Risk Analysis of Energy in Vietnam*

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Abstract

The purpose of the paper is to estimate market risk for the ten major industries in Vietnam. The focus is on the *Energy* sector, which has been designated as one of the four key industries, together with *Services, Food, and Telecommunications*, targeted for economic development by the Vietnam Government through to 2020. *Oil and Gas* is a separate energy-related major industry. The data set is from 2009 to 2017, which is decomposed into two distinct sub-periods after the Global Financial Crisis (GFC), namely the immediate post-GFC (2009-2011) period and the normal (2012-2017) period, in order to identify the behaviour of market risk for Vietnam major industries. Two widely-used approaches to measure and analyze risk are used in the empirical analysis, namely Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR). The empirical findings indicate that *Energy* and *Pharmaceuticals* are the least risky industries, whereas *Oil and Gas* and *Securities* have the greatest risk. In general, there is strong empirical evidence that the four key industries display relatively low risk. For public policy, the Vietnam Government's pro-active emphasis on the targeted industries, including *Energy*, to achieve sustainable economic growth and national economic development, seems to be working effectively.

Keywords: Market risk, Energy, Industries, Value-at-Risk, Conditional Value-at-Risk, Sustainable growth, Economic development, Vietnam.

JEL: C10, G10, E32.

1. Introduction

In the process of integration into the global economy, the development of the Vietnam financial market is unavoidable. The financial market is expected to offer many attractive channels of capital mobilization, as well as a wide variety of investments with considerably variable risks. Financial markets will necessarily provide great incentives for the relevant national agencies to improve the underlying legal framework in order to promote sustainable development of the economy and to strengthen the trust of financial investors.

Based on the Resolution of the 11th Congress of the Communist Party of Vietnam on Orientation and Solutions for Development of Major Economic Industries to 2020, the Vietnam Government has devoted considerable attention to investing in four key industries, specifically *Energy, Services, Food,* and *Telecommunications*. However, this focus should not be interpreted as drawing attention from the development of other industries in the process of national economic growth and development.

In order to make optimal financial decisions, investors need to consider the risk levels of stocks compared with other financial assets in the same industry, as well as stocks in competing industries, and in the market overall. Each investor needs to determine the risk levels of stocks and industries for diversifying their portfolios in order to minimize the risks, given expected returns. Estimating risks for various stocks and industries is an important and essential tool for investors to improve investment efficiency, and to achieve optimal outcomes through efficient hedging of financial portfolios.

Some attempts have been found in empirical studies in the context of measuring risk in Vietnam, but they have focused solely on the banking system. The literature review in the following section shows that no attempts seem to have been made to estimate market risk for industries using a combination of two widely-used risk measures, namely Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR), in the context of Vietnam.

For this reason, the present paper is intended to provide empirical evidence in relation to the market risks of the major industries in Vietnam, and their ranking over the last decade since the national stock market was established in Hanoi and Ho Chi Minh City.

The primary purpose of the paper is to estimate market risk for the major industries in Vietnam. The focus is on the *Energy* sector, which has been designated as one of the four key industries, together with *Services, Food, and Telecommunications*, targeted for economic development by the Vietnam Government through to 2020. *Oil and Gas* is a separate energy-related major industry. The data set is from 2009 to 2017, which is decomposed into two distinct sub-periods after the Global Financial Crisis (GFC), namely the immediate post-GFC (2009-2011) period and the normal (2012-2017) period, in order to identify the behaviour of market risk for the major industries in Vietnam.

The remainder of the paper is structured as follows. A discussion of the key risk measures, namely the VaR and CVaR approaches, is given in Section 2, followed by a summary of the relevant empirical studies worldwide. Section 3 presents the data, and the empirical findings are evaluated in Section 4. Some concluding comments and policy implications are reported in Section 5.

2. Literature Review

2.1 Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR)

Many methods have been used for assessing and estimating the level of market risk for an industry. Of the numerous methods for the purpose of measuring risk, Value-at-Risk (VaR) is one of the fundamental and key approaches for this purpose. It is assumed that market movements are normal, and there are no portfolio transaction costs. An index with a given probability and intervals, VaR, is considered as a threshold where the likelihood of a loss over the market-adjusted value of the index over a given time period exceeds the value at the given probability level.

