Time-Varying Beta And The Subprime Financial Crisis: Evidence From U.S. Industrial Sectors

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ABSTRACT

In the current study, we investigate the effect of the subprime financial crisis on the time-varying beta of 10 U.S. industrial sectors. We use daily data, during the period 2002 through 2014, and the bivariate BEKK-GARCH model to the conditional capital asset pricing model (CAPM) to create the time-varying betas for the 10 sectors. After controlling for local and global volatilities, the data enable us to confirm the different magnitudes of influence of the subprime crisis on the 10 industrial sectors. The results are important for investors and portfolio managers, and may have policy implications.

Keywords: Subprime Financial Crisis; Time-Varying Beta; Capital Asset Pricing

1. INTRODUCTION

Assuming that beta in the capital asset pricing model (CAPM) remains constant over time (Fama & MacBeth, 1973; Jensen, 1968; and others) is questionable since expected returns depend on the information available at any particular point in time, and thus are time varying (Collins et al., 1987; Sunder, 1980). A wide body of literature (Ferson & Harvey, 1991, 1994; Saleem & Vaihekoski, 2010) has suggested that estimating beta with OLS does not reflect its real dynamics. Furthermore, Groenewold and Fraser (1999), Lettau and Ludvigson (2001), Wang (2003), Lewellen and Nagel (2006), and Beach (2011) show that the conditional CAPM with a time-varying beta outperforms the unconditional CAPM with a constant beta.

The multivariate GARCH models, with time-varying conditional variances and covariances, offer an alternative to the constant systematic risk in the CAPM model, which overcomes this limitation (Ferson & Korajczyk, 1995; Li, 2013; Morelli, 2014; Tsai et al., 2014). In this study, we use the bivariate BEKK GARCH model to estimate time-varying betas.

The aim of this paper is to investigate the effects of the subprime crisis (2007–2009) on the time-varying betas of 10 U.S. industrial sectors. Although a large body of literature has described and debated the magnitude and the causes of the subprime crisis (Basse et al., 2009; Kim et al., 2013; Pennathur et al., 2014; Taylor, 2009; and others), to our knowledge, this is the first study to investigate its influence on time-varying beta for U.S.industrial sectors. Our analysis is important for international investors and portfolio managers, and has policy implications in the U.S. equity markets.

The paper is organized as follows. Section 2 presents the empirical methodology. Section 3 describes the data used. The empirical results are presented in Section 4, and Section 5 provides concluding remarks.

2. EMPIRICAL METHODOLOGY

2.1 Conditional CAPM

In this study, we adopt the conditional CAPM. It takes into consideration current expectations for future returns, and allows conditional variances and covariances—and hence time-varying beta (Bodurtha & Mark, 1991).

$R_{i,t}$ is the daily return on asset i, and $R_{m,t}$ is the return on the U.S. market portfolio m. The conditional CAPM may be expressed as follows:

$$(r_{i,t}|I_{t-1}) = \beta_{iI_{t-1}} E(r_{m,t}|I_{t-1}) \tag{1}$$

where $r_{i,t}$, and $r_{m,t}$ are excess returns over the risk-free asset return, and $E(|I_{t-1})$ is the conditional expectation on the economic information available at time $(t-1)$ for investors, where

$$\beta_{iI_{t-1}} = \frac{cov(R_{i,t}, R_{m,t}|I_{t-1})}{var(R_{m,t}|I_{t-1})} = \frac{cov(r_{i,t}, r_{m,t}|I_{t-1})}{var(r_{m,t}|I_{t-1})} \tag{2}$$

In order to calculate conditional variances and covariances, we refer to the BEKK multivariate GARCH model, introduced by Engel and Kroner (1995). The conditional covariance matrix of bivariate BKKK GARCH(1,1) is parameterized as:

$$y_t = \mu + \varepsilon_t \tag{3}$$

$$\frac{\varepsilon_t}{\Omega_{t-1}} \sim N(0, H_t) \tag{4}$$

$$H_t = C'C + A'\varepsilon_{t-i}\varepsilon'_{t-i}A + B'H_{t-1}B$$

$$H_t = C'C + \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-i}\varepsilon_{2,t-i} \\ \varepsilon_{2,t-i}\varepsilon_{1,t-i} & \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} + \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix}' H_t \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \tag{5}$$

where $\boldsymbol{C}$ is a lower triangular matrix with intercept parameters, and A and B are 2×2 square matrices of parameters.

