Cascade Effect: Measuring the Contagion Risk of Energy Companies

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Abstract

This study investigates the contagion risk contribution of the energy sector using the delta Conditional Value-at-Risk ($\Delta CoVaR$) approach of Adrian and Brunnermeier (2016) based on quantile regression. This methodology allows us to identify a measure of contagion risk for the energy sector, to single out the systemically important energy "institutions", and to assess whether there are risk spillovers from the energy sector to the whole economy. The results show that energy markets contribute to contagion risk and that there are spillovers from the energy sector to the entire economic system. Additionally, we investigate three subperiods (pre-crisis, crisis, and post-crisis) and document that the contagion risk has exerted the most negative consequences for the entire economy during the crisis period.

Keywords: *Contagion risk, energy companies,* $\Delta CoVaR$

1. Introduction

The impact of the global financial crisis made the reduction of systemic risk and the spreading of contagion a top priority for policy makers. Systemic risk arises if the distress in one institution or group of financial institutions (e.g., a bank or a financial company) threatens the functioning of the entire financial system and then spills over to the rest of the economy (Hellwig, 1998).

The global financial crisis has, indeed, demonstrated that breakdowns in individual parts or components of the financial system, could have disruptive effects for the entire financial network and contagion effects could spread out to the economy at large. The collapse of important financial institutions, such as the Lehman Brothers, in fact, produced long-lasting consequences for the U.S. and European economies. According to Laeven and Valencia (2012), the recent banking crises caused a median output loss of 25% of GDP and a median increase in public debt of 24% of GDP.

Starting from this background, the present study aims to move the attention from the traditional financial sector to the energy sector by examining the potential contagion risks

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coming from energy companies that compose the S&P500 Index. The purpose is twofold: i) we establish if energy companies entering the S&P500 index (individually or as a whole by the means of the S&P500 Energy index) are systemically risky; and ii) we rank the most risky energy enterprises according to their contagion impact to the rest of the economy proxied by the S&P500 Ex Energy index.

Differently from the extant literature that has extensively investigated the transmission of risks from one financial institution to another within the same sector, we focus on whether and to which extent the risk of a distress of one energy company or group of companies can affect the entire system represented by the economy at large. Indeed, the spillover effects generated from the energy sector can be so strong to trigger economic instability, that can be so severe to hamper economic growth and welfare.

In our analysis, the risk of contagion coming from the energy sector is therefore caused by extreme price shocks (i.e., abnormal price falls located on the far left tail of the return distribution) of a given company that can transmit across the sector and affect negatively the entire economy. Technically, the risk of extreme price shocks and their impact on the economy are identified by the $\Delta CoVaR$ measure of risk, recently proposed by Adrian and Brunnermeier (2016). Thus, $\Delta CoVaR$ captures the potential for the propagation of specific company or group of companies distress within the sector and toward the entire economy by gauging the increase in tail co-movements.

The rationale for examining the contribution to contagion risk coming from energy companies is driven by the fact that commodity trading could cause an analogous degree of risk as the one caused by financial markets. The global financial crisis, in fact, prompted dramatic consequences: stock markets plunged, banks collapsed and the entire global financial system was on the verge of catastrophe. A similar economic scenario could be set off by the collapse in oil prices. The recent crash in crude-oil prices has in fact sucked out energy firms' profits and put pressure on their debt service.

Besides, with the new European market infrastructure regulation (EMIR) package, the EU has pointed out that systemic risk and contagion effects can be channelled from energy and food sectors to the financial sector through the use of derivatives. In this context, we evaluate if there are systemically important energy "*institutions*" because evaluating the risk stemming from important energy companies is of great importance for the regulators. In addition, there is a certain similarity between energy companies and financial institutions. Both are crucial to all the sectors of the economy and the distress in one or group of them is susceptible to trigger cascading effects with serious damages to the whole economy. Indeed, demand for energy is usually inelastic, showing evidence of the strong dependence of the entire economy on energy prices. Integration of conventional asset markets may further allow shocks to easily propagate and trigger waves of contagion. Therefore, the identification of contagion risk not only in the financial system, but also in the energy system becomes a key priority to achieve macroeconomic stability.