It is generally agreed that the greatest attraction of VaR is that it represents risk in the form of a single number or index. VaR is defined as the maximum amount a portfolio can lose at a certain level of confidence, typically 95 per cent. For a comparison of VaR and Expected Shortfall as alternative measures of risk under the Basel III Accord using Stochastic Dominance, see Chang et al. (2019).

Although it is well known and is widely used, VaR has a number of disadvantages. Arztner et al. (1997, 1999) proposed that VaR contained inconvenient mathematical attributes, such as lack of surplus and convexity. In addition, the authors also argued that VaR is based on the assumption of a distribution that is in proportion to the standard deviation. McKay and Keefer (1996) and Mauser and Rosen (1999) discuss the practical case whereby VaR is calculated on the basis of a combination of portfolios, which might outperform the overall risk of an individual portfolio.

These authors also emphasize that an unresolved problem with VaR is that it can be difficult to optimize when the level of market risk is computed under various scenarios. This view is based on the argument that the function of a positional portfolio may exhibit multiple local extrema, which incorporates uncertainty in determining the set of optimal possibilities and the overall value of VaR.

Conditional Value-at-Risk (CVaR) is considered to be a more effective alternative measure and estimate of the level of market risk in comparison with VaR. CVaR can be used to measure a conditional marginal value that is beyond the possibility of the VaR approach. Allen and Powell (2006) considered CVaR as a substitute for VaR in measuring market and credit risks. In a similar vein, Pflug (2000) demonstrated that CVaR is a rigorous risk measure which incorporates many desirable attributes, such as convexity and monotonicity, that are two inherent properties that are not properties of the VaR approach.

Furthermore, VaR does not represent the probable loss range, except for the first threshold value. In contrast, CVaR determines the number of losses that may be encountered in the tail distribution. Rockafellar and Uryasev (2002) analyzed CVaR for portfolio optimization problems, and provided evidence that CVaR was more effective than VaR for practical purposes.

In practice, the Basel Accord regulations require the amount of capital to be retained in the banking system to be calculated on a daily basis. According to the regulations, the VaR approach is a highly recommended tool for calculating the amount of capital that must be retained by commercial banks and other deposit-taking financial institutions against potential losses on a daily basis. As previously discussed, VaR measures the potential loss over a given period of time for given level of confidence (that is, reliability).

The retention of adequate funds by commercial banks to accommodate expected financial losses on a daily basis is intend to offset the chances of bankruptcy. The amount of capital reserves is intended to be sufficient for the bank to accommodate abnormal occurrences. In addition, accurate estimation of the level of reserves that are not in excess of the required level, can help banks to enhance their financial performance.

Other VaR applications for credit risk include, to name a few, the diagonal model (Bollerslev et al., 1988), multivariate GARCH, otherwise known as BEKK (Engle and Kroner 1995), CreditMetrics (Gupton et al., 1997), CreditPortfolioView (Wilson, 1998), dynamic multivariate conditional correlation GARCC (McAleer et al., 2008; McAleer, 2018), and iTransition (Allen and Powell, 2009).

According to Allen et al. (2012), there are three main methods for undertaking VaR measurements:

(i) Parametric,
(ii) Historical,
(iii) Monte Carlo Simulation.

While the parametric approach assumes that the rates of return and risk follow a particular distribution (such as normal), the historical methods use no assumption and use the actual observations of returns. Monte Carlo Simulation generates random numbers (and returns) that are based on predetermined indicators.

VaR determines the maximum loss value for a given period of time associated with a predetermined level of confidence. However, VaR does not present any other possible losses other than the specified VaR. Samanta et al. (2005) criticize VaR risk measurement because it did not measure the losses in the tails of the distribution. CVaR overcomes this problem by measuring the distribution losses in the tails as the key purpose in using CVaR is to measure the earnings that exceed the expected daily financial losses.

For example, if VaR is measured at the 95 per cent confidence level, CVaR(α) is an average of the worst 5 per cent of the returns (α = 0.05). CVaR is usually calculated as a percentage. For example, 0.01 CVaR daily at a 95 per cent confidence level means that the loss should not exceed an average of 1 per cent in the worst 5 per cent of cases. CVaR has been used in a wide range of optimization (Alexander et al., 2003; Bird et al., 2013), risk management and optimization (Sarykalin et al., 2008) problems. Boubakera and Sghaierb (2013) studied CVaR in simulations of the dependence structure between financial assets, the adequacy of bank capital (Allen et al., 2016), and risk analysis during financial crises (Allen et al., 2012; Toquea and Terrazab, 2014).

