambda W') = tr(\Lambda) = \lambda_1 + \lambda_2 + \cdots + \lambda_p$$

Where $W = [e_1, e_2, \cdots, e_p]$ and Λ is a diagonal matrix with the eigenvalues λ_i.

Thus, $P = XW$ and the PCA defines the total proportion of the total variance of X due to the kth principal component, as $\lambda_k / \sum_{i=1}^{p} \lambda_i$.

Since $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p$, the first column vector of P is the first principle component P_1 that explains the greatest variance of the data set X. Table 4 shows the results of the PCA on the 11 sector portfolios in Hong Kong. The results show that almost half of the variance in the sector portfolios can be explained by the first principal component in the PCA, which represents the systematic risk. Table 5 shows the correlations between the first principal components for each of the 11 portfolios, which vary from around 60% to 90% and are highly correlated to each other. Figure 1 illustrates the first principal components.

Table 4: Principal Component Analysis (PCA) Results

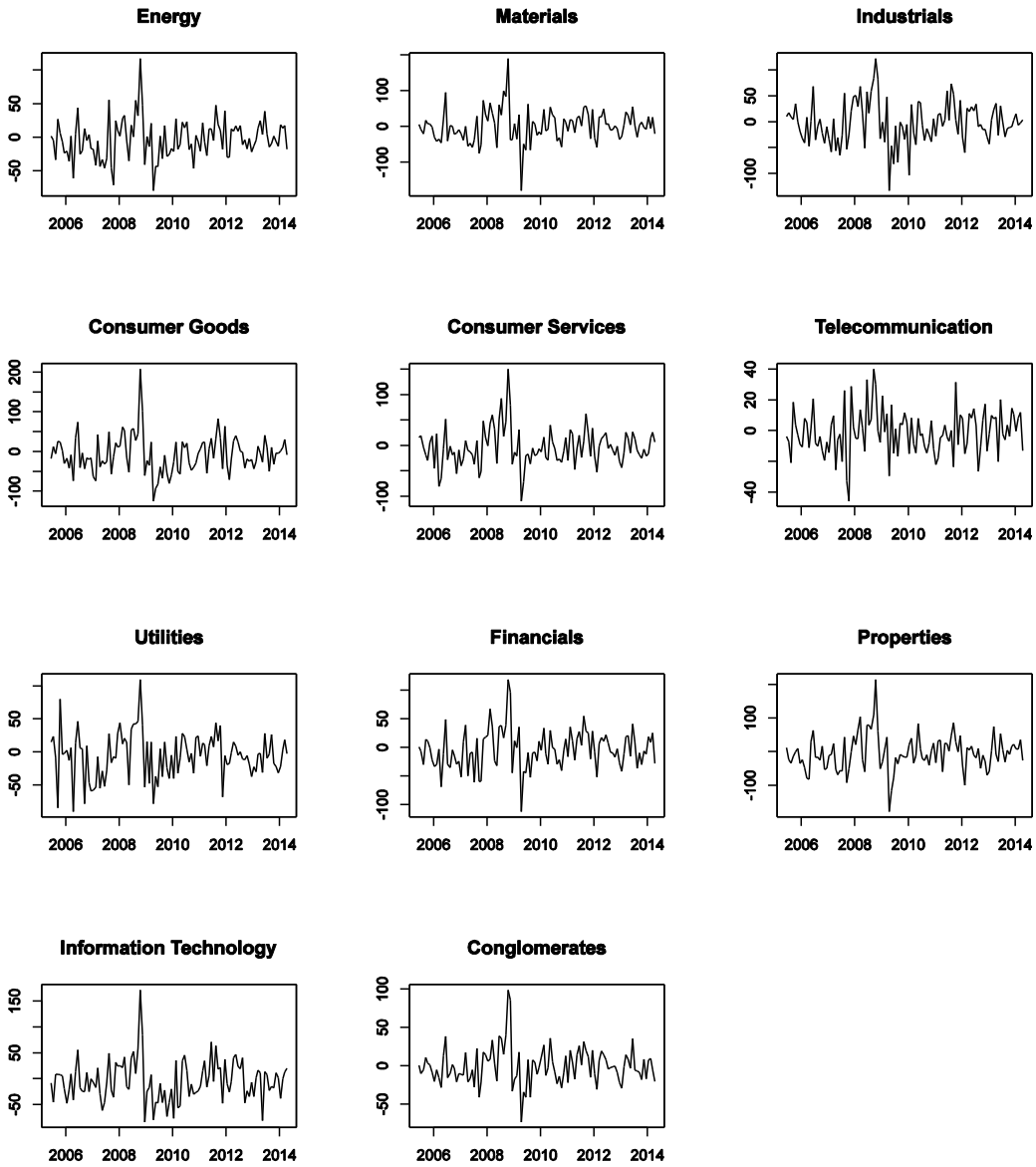
Sector	No. of Stocks	Variance Explained by the First Principle Component	Variance Explained by the First Three Principle Components
Energy	10	42.70%	70.52%
Materials	14	48.50%	70.47%
Industrial	19	37.70%	65.77%
Consumer Goods	35	31.75%	44.58%
Consumer Services	18	40.81%	71.41%
Telecommunications	5	44.74%	76.13%
Utilities	18	37.67%	63.01%
Financial	16	55.59%	76.12%
Real Estate and Constructions	30	50.59%	64.09%
Information Technology (IT)	16	39.30%	57.08%
Conglomerates	8	59.74%	81.59%