In order to measure a single energy company's contribution to contagion risk and which institutions are in fact systemically important, we use the Conditional Delta Value at Risk ($\Delta CoVaR$) methodology developed by Adrian and Brunnermeier (2016) and the tests of significance and dominance proposed by Bernal et al. (2014). Although a large number of risk measures, such as the Systemic Risk Index (Acharya et al., 2012, 2010; Brownlees and Engle, 2017) and the Game theoretic "Shapley Value" (Tarashev et al., 2016; Drehmann and Tarashev, 2013), have been proposed in the literature[1], we focus on the $\Delta CoVaR$ approach since it can be seen as a measure more closely capturing contagion risks[2]. Conversely, the Systemic Risk Index and the "Shapley Value" are measures that more closely capture the exposure to common shocks that affect the whole financial system. In addition, the $\Delta CoVaR$ measure is a more flexible approach that nicely allows us to assess interconnectedness across sectors and, given that it relies on high-frequency data[3], is a highly reactive "bottom-up" risk measure. In particular, $\Delta CoVaR$ enables gauging the severity of distress in the system, conditional on distress in a given company or in a group of companies. The test of significance of $\Delta CoVaR$ allows determining whether or not an energy "institution" can be classified as being systemically important on the basis of the estimated contagion risk contribution. Therefore, this measure quantifies the potential "cascade" effects in the system given distress in a specific company. Finally, the test of dominance enables testing whether or not, according to $\Delta CoVaR$, one energy "institution" is more systemically important than another.

The study provides several contributions to the extant literature. It explicitly examines the extent to which the energy sector contribute to contagion risk. In this sense, contagion risk quantifies the extent to which a tail event in a particular energy company can generate

[1] See Bisias et al. (2012) for a comprehensive survey.

[2] The prefix "Co" in $\Delta CoVaR$ stands for Contagion, Conditional, Co-movement.

[3] Indeed, price and stock returns, used to compute the $\Delta CoVaR$, reflect information more rapidly than non-trading-based measures such as accounting variables, especially considering that such information is mostly not available on a daily frequency.

and spread out a tail event to other energy companies and to the rest of the economy.

The focus on how energy companies contribute to contagion risk has hardly been the subject of research. To our knowledge, only the study by Algieri and Leccadito (2017) has examined contagion risk in the energy, food and metal markets, but a thorough analysis that scrutinizes specific energy companies and establishes which of them contributes the most to contagion risk with spillover effects across the sector has so far not been undertaken. Put differently, we move the attention from energy markets as in Algieri and Leccadito (2017), to the energy sector. An interesting study that looks at systemic risk is provided by Kerste et al. (2015). The authors using a risk measure based on the expected fraction of additional failing firms methodology found that contagion runs from the banking sector towards the energy sector, but not vice-versa.

Differently from Algieri and Leccadito (2017) and Kerste et al. (2015), we rank energy companies on the basis of their contribution to contagion risk and examine three time frames: a pre-crisis period (2005-2006), a crisis period (2007-2011), and a post-crisis period (2012-2013) with the objective to identify differences and similarities across times and evaluate whether our findings are sensitive to the considered sample period.

An additional novelty of the study relates to the use of the $\Delta CoVaR$ risk measure to detect impacts and interactions within the energy sector, and examine dependence during extreme market events. This methodology has been generally applied to financial institutions. We extend it to energy companies and, in addition, we develop a new joint significance (or dominance) test that combines significance (or dominance) tests corresponding to different probability levels.

The remainder of the study is organized as follows: Section 2 depicts the adopted methodology, Section 3 describes the data used in the study, Section 4 presents the empirical analysis and discusses the results, and Section 5 concludes.

2. Methodology

Let $\{R_t^{system}\}_t$ and $\{R_t^i\}_t$ denote the time-series of returns[4] of a financial market index ("the system") and of energy company i (or an index comprising energy companies),

[4]Price returns R_t are daily logarithm price differential, i.e., $R_t = \ln S_t - \ln S_{t-1}$ where S_t is the price of the stock at time t.

respectively. The $CoVaR^{system|i}$ is the Value-at-Risk[5] (VaR) of the financial system conditional on the company log-returns being equal to its level of VaR for a τ_i^{th} quantile (i.e., $R^i = VaR_{R^i}(\tau_i)$). Put differently, given some critical level τ, the $CoVaR$ measure is defined as the quantile of the system conditional on R^i being equal to its $\tau_i - VaR$ (i.e. the quantile of the distribution of R^{system} conditional to $R^i = VaR_{R^i}(\tau_i)$). Formally,

$$\mathbb{P}\left(R^{system} \leq CoVaR^{system|i}(\tau)|R^i = VaR_{R^i}(\tau_i)\right) = \tau$$

and

$$\mathbb{P}\left(R^i \leq VaR_{R^i}(\tau_i)\right) = \tau_i.$$

Adrian and Brunnermeier (2016) propose to measure the effect of an extreme event affecting company i on the system by the difference between the $CoVaR$ of the system when company i is in distress – i.e., when it is at a critical tail level such as $\tau_i = 1\%$ – and the $CoVaR$ of the same system when company i is at a "normal" or uncritical level – i.e., when it is at $\tau_i = 50\%$. In detail, the $\Delta CoVaR$ measure they introduce is defined as

$$\Delta CoVaR^{system|i}(\tau) = CoVaR^{system|R^i=VaR_{R^i}(\tau_i)}(\tau) - CoVaR^{system|R^i=VaR_{R^i}(50\%)}(\tau)$$

and quantifies the increase in the contagion risk when the institution experiences extreme events.