2.1 Empirical Analysis

Various papers have attempted to estimate the market risk level using the VaR and CVaR methods concurrently. Powell et al. (2017) categorized the S&P Goldman Sachs Commodity Index into groups, and used the modified CVAR method to assess the level of risk in particular periods, as classified according to GDP growth. The findings from this empirical study indicate that there are marked differences in the levels of risk for the various commodities for a variety of sub-samples.

Adesi (2016) used the VaR and CVaR methods to examine options prices. The empirical results showed that when the measurement method changed, the estimates from CVaR were less sensitive than those arising from VaR. Valecký (2012) used a mixture of normal distribution VaR to estimate the market risk of four European market portfolios (namely, the Vienna Stock Exchange Austrian Traded Index - ATX, Deutsche Boerse AG German Stock Index - DAX, Financial Times Stock Exchange 100 Index - FTSE 100, and Prague Stock Exchange Index - PX). The empirical outcomes showed that, with higher reliability, the VaR figure estimated by the Markov-Switching normal distribution provided more accurate estimates than did the other distributions.

Allen et at. (2012) examined the relationship between market and credit risk of European industries using VaR, CVaR and the KMV/Merton methods. The empirical findings indicated that Telecommunication and Information Technology is one of the highest risk industries in the pre-GFC period. However, during the GFC, the Financial and Consumer Discretionary industries were found to be among the highest risk industries.

Kourouma et al. (2011) evaluated VaR and Expected Shortfall of Standard & Poor’s Aggregate 500 Index (S&P500), Cotation Assistée en Continu - French stock market index (CAC 40), and Wheat and Crude oil indexes, during the GFC. The empirical results show that unconditional

VaR is not as effective as the conditional models. Overall, the conditional EVT model gave more accurate and reliable outcomes in predicting property losses..

Allen and Powell (2007) analyzed the market risk of industries in Australia using VaR and CVaR, and measured credit risk using the KMV/Merton model. The empirical results showed that the Technology industry has high risk. Meanwhile, both models showed a significant association among the industry rankings over a period of seven years.

Harmantzis et al. (2006) compared the performance of VaR and Expected Shortfall by examining the daily returns of popular indices and currencies from 1990 to 2003. The empirical results indicated that, for a 95 per cent level of confidence, the impact of window size on performance was not determined, while the reliability was more pronounced at the 99 per cent level of confidence.

Moreover, non-fat tailed models can predict risk less accurately than their fat-tailed counterparts. Allen and Powell (2006) argued that CVaR is actually considered as a VaR equivalent method for measuring market and credit risks. Rockafellar and Uryasev (2002) used CVaR for portfolio optimization problems and provided empirical evidence to support the view that CVaR is more effective than VaR. Moreover, it was found that CVaR could be reduced efficiently using linear programming and non-smooth optimization techniques.

Chang et al. (2019) use stochastic dominance to order distributions in terms of welfare and portfolio selection using VaR and Expected Shortfall. “Welfare costs” of the Basel III reforms in terms of capital requirements and penalties are a central concern for risk managers and regulators. A uniform ranking analysis based on stochastic dominance is provided as an effective tool for comparing distributions of daily capital requirement charges that can be produced under different regulations. The empirical results suggest that Expected Shortfall should be preferred by risk averse policy makers, who favour larger but less volatile capital requirements, and which reduces the sensitivity of capital charges to changes in the probability of default.

3. Data and Methodology

This section estimates the levels of market risk for the ten major industries in Vietnam, namely *Banking, Education, Energy, Food, Oil and Gas, Pharmaceutical, Real Estate, Securities,* *Services,* and *Telecommunications*. Of the ten industries, four key sectors, specifically *Services, Energy, Telecommunications,* and *Food*, will receive particular attention in the empirical analysis because they are targeted industries by the Vietnam Government in the national economic strategy through to 2020.