Table 5: Correlation of the First Principal Component of the 11 Sector Portfolios

	Energy	Material	Industrial	Consumer Goods	Consumer Services	Telecom-munication	Utilities	Financial	Real Estate	IT	Conglo-merates
Energy	1.0000	0.8686	0.8393	0.8274	0.7364	0.5879	0.6716	0.8505	0.8052	0.7469	0.8318
Material	0.8686	1.0000	0.8283	0.7881	0.7683	0.5959	0.6837	0.7929	0.8436	0.6917	0.8036
Industrial	0.8393	0.8283	1.0000	0.8343	0.7548	0.5314	0.7404	0.8223	0.7873	0.8092	0.8287
Consumer Goods	0.8274	0.7881	0.8343	1.0000	0.8313	0.4513	0.7305	0.8463	0.8340	0.8366	0.8484
Consumer Services	0.7364	0.7683	0.7548	0.8313	1.0000	0.4896	0.6573	0.8235	0.8494	0.7268	0.8581
Telecomm-unication	0.5879	0.5959	0.5314	0.4513	0.4896	1.0000	0.3996	0.5991	0.5060	0.4653	0.5549
Utilities	0.6716	0.6837	0.7404	0.7305	0.6573	0.3996	1.0000	0.6754	0.6872	0.6711	0.6777
Financial	0.8505	0.7929	0.8223	0.8463	0.8235	0.5991	0.6754	1.0000	0.8483	0.7440	0.9028
Real Estate	0.8052	0.8436	0.7873	0.8340	0.8494	0.5060	0.6872	0.8483	1.0000	0.7352	0.8738
IT	0.7469	0.6917	0.8092	0.8366	0.7268	0.4653	0.6711	0.7440	0.7352	1.0000	0.7711
Conglo-merates	0.8318	0.8036	0.8287	0.8484	0.8581	0.5549	0.6777	0.9028	0.8738	0.7711	1.0000

The first principal component series P_1 represents the portfolios' primary risk factors. According to Sharpe (1964), the stock return's primary risk factor is the non-diversifiable systematic risk resulting from changes in economic activity. Different portfolios have differing sensitivity to systematic risk, and the first principal component describes the degree it is affected.

Figure 1: The First Principal Component Series of the 11 Sector Portfolios



3.2 Analysis of the Determinants of Systematic Risk in Hong Kong Stock Market the findings

The literature generally agrees that systematic risk is time-varying. Basu and Stremme (2007) and Adrian and Franzoni (2009) suggest that beta (systematic risk) is time-varying, and Abell and Krueger (1989), Groenewold and Fraser (1997), Patro et al., (2002), and Espe and Simlai (2012) studied macroeconomic determinants of time-varying beta. To capture the potentially autoregressive characteristic of systematic risk, the relationship

between the first principal component P_is and k macroeconomic factors F_k is tested using the following autoregressive distributed lag (ARDL) model:

$$P_{1,j}^{j} = \alpha + \sum_{i=1}^{m} \theta_i P_{1,t-i}^{j} + \sum_{m=1}^{k} \sum_{l=0}^{q} b_{m,l}^{j} F_{m,t-l} + \epsilon_{j,t} \quad (12)$$

Where $P_{1,t}^{j}$ is the first principal component of the sector portfolio j at time t, $\epsilon_{j,t}$ is random error, and $F_{i,t}$ are the macroeconomic variables discussed before. Table 6 shows that all first principal components in each sector portfolio are I(0) stationary.