The time-varying beta (β) for asset i, is obtained as:

$$\beta_{it} = \frac{\widehat{H}_{12,t}}{\widehat{H}_{22,t}} \tag{6}$$

where $\widehat{H}_{12,t}$ is the estimated conditional covariance between the industrial sector returns and the portfolio market returns, and $\widehat{H}_{22,t}$ is the estimated conditional variances of the portfolio market returns.

2.2 Testing the Effects of the Subprime Financial Crisis

In order to investigate the effect of the subprime crisis on the time-varying beta of the 10 industrial sectors, we estimate the following OLS regression:

$$\beta_{it} = \alpha_0 + \alpha_1 CV_{it-1} + \alpha_2 MV_{t-1} + \alpha_3 GV_{it-1} + \varepsilon_{it} \tag{7}$$

where β_{it}, is time-varying beta, CV_{it-1}, is the conditional volatility of industrial sector i returns, MV_{t-1} is the market conditional volatility, GV_{it-1} is the conditional global volatility, and ε_t is the error term. If the three parameters (α_1, α_2, and α_3) are positive, the beta should increase in response to the volatility of the sector, the U.S. market, and the global market. This study takes into account the pre-crisis period (Jun 2002–July 2007), the crisis period (August 2007–February 2009), and the post-crisis period (March 2009 –January 2014).

3. DATA

In this study, our data is composed of the daily data of 10 industrial stock indices. The 10 industrial sectors are consumer discretionary, consumer staples, energy, financials, health care, industrials, information technology (IT), materials, telecom services, and utilities. The industrial sectors are defined in Table 1. The market index is represented by the USA MSCI stock index. Three-month Treasury bills are used for the risk-free asset return. The global factor is presented by the MSCI world stock index. The range of data is from June 4, 2002 to January 16, 2014. All data are obtained from the Datastream database.

The daily returns are as follows:

$$R_{i,t} = 100 \times log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{8}$$

where $P_{i,t}$ is the price of index i at time t.

The excess returns are expressed as follows:

$$r_{i,t} = 100 \times log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) - \frac{1}{250}\log\left(1 + r_f\right) \tag{9}$$

where r_f is the risk-free asset return.

Table 1: Sector Classifications and Summary Statistics of Returns

Sectors	Industry Groups	June 2002-January 2014		June 2002-July 2007		August 2007-February 2009		March 2009-January 2014	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Consumer Discretionary	Retailing, Media, Consumer Durables and Apparel, Consumer Services, Automobiles and Components	2.80	1.44	2.06	1.10	-19.18	2.42	10.71	1.31
Consumer staples	Household and Personal Products, Beverage and Tobacco, Food, Food and Staples Retailing	2.16	0.89	1.29	0.74	-6.43	1.48	5.87	0.77
Energy	Energy	3.78	1.78	7.11	1.38	-12.17	3.17	5.43	1.51
Financials	Real Estate, Insurance, Diversified Financials, Banks	-0.03	1.99	2.16	1.02	-31.30	3.82	7.78	1.88
Health care	Pharmaceuticals and Biotechnology, Health Care Equipment and Services	2.71	1.10	1.61	0.97	-9.04	1.67	7.67	0.98
Industrials	Transportation, Commercial Services and Supplies, Capital goods	2.72	1.43	3.96	1.03	-20.68	2.30	9.00	1.43
IT	Semiconductors, Technology Hardware and Equipment, Software and Services	2.77	1.53	2.88	1.48	-14.28	2.26	8.19	1.25
Materials	Materials	2.72	1.67	4.27	1.23	-18.03	2.85	7.81	1.55
Telecom	Telecommunication Services	1.86	1.42	3.73	1.27	-15.25	2.40	5.42	1.13
Utilities	Utilities	1.57	1.20	3.17	1.08	-9.96	2.00	3.61	0.93