The data for each industry cover the 9-year period from 2009 (the first year when relevant data became available) through to 2017, and are collected from a financial website at http://cophieu68.vn.

Among various methods for calculating VaR, as previously presented, a parametric approach used by RiskMetrics (J.P. Morgan and Reuters) (see Gupton et al., 1997) is used in the empirical analysis. In the parametric approach, it is hypothesized that the rates of return and risk follow the standard normal distribution, with given parameters. In this method, the following steps are used to calculate VaR.

First, the current value V_0 of the portfolio is calculated. Second, the expected rate of return m and the deviation of the squared yield of the portfolio, σ, is estimated. Third, VaR is determined by the following expression:

$$VaR = V_0 * (\mu_p - \alpha * \sigma_p).$$

For simplicity, VaR is calculated in term of percentages rather than absolute values. It is noted that the parametric CVaR is calculated by the average returns beyond the parametric VaR. This practice follows the approach adopted in various studies, such as Allen et al. (2012) and Powell et al. (2017), among others.

It is generally agreed that the GFC impacted the world, including Vietnam, in October 2008. The following empirical analysis does not examine the levels of market risk of the ten major industries in Vietnam prior to and during the GFC (2007-2009) as the lack of available data precludes such an analysis.

Consequently, the change of the market risk levels of the major industries in Vietnam are considered for two distinct periods, namely: (i) the recovery period, which includes the 2009-2011 (or immediate post-GFC) period; and (ii) the normal phrase, after the immediate recovery period, 2012-2017. Although somewhat arbitrary, the distinction between the two periods is expected to shed light on the policies and investment decisions in relation to any consideration of the different levels of market risk over time.

4. Empirical Results

Daily VaR and CVaR (both at the 95 per cent confidence level) of ten major industries for the full sample period, 2009-2017, are presented in Table 1. Figures 1 and 2 show the daily VaR and CVaR at the 95% confidence level for the ten industries. The general trend of the market risks for the ten industries in Vietnam is to decline from 2009 to 2013, increase until 2014, and then continue to decline toward the end of the sample period.

However, the common observation from the empirical findings is that the level of market risk for all industries has decreased from 2009 through to 2017. For the period 2009-2017, the level of risk for *Energy* declined. At the 95 per cent confidence level, in 2009, the largest loss for *Energy* is 4.31% of investments, whereas this loss has been reduced substantially to 0.96% in 2017. Overall, Oil and Gas mirrors the movements in VaR for Energy, whereas the movements in CVaR are different for *Energy* and *Oil and Gas*. This reflects the different underlying financial risk factors for *Energy* and *Oil and Gas* in Vietnam.

In comparison with the other industries in Vietnam, the level of market risk for *Securities* fluctuates over the period. For this industry, with 95 per cent confidence, the largest loss was 5.92% in 2009. This level then gradually decreased over the following years. This industry was then hit with an increase of market risk of 4.11% in 2012, which decreased to 2.64% in 2013, to 4.13% in 2014, and then gradually decreased to 1.86% in 2017. For all ten industries, the levels of market risk over the period has changed consistently, based on both the VaR and CVaR approaches.

When the full sample period of 2009-2017 is considered, as presented in Table 2, risk according to VaR varies within the range (1.88%, 4.56%), whereas a slightly higher range of (2.58%, 5.22%) is found under the CVaR approach.

As can be seen clearly in Table 3, the estimates of the levels of market risk for the major industries suggest that, while *Pharmaceutical* and *Energy* are the least risky industries, *Oil and Gas* and *Securities* are the highest risk industries in Vietnam for the normal 2012-2017 period.

However, the post-GFC period reveals some differences, where *Securities* and *Services* are the industries have the highest risk, while the least risky industries are *Food* and *Pharmaceutical*. These empirical findings are consistent for both VaR and CVaR.

We now shift attention to the four targeted industries in Vietnam, namely *Energy, Services, Food,* and *Telecommunication*. Among these four industries in terms of the market risk levels, *Service* is the highest risk industry, whereas *Food* has the lowest risk, as presented in Table 4. The levels of market risk for these four industries are the highest in 2009, with some fluctuations in 2012, then gradually decreasing toward the end of 2017. The Spread of the market risk levels for all four industries indicates that the relative levels of ranking risk is not uniform over the full sample period.