Table 6: Augmented Dickey-Fuller Unit Root Test of the First Principal Components Results

		ADF test statistic	Stationary	Integrated Order
Energy		-8.49	Yes	I(0)
Materials		-8.64	Yes	I(0)
Industrial		-8.09	Yes	I(0)
Consumer Goods		-7.24	Yes	I(0)
Consumer Services		-7.54	Yes	I(0)
Telecommunications		-10.97	Yes	I(0)
Utilities		-8.72	Yes	I(0)
Financial		-8.00	Yes	I(0)
Real Estate		-6.79	Yes	I(0)
Information Technology		-7.71	Yes	I(0)
Conglomerates		-7.73	Yes	I(0)

Table 7: Estimates of the Determinants of the First Principal Component

	Energy	Materials	Industrial	Consumer Goods	Consumer Services	Telecom-municat-ions	Utilities	Financial	Real Estate	IT	Conglom-erates
Coefficients											
Constant	85.69 (26.27)***	129.49 (41.64)***	121.60 (37.02)***	127.25 (41.19)***	37.33 (19.01)*	35.11 (13.86)**	76.03 (31.32)**	42.22 (17.09)**	49.72 (25.30)*	94.73 (35.69)***	54.98 (21.91)**
AR(1)			0.18 (0.09)*	0.26 (0.09)***	0.18 (0.10)*			0.1914 (0.09)**	0.36 (0.09)***	0.19 (0.09)**	0.22 (0.09)**
Total Unemployment Rate	-38.38 (10.65)***	-54.97 (16.89)***	-50.26 (15.09)***	-54.01 (16.82)***		-15.24 (5.62)***	-33.86 (12.70)***			-40.31 (14.53)***	-22.80 (8.90)**
Unemployment Rate (Service Sector)					11.45 (5.96)*						
Unemployment Rate (Financial and Real Estate Sector)					-34.24 (10.81)***			-15.1430 (5.89)**	-18.20 (8.77)**		
Inflation (t-1)	-5.1948 (2.91)*		-8.11 (4.04)**				-8.17 (3.47)**	-7.6389 (3.40)**		-8.94 (3.83)**	
Changes in Interest Rates (3-m HIBOR)									28.01 (11.55)**	15.94 (8.65)*	12.35 (5.32)**
Trade Balance (x1,000) (t-2)	5.3586 (2.74)*	9.13 (4.34)**	9.69 (3.82)**	11.21 (4.25)***	54.95 (32.07)*	2.63 (1.45)*	5.65 (3.27)*			6.82 (3.68)*	4.43 (2.26)*
R^2	0.1415	0.0953	0.1758	0.1851	0.1822	0.06749	0.1084	0.1421	0.2214	0.1973	0.1612
N	106	106	106	106	106	106	106	106	106	106	106
DW Stats	1.7762	1.6780	1.9426	1.8626	1.9223	2.2045	1.7425	1.9409	1.8742	1.9061	1.9258

Note: This table presents the results of the ARDL model of the first principal component estimates. The ARDL model is represented as $P_{1,t}^{j} = \alpha + \sum_{i=1}^{m} \theta_i P_{1,t-i}^{j} + \sum_{m=1}^{k} \sum_{l=0}^{q} b_{m,l}^{j} F_{m,t-l} + \epsilon_{j,t}$. Numbers in parentheses are standard errors. *** represents significance at the 1% level, ** represents significance at the 5% level, * represents significance at the 10% level.