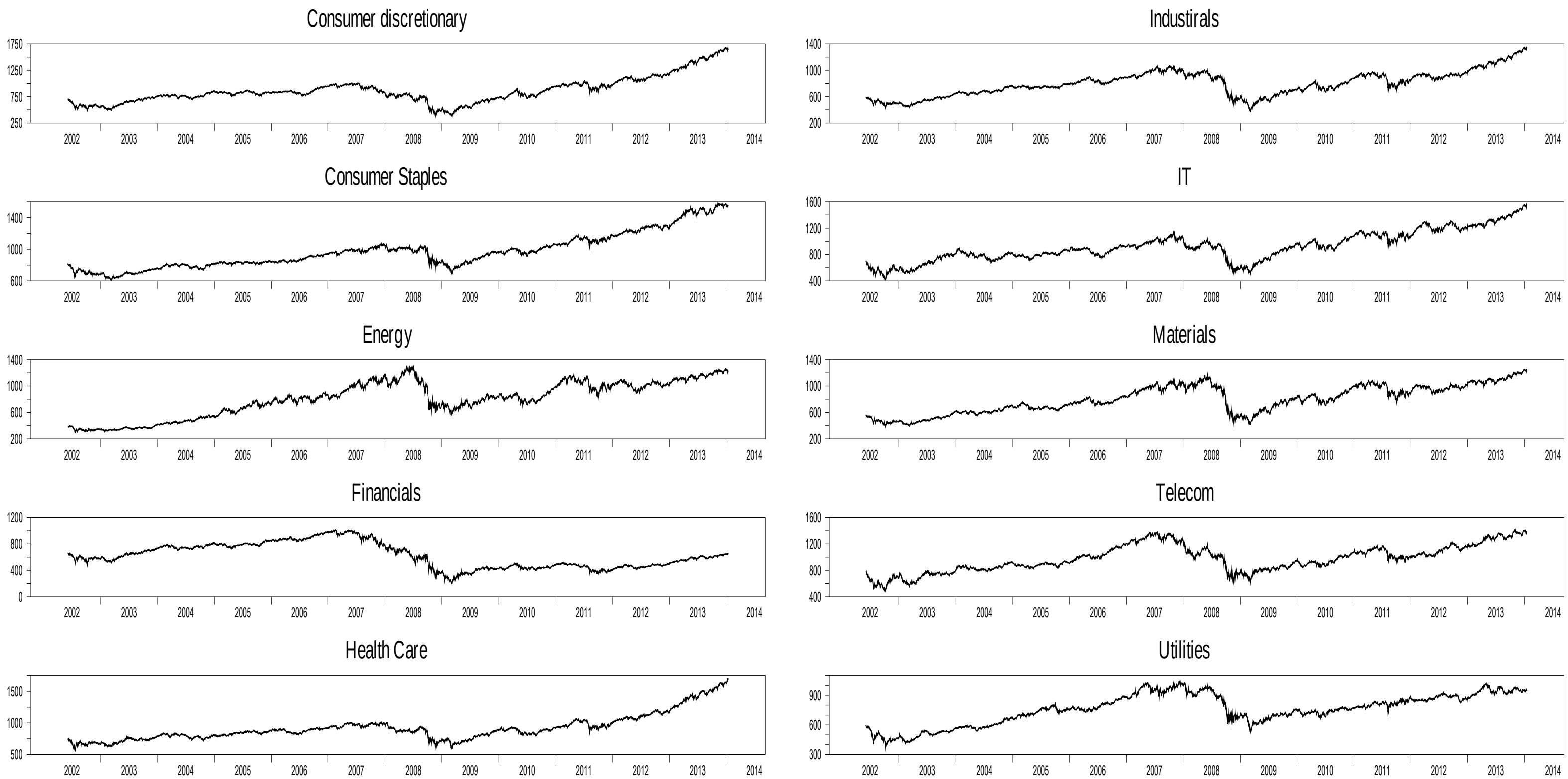

Figure 1: Industrial Sector Index Evolutions

Figure 1 shows the 10 sector index evolutions. Table 1 reports the sample means and standard deviations of returns for each of the 10 U.S. sectors. We also provide descriptions of each industrial group. For the studied sample period, financial sector offers the lowest return (-0.03%) and the highest standard deviation (1.99%). The energy sector is the best performer with an average return of 3.87%. Consumer staples seem to be less exposed to fluctuations (0.89%). During the financial crisis, all sector average returns are negative, reaching -31.3% for the financial sector. The consumer staple sector is the least affected by the subprime crisis in terms of average returns (-6.43%) and standard deviation (1.48%).