Table 5 presents empirical evidence to show that the levels of market risk for the four targeted industries have decreased substantially from the post-GFC period (2009-2011) to the normal period (2012-2017). In particular, the VaR results suggest that the levels of market risk are reduced from 31% for *Food* to 46% for *Services*, from the former to the latter period. Based on CVaR, the range of reduction is 19% for *Telecommunication* to 40% for *Services*.

Finally, Table 6 presents a summary of rankings for the four targeted industries over the two periods. On balance, *Services* is generally ranked the highest risk industry, whereas *Energy* and *Food* have relatively low market risk among the four industries using both VaR and CVaR.

5. Concluding Remarks and Policy Implications

The primary purpose of the paper was to estimate market risk for the ten major industries in Vietnam for the period 2009-2017. The primary focus was on the *Energy* sector, which has been designated as one of the four key industries, together with *Services, Food, and Telecommunications*, targeted for economic development by the Vietnam Government through to 2020. *Oil and Gas* is a separate energy-related major industry.

The data set was decomposed into two distinct sub-periods after the Global Financial Crisis (GFC), namely the immediate post-GFC (2009-2011) period and the normal (2012-2017) period, in order to identify the behaviour of market risk for the ten major industries in Vietnam, with an emphasis on *Energy* and *Oil and Gas.*

The paper presented empirical evidence in relation to the market risk level of all the major industries. Based on the VaR and CVaR approaches, the empirical findings indicated that the levels of market risk across all the ten major industries had been reduced substantially from 2009 (the first year after the end of the GFC) to 2017, the most recent year in the sample. *Energy* and *Pharmaceuticals* were generally considered to be the safest industries in Vietnam, with the lowest levels of market risk, whereas *Oil and Gas* and *Securities* were found to have the greatest market risk.

The four industries that have been targeted by the Government were relatively less risky in comparison with the other six major industries. This suggests that the *Energy* and *Oil and Gas* industries do not display similar levels of market risk. The empirical findings support the call for the Vietnam Government to take courage in diverting attention from the riskier industries in order to achieve a more balanced outcome for the economy. The empirical analysis provides additional evidence for financial investors in Vietnam to expect respectable returns on their investment portfolios. In general, investors would need to distinguish the *Energy* and *Oil and Gas* industries in terms of their levels of market risk.

The paper also presented important evidence that Vietnam industries have substantially improved the economic performance over the full sample, moving from relatively higher levels of market risk in the immediate post-GFC period (2009-2011) to a lower risk environment for what is widely considered to be a normal period (2012-2017) several years after the end of the calamitous GFC.

Table 1

VaR and CVaR at 95% Confidence by Year, 2009-2017

Year	Banking	Education	Energy	Food	Oil & Gas	Pharma	Real Estate	Securities	Services	Telecom
VaR at 95% confidence level										
2017	1.59	1.52	0.96	0.94	2.03	1.32	1.29	1.86	2.78	1.82
2016	1.98	4.05	1.26	2.13	3.40	2.14	1.97	2.03	1.98	1.51
2015	2.85	2.73	1.49	2.00	3.19	1.74	1.75	2.71	1.92	1.96
2014	1.95	1.96	2.22	1.90	3.38	1.95	2.61	4.13	2.24	2.93
2013	2.19	1.71	2.69	2.31	2.64	2.06	2.47	2.70	2.09	2.10
2012	2.77	2.62	2.66	2.52	3.30	2.30	3.01	4.11	2.44	2.26
2011	2.88	2.25	2.30	1.86	3.25	1.64	2.80	3.73	3.36	2.45
2010	2.54	3.58	2.88	2.67	3.37	1.76	2.87	4.04	4.16	2.91
2009	4.69	4.01	4.31	4.08	4.45	3.27	4.37	5.92	4.85	4.26
Mean	**2.35**	**2.61**	**2.31**	**2.27**	**3.18**	**2.04**	**2.36**	**3.14**	**2.87**	**2.47**
CVaR at 95% confidence level										
2017	2.37	2.15	1.40	1.07	2.46	1.77	1.93	3.06	4.03	3.21
2016	2.90	5.88	1.67	3.03	4.50	2.81	2.74	2.82	2.68	2.38
2015	3.67	3.44	1.95	2.73	5.12	2.40	2.37	3.97	2.78	3.00
2014	3.00	2.64	3.14	3.07	4.99	3.23	3.69	5.91	3.37	4.19
2013	3.18	2.18	3.67	3.36	3.47	3.04	3.22	3.72	2.56	2.91
2012	3.77	3.77	3.65	3.18	4.39	3.00	3.78	4.78	3.03	3.10
2011	3.24	2.94	3.04	2.49	4.19	2.38	3.48	4.40	4.19	3.27
2010	3.42	4.54	3.69	3.45	4.27	2.42	3.6	4.86	5.19	3.57
2009	5.37	4.86	4.77	4.56	4.97	4.02	4.94	6.41	5.97	4.74
Mean	**3.31**	**3.58**	**3.00**	**2.99**	**4.49**	**2.90**	**3.16**	**4.24**	**3.75**	**3.37**