4. Results and Findings

The empirical results of the ARDL models yield three interesting observations. First, table 7 shows the principal components are serially correlated in one lag; the auto-regression coefficient is significant in more than half of the regression models, suggesting that systematic risk is autoregressive with a coefficient of approximately 0.2. Second, the principal components have a non-zero mean; the constants in the regression results are highly significant in all models, suggesting that systematic risk has a non-zero mean. Third, unemployment rate and trade balance provide significant explanatory power of the first principal components, where trade balance is significant in 9 out of 11 regressions, and unemployment rate is significant in all 11, suggesting that unemployment rate and trade balance explain systematic risk. However, Section 2 finds that the two factors are I(1) co-integrated, confirming that the regression statistics results in Table 7 do not contain a false regression. Equation (13) shows the generalised model for the portfolio i based on the results in Table 7, where SF_j^i are significant factors other than unemployment rate and trade balance. Equation (15) is obtained by rewriting equations (6) to (14) and substitute them into equation (13).

$$P_t^i = \alpha + b_{i,1}UR_t + b_{i,2}TB_{t-2} + \sum_{j=1}^{p} b_{i,2+j}SF_j^i + \epsilon_{i,t} \tag{13}$$

$$TB_{t-2} = \left(\frac{1}{\delta_1}\right)(-\theta_0 + UR_{t-1} + \theta_1 UR_{t-2} - \theta_2 UR_{t-3} - r_{t-1}) \tag{14}$$

$$P_t^i = a_{i,0} + a_{i,1}P_{t-1}^i + a_{i,2}UR_t + a_{i,3}UR_{t-1} + a_{i,4}UR_{t-2} + a_{i,5}UR_{t-3} + a_{i,6}r_{t-1} + \sum_{j=1}^{p} a_{i,6+j}SF_j + \epsilon_{i,t} \tag{15}$$

Clearly, both an increase in trade surplus and a decrease in unemployment rate signal a positive economic growth. A continuous increase in trade surplus indicates that there has been continuity in demand for exports is larger than the demand for the foreign goods and services; therefore; the domestic demand for workers increases leading to a lower unemployment rate within the country. Given this, one may expect that the trade surplus should co-integrated with employment rate, but not the unemployment rate. However, recent studies (see, for example Nanthakumar et al., 2011; Alawin, 2013; Nwaka et al., 2015) show that the linkage between the trade and employment is complex and county-specific. Gould et al. (1993) examined the relationship between imports, exports and unemployment of twenty-three Organization for Economic Cooperation and Development (OECD) countries; they found that there is no simple causal link between trade balance and unemployment for all the countries in the period of 1950 to 1988. Nevertheless, the result in equation (15) shows that the first principal component can be explained by the error correction force for the long-run equilibrium between the co-integrated series unemployment rate and trade balance; this correction force contributes to the systematic risk in the Hong Kong stock market. The result may be explained by the economic states implied by the trade balance and unemployment rate. As most of the macroeconomic indicators are trailing indicators, a continue widening (narrowing) spread between the trade balance and unemployment rate often signalling the economic growth reaching to a peak (trough) and may eventually revert. Such correction force representing a change in economic state and that is a source of systematic risk.

5. Summary and Conclusions

This paper proposes a two-step approach to examine the macroeconomic determinants of systematic risk. The aim of this paper is not on identifying the risk factors that contribute to the risk premium of stock returns, but on proposing a statistical method to identifying the systematic risk factors. Unlike the traditional approaches using models with inherent risks to model time-varying beta that explains the risk premium (but not the constitutional factors), the two-step approach taken in this study extracts systematic risk using PCA provides a better understanding of the sources of systematic risk.

It was motivated by the idea of Sharpe (1964) that the stock return's primary risk factor is the non-diversifiable systematic risk resulting from changes in economic activity, and this study takes the first principal component from the PCA to represent it. The results show that the first principal component explains up to half of the variance in the stock returns that conformed the intuition. The two-step approach is applied to study the systematic risk in the Hong Kong stock market. The method is tested empirically using the data of the Hong Kong stock market covering 189 stocks divided into 11 portfolios according to the Hang Seng Composite Industry Indices classifications. Results show that macroeconomic factors of the unemployment rate and trade balance in Hong Kong are co-integrated, and that any deviation in unemployment rates from the long-run equilibrium will be corrected by a force that is one of the sources of systematic risk. Further, the study also finds that systematic risk is autoregressive and has a non-zero mean. The proposed two-step approach possess relies on PCA and the effectiveness depends on the sample size. An interesting direction for future research is to examine the macroeconomic determinants by the two-step approach in other countries.

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