4. ESTIMATION RESULTS

Table 2 shows the mean of the time-varying beta of each sector during the entire period (June 2002–January 2014), the pre-crisis period (June 2002–July 2007), the crisis period (August 2007–February 2009), and the post-crisis period (March 2009–January 2014). Figure 2 shows the time-varying beta of the 10 industrial sectors. There is an increase in the mean of beta from the pre-crisis period to the crisis period for consumer staples, energy, financials, IT, and telecom services, and a decrease in the systematic risk for other sectors. The financial sector is the most affected by the sub-prime financial crisis (as shown in Figure 2). Its mean value reached 1.6 in the crisis period, compared to unity for the pre-crisis period.

Table 2: Mean Beta During all Four Periods

	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care
June 2002- January 2014	1.062	0.619	1.082	1.198	0.786
June 2002- July 2007	1.054	0.646	1.002	0.993	0.835
August 2007- February 2009	1.080	0.565	1.014	1.594	0.637
March 2009- January 2014	1.065	0.608	1.188	1.287	0.783
	Industrials	**IT**	**Materials**	**Telecom**	**Utilities**
June 2002- January 2014	1.148	1.093	1.212	0.905	0.678
June 2002-July 2007	1.284	1.049	1.185	0.953	0.723
August 2007- February 2009	1.005	1.070	1.166	0.965	0.675
March 2009- January 2014	1.051	1.146	1.257	0.834	0.632

Table 3 presents the estimation of Equation 7 for all industrial sectors of the U.S. economy. We apply OLS regression method for all sectors for the four periods. All regressions are corrected for serialcorrelation by means of the Cochran–Orcutt method. The Durbin-Watson statistics are between 1.91 and 2.18. The coefficient of determination (R^2) ranges from 0.123 to 0.775.The constant term is significant for all sectors and for all sub-periods. There is strong evidence that conditional volatilities affect the systematic risk (beta) of industrial sectors. Parameters are significant at 1% and are all less than unity in absolute value. Signs relative to conditional volatilities are positive, except for the energy sector during the financial crisis. For the entire sample, the consumer staples, health care, and utilities sectors are the most affected by the conditional volatilities.