Table 2

Sub-sample Mean VaR and CVaR at 95% Confidence, 2009-2017

Period	Banking	Education	Energy	Food	Oil & Gas	Pharma	Real Estate	Securities	Services	Telecom
					VaR at 95% confidence level					
Normal	2.22	2.43	1.88	1.97	2.99	1.92	2.18	2.92	2.24	2.10
Post-GFC	3.37	3.28	3.16	2.87	3.69	2.22	3.35	4.56	4.12	3.21
					CVaR at 95% confidence level					
Normal	3.15	3.34	2.58	2.74	4.15	2.71	2.96	4.05	3.07	3.13
Post-GFC	4.01	4.12	3.83	3.50	4.48	2.94	4.01	5.22	5.11	3.86

Note: "**Normal**" and "**Post-GFC**" periods represent 2012-2017 and 2009-2011, respectively.

Table 3

Sub-sample Ranking of Ten Industries, 2009-2017

Period	Banking	Education	Energy	Food	Oil & Gas	Pharma	Real Estate	Securities	Services	Telecom
					VaR at 95% confidence level					
Normal	5	3	10	8	1	9	6	2	4	7
Post-GFC	4	6	8	9	3	10	5	1	2	7
					CVaR at 95% confidence level					
Normal	4	3	10	8	1	9	7	2	6	5
Post-GFC	5	4	8	9	3	10	6	1	2	7

Note: 1 represents the highest risk level while 10 represents the lowest.
"**Normal**" and "**Post-GFC**" periods represent 2012-2017 and 2009-2011, respectively.

Table 4

Ranking of Four Targeted Industries by Year, 2009-2017

Year	Services	Energy	Telecom	Food
		VaR at 95% confidence level		
2017	1	3	2	4
2016	2	4	3	1
2015	3	4	2	1
2014	2	3	1	4
2013	4	1	3	2
2012	3	1	4	2
2011	1	3	2	4
2010	1	3	2	4
2009	1	2	3	4
Mean	**1**	**3**	**2**	**4**
Spread	3	3	3	3
		CVaR at 95% confidence level		
2017	1	3	2	4
2016	2	4	3	1
2015	2	4	1	3
2014	2	3	1	4
2013	4	1	3	2
2012	4	1	3	2
2011	1	3	2	4
2010	1	2	3	4
2009	1	2	3	4
Mean	**1**	**3**	**2**	**4**
Spread	3	3	2	3

Note: 1 represents the highest risk level while 4 represents the lowest.
Spread is calculated as the difference between the highest and lowest ranking for an industry within the sample period.

Table 5

Sub-sample VaR and CVaR of Four Key Industries, 2009-2017

Period	Services	Energy	Telecom	Food
		VaR at 95% confidence level		
Normal	2.24	1.88	2.10	1.97
Post-GFC	4.12	3.16	3.21	2.87
% change	**-46**	**-41**	**-35**	**-31**
		CVaR at 95% confidence level		
Normal	3.07	2.58	3.13	2.74
Post-GFC	5.11	3.83	3.86	3.50
% change	**-40**	**-33**	**-19**	**-22**

Note: "**Normal**" and "**Post-GFC**" periods represent 2012-2017 and 2009-2011, respectively.