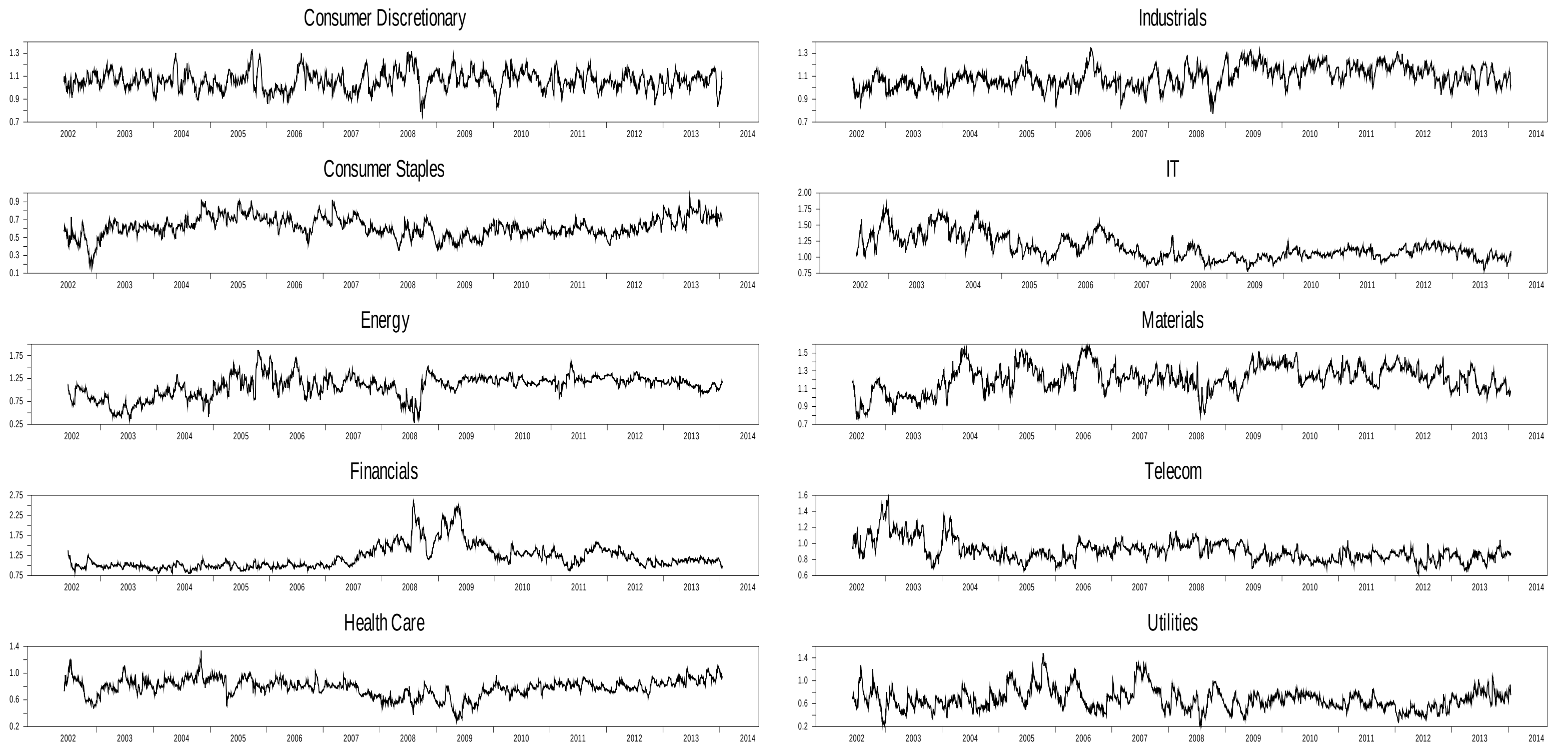

Figure 2: Time-Varying Beta for the 10 U.S. Industrial Sectors

Table 3: The Effects of Volatility on the Time-Varying Beta of 10 U.S. Sectors During the Four Periods of Study

Time	Constant		*CV*		*MV*		*GV*		*N*	R^2	*DW*
Consumer Disc											
June 2002- January 2014	1.050***	(0.000)	0.0488***	(0.000)	-0.0110***	(0.004)	-0.0579***	(0.000)	3032	0.264	2.01
June 2002-July 2007	1.044***	(0.000)	0.0975***	(0.000)	-0.135***	(0.000)	0.0177	(0.423)	1345	0.270	2.04
August 2007- February 2009	1.048***	(0.000)	0.0453***	(0.000)	0.00946*	(0.064)	-0.0820***	(0.000)	413	0.511	2.18
March 2009- January 2014	1.054***	(0.000)	0.0612***	(0.000)	-0.0400***	(0.000)	-0.0341***	(0.004)	1274	0.283	2.03
Consumer Staples											
June 2002- January 2014	0.636***	(0.000)	0.110***	(0.000)	0.00960	(0.131)	-0.0979***	(0.000)	3032	0.259	1.98
June 2002-July 2007	0.697***	(0.000)	0.110***	(0.000)	0.107***	(0.000)	-0.300***	(0.000)	1345	0.507	2.04
August 2007- February 2009	0.556***	(0.000)	0.0690***	(0.000)	-0.0137**	(0.045)	-0.0209***	(0.001)	413	0.268	2.09
March 2009- January 2014	0.644***	(0.000)	0.129***	(0.000)	0.0264**	(0.021)	-0.139***	(0.000)	1274	0.375	1.97
Energy											
June 2002- January 2014	1.052***	(0.000)	0.0428***	(0.000)	-0.226***	(0.000)	0.214***	(0.000)	3032	0.123	1.91
June 2002-July 2007	0.779***	(0.000)	0.245***	(0.000)	-0.206***	(0.000)	-0.120*	(0.053)	1345	0.609	2.00
August 2007- February 2009	0.903***	(0.000)	-0.0346***	(0.000)	-0.0639***	(0.000)	0.228***	(0.000)	413	0.439	1.98
March 2009- January 2014	1.157***	(0.000)	0.0687***	(0.000)	-0.164***	(0.000)	0.0910***	(0.000)	1274	0.213	1.98
Financials											
June 2002- January 2014	1.118***	(0.000)	0.0407***	(0.000)	-0.210***	(0.000)	0.213***	(0.000)	3032	0.630	1.91
June 2002-July 2007	0.975***	(0.000)	0.112***	(0.000)	-0.179***	(0.000)	0.0933***	(0.000)	1345	0.306	2.02
August 2007- February 2009	1.486***	(0.000)	0.0290***	(0.000)	-0.108***	(0.000)	0.0556***	(0.001)	413	0.583	1.99
March 2009- January 2014	1.122***	(0.000)	0.0231***	(0.000)	-0.219***	(0.000)	0.336***	(0.000)	1274	0.775	1.92
Health Care											
June 2002- January 2014	0.797***	(0.000)	0.108***	(0.000)	0.0462***	(0.000)	-0.176***	(0.000)	3032	0.358	1.94
June 2002-July 2007	0.849***	(0.000)	0.148***	(0.000)	-0.00743	(0.645)	-0.212***	(0.000)	1345	0.485	2.05
August 2007- February 2009	0.623***	(0.000)	0.0377***	(0.000)	0.0209***	(0.002)	-0.0550***	(0.000)	413	0.316	2.05
March 2009- January 2014	0.846***	(0.000)	0.133***	(0.000)	0.0881***	(0.000)	-0.280***	(0.000)	1274	0.497	1.92
Industrials											
June 2002- January 2014	1.075***	(0.000)	0.0321***	(0.000)	-0.142***	(0.000)	0.151***	(0.000)	3032	0.260	1.95
June 2002-July 2007	1.048***	(0.000)	0.119***	(0.000)	-0.162***	(0.000)	0.0196	(0.344)	1345	0.214	2.03
August 2007- February 2009	1.074***	(0.000)	0.0249***	(0.000)	-0.0335***	(0.002)	0.00408	(0.802)	413	0.398	1.99
March 2009- January 2014	1.107***	(0.000)	0.0448***	(0.000)	-0.148***	(0.000)	0.142***	(0.000)	1274	0.327	2.00
Information Tech											
June 2002- January 2014	1.116***	(0.000)	0.0894***	(0.000)	-0.0876***	(0.000)	-0.0267**	(0.011)	3032	0.336	1.90
June 2002-July 2007	1.255***	(0.000)	0.166***	(0.000)	-0.298***	(0.000)	-0.0614***	(0.003)	1345	0.481	1.94
August 2007- February 2009	1.009***	(0.000)	0.0245***	(0.000)	-0.0203**	(0.023)	-0.0109	(0.294)	413	0.172	1.94
March 2009- January 2014	1.092***	(0.000)	0.0284***	(0.000)	0.0119	(0.229)	-0.0966***	(0.000)	1274	0.233	1.92
Materials											
June 2002- January 2014	1.191***	(0.000)	0.0639***	(0.000)	-0.156***	(0.000)	0.0803***	(0.000)	3032	0.169	1.93
June 2002-July 2007	1.111***	(0.000)	0.250***	(0.000)	-0.348***	(0.000)	-0.00563	(0.881)	1345	0.524	2.00
August 2007- February 2009	1.149***	(0.000)	0.0138***	(0.000)	-0.0322**	(0.016)	0.0180	(0.346)	413	0.0357	1.99
March 2009- January 2014	1.226***	(0.000)	0.0886***	(0.000)	-0.189***	(0.000)	0.0752***	(0.000)	1274	0.309	1.96

Table 3 cont.

Time	Constant		*CV*		*MV*		*GV*		*N*	R^2	*DW*
Telecom SVC											
June 2002- January 2014	0.876***	(0.000)	0.0936***	(0.000)	-0.0331***	(0.000)	-0.0847***	(0.000)	3032	0.453	1.98
June 2002-July 2007	0.902***	(0.000)	0.144***	(0.000)	-0.182***	(0.000)	-0.00692	(0.854)	1345	0.557	1.98
August 2007- February 2009	0.942***	(0.000)	0.0283***	(0.000)	-0.00685	(0.361)	-0.0298**	(0.018)	413	0.159	2.05
March 2009- January 2014	0.812***	(0.000)	0.0649***	(0.000)	-0.0290***	(0.002)	-0.0207*	(0.051)	1274	0.281	2.00
Utilities											
June 2002- January 2014	0.679***	(0.000)	0.0821***	(0.000)	0.0184*	(0.087)	-0.120***	(0.000)	3032	0.249	1.94
June 2002-July 2007	0.767***	(0.000)	0.143***	(0.000)	0.116***	(0.000)	-0.464***	(0.000)	1345	0.338	1.98
August 2007- February 2009	0.650***	(0.000)	0.0612***	(0.000)	-0.0198	(0.246)	-0.0361	(0.104)	413	0.285	1.98
March 2009- January 2014	0.624***	(0.000)	0.160***	(0.000)	0.0285**	(0.029)	-0.159***	(0.000)	1274	0.324	1.99

CV is the conditional variance of the industrial sector, MV the conditional variance of the market, and GV the conditional variance of the global market. (*), (**), and (***) indicate significance levels at 10%, 5%, and 1%, respectively. *p-values* are in parentheses. DW is the Durbin-Watson test for autocorrelation, and R^2 is the adjusted coefficient of determination.