Table 6

Sub-sample Ranking of Four Key Industries, 2009-2017

Period	Services	Energy	Telecom	Food
		Based on VaR at 95% confidence level		
Normal	1	4	2	3
Post-GFC	1	3	2	4
		Based on CVaR at 95% confidence level		
Normal	2	4	1	3
Post-GFC	1	3	2	4

Note: 1 represents the highest risk level while 4 represents the lowest.
"**Normal**" and "**Post-GFC**" periods represent 2012-2017 and 2009-2011, respectively.

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Figure 1: Daily VaR at 95% Confidence for Ten Industries

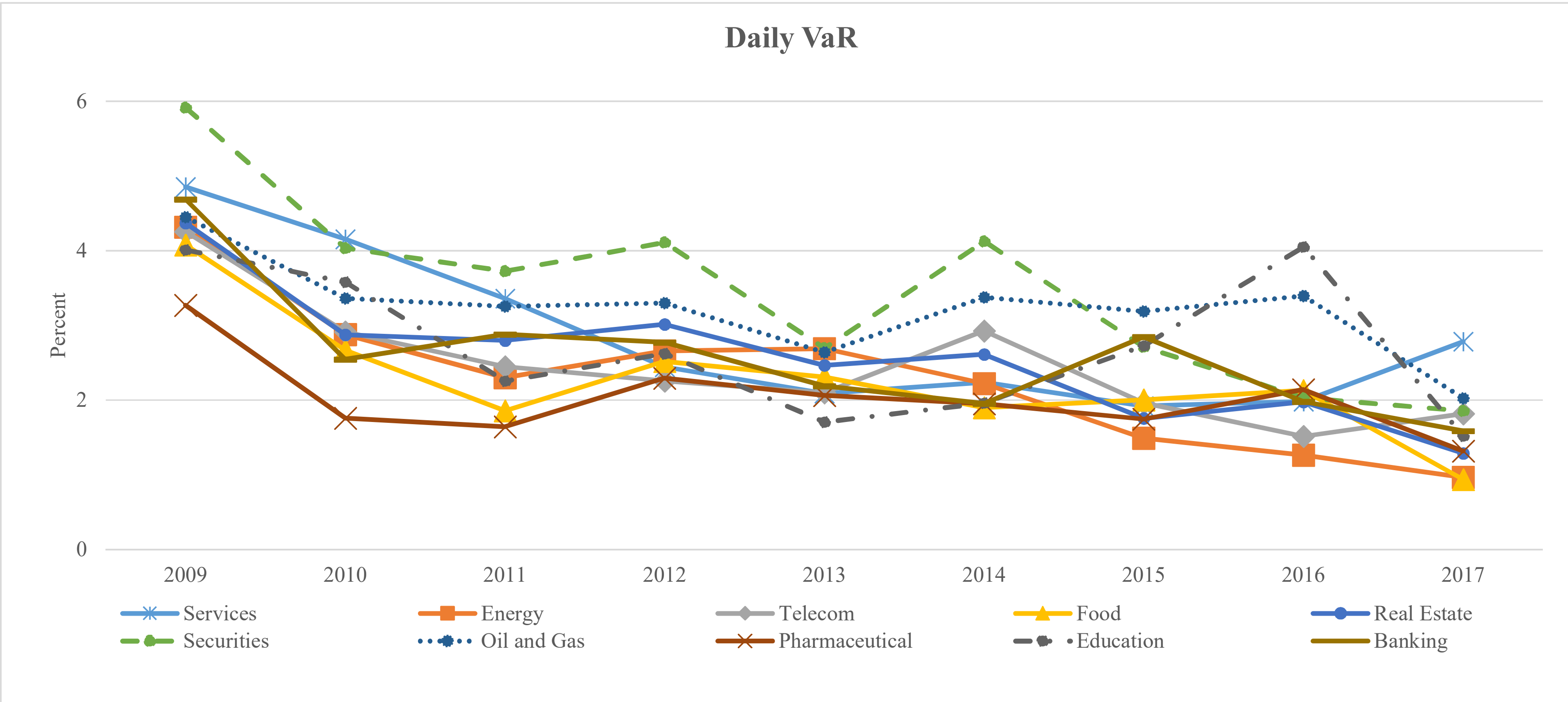

Figure 2: Daily CVaR at 95% Confidence for Ten Industries