The market factor has a significant influence on time-varying beta. The magnitudes of the coefficients are small and less than unity for all industrial sectors. The signs of market factor parameters are negative except for health care and utilities. For the entire sample, the negative sign shows that evolution of the market index and the industrial sector indexes are in the same direction, except for the health care and utilities indexes. This finding may be useful for portfolio management, which is important for portfolio diversification in the U.S. market. However, during the crisis period, the effect of market volatilities is mostly negative and smaller is absolute value. These findings are similar to those of Choudhry et al. (2010) and Choudhry (2005). Therefore, the consumer discretionary and health care sectors are more attractive for investors during the financial crisis. The cost of capital of these sectors is less expensive during turmoil periods (Kahle & Stulz, 2013).

For the entire sample, global volatility has an overall effect on time-varying beta; however, this effect differs across sectors. The positive coefficients show that the energy, financials, industrial, and materials sectors are affected by trends in international stock markets, whereas the others sectors do not suffer from international fluctuations. During the financial crisis, the global factor coefficients have the same signs for industrial sectors, that is, the financial crisis did not affect the dependence between global and U.S. markets. The financial sector was the most affected during the financial crisis; the influence of global factor in this sector is twice as large as for the entire period. Therefore, financial sector is riskier than other sectors. These findings have implications for portfolio managers' and investors' decisions.

CONCLUSION

Using daily index returns for 10 sectors of the U.S. economy over the period June 2002 to January 2014, we empirically computed time-varying betas by means of the bivariate GARCH model (BEKK). We further investigated the effects of the financial crisis on the time-varying beta using the conditional volatilities of the industry, the U.S. market, and global factors, respectively, as explanatory variables. We then further divided the entire period into three sub-periods: pre-crisis (June 2002–July 2007), crisis (August 2007–February 2009), and post-crisis (March 2009–January 2014). We conducted estimations for the entire period and the three sub-periods to investigate the potential effects of volatilities on time-varying systematic risk.

Many conclusions can be drawn from the empirical results, which are somewhat mixed. First, there was a rise in the mean beta of consumer staples, energy, financials, IT, and telecom services, and a fall in the systematic risk of the other sectors. The financial sector was most affected by the sub-prime financial crisis; systematic risk reached 2.62 on August 24, 2008, with a mean value of 1.6 during the crisis period compared to unity in the pre-crisis period. Second, we found that during the crisis period, a rise in conditional volatilities increased time-varying beta for all sectors except the energy sector. The increase in beta subsequent to higher volatility in industrial sectors has a direct implication for the cost of capital and for investors' decisions related to portfolio management. For market volatility, its effect on systematic risk is tiny and mostly negative.

During the crisis period, the consumer discretionary and health care sectors offered the highest expected returns. Increasing the market risk of these sectors leads investors to require higher returns for holding these sector's shares. We may think about the "flight to quality" effect for these two sectors, as it is easier to convert their shares into liquidity during crisis periods (Brière et al., 2012; Guerrieri & Shimer, 2012; Rösch & Kaserer, 2013). We also found that global conditional volatility maintains the same influence on U.S. industrial sectors for all sub-periods, including the crisis period. The energy, financial, industrial, and materials sectors were most affected by trends in international stock markets. We notice that the financial sector was most affected during the financial crisis, as the influence of the global factor was twice that of the entire period of the study. Overall, our results are in line with those of Kim et al. (2013), who revealed that the real economy, in terms of investments and employment, is hardly affected by a country's financial sector turmoil. Our results also confirm the empirical evidence of Pennathur et al. (2014), who found that except for the Troubles Assets Relief Program (TARP), the impact of major U.S. government interventions on the financial sector were value decreasing and risk increasing. At this stage, we think that a further investigation of regulatory measures and supervisory power preceding the sub-prime crisis could provide further insights and deepen our understanding of the functioning of stock markets and the financial sector during turmoil periods.

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