In our application, we implement a battery of *significance* tests with null hypothesis:

$$H_0: \quad \Delta CoVaR^{system|i}(\tau) = 0, \quad \tau \in \mathcal{T} \subset (0,1)$$

Rejection of such hypothesis implies that energy company i (or the aggregated energy index) truly contributes to contagion risk.

We also carry out a set of *dominance* tests, with null hypothesis:

$$H_0: \quad |\Delta CoVaR^{system|i}(\tau)| \leq |\Delta CoVaR^{system|j}(\tau)|, \quad \tau \in \mathcal{T} \subset (0,1).$$

The latter test is useful to rank different energy companies based on the impact on the system. In particular, the rejection of the null implies that company i dominates company j, i.e., company i is systemically riskier than company j.

[5]The Value-at-Risk is a probabilistic measure that evaluate the potential loss in value/returns of a risky asset or portfolio over a defined period (e.g., one day) for a given confidence interval. For instance, if 1 day-VaR on an asset is 1 million with 95% confidence level, there is a only a 5% chance that the value of the asset will drop more than 1 million over any given day. The VaR is the maximum loss of value, which statistically corresponds to the lower (left) tail of the unconditional value/return distribution with a 5% cumulative value.

2.1. Estimation

In order to construct the $\Delta CoVaR$ measures we implement a six-step estimation procedure.

Step 1 We first run the τ_i-quantile regression following Koenker (2005), among the others:

$$R_t^i = \alpha_i + \gamma_i M_t + e_t^i \tag{2.1}$$

where the error term e_t^i is assumed to be i.i.d with zero mean and unit variance and independent of the set of explanatory variables M_t.

Step 2 We obtain the τ_i–VaR for energy company i as the predicted value

$$\widehat{VaR}_t^i(\tau_i) = \hat{\alpha}_i + \hat{\gamma}_i M_t. \tag{2.2}$$

Here $\hat{\alpha}_i$ and $\hat{\gamma}_i$ represent the estimated parameters from eq. (2.1).

Step 3 We repeat the first two steps using 0.5 instead of τ_i to obtain 50%–VaR for financial institution i.

Step 4 We run the τ-quantile regression:

$$R_t^{system} = a + bR_t^i + cN_t + \epsilon_t \tag{2.3}$$

where the error term ϵ_t is assumed to be i.i.d with zero mean and unit variance and independent of R_t^i and of the set of explanatory variables N_t.

Step 5 We compute the following $CoVaR$ measures:

$$\widehat{CoVaR}_t^{system|R^i=VaR_{R^i}(\tau_i)}(\tau) = \hat{a} + \hat{b}\widehat{VaR}_t^i(\tau_i) + \hat{c}N_t$$
$$\widehat{CoVaR}_t^{system|R^i=VaR_{R^i}(50\%)}(\tau) = \hat{a} + \hat{b}\widehat{VaR}_t^i(50\%) + \hat{c}N_t$$

where $\hat{a}$, $\hat{b}$, and $\hat{c}$ represent the estimated parameters from eq. (2.3).

Step 6 We obatain the estimated $\Delta CoVaR$ measure as the following difference:

$$\Delta\widehat{CoVaR}_t^{system|i}(\tau) = \widehat{CoVaR}_t^{system|R^i=VaR_{R^i}(\tau_i)}(\tau) - \widehat{CoVaR}_t^{system|R^i=VaR_{R^i}(50\%)}(\tau).$$

2.2. Testing Procedures

To implement the significance and dominance tests, we extend the testing procedure proposed by Bernal et al. (2014). For a fixed value of τ, the authors test whether or not the cumulative distribution functions (CDFs) of $CoVaRs$ at a the τ_i level and at the 50% level are different from each other. This is achieved by bootstrapping the Kolmogorov-Smirnov (KS) test statistic using the procedure proposed by Abadie (2002). The KS test cannot be used directly because the estimated distributions introduce an unknown nuisance parameter that jeopardizes the distribution-free character of the KS test. Hence, Bernal et al. (2014) use the method of Abadie (2002) that allows to obtain critical values by resampling the test statistic under conditions consistent with the null hypothesis. The method of Abadie (2002) consists in a nonparametric i.i.d. block bootstrap in stochastic dominance tests, in which data are divided into blocks that are resampled to replicate the time-dependent structure of the original data.

The two-sample Kolmogorov-Smirnov statistic is defined as:

$$K_{mn}(\tau) = \sup_u |F_m(u) - G_n(u)|, \tag{2.4}$$

where m and n are the size of the two samples and $F_m(u)$ and $G_n(u)$ are the CDFs of the $CoVaR^{system|R^i=VaR_{R^i}(\tau_i)}(\tau)$ and $CoVaR^{system|R^i=VaR_{R^i}(50\%)}(\tau)$, respectively.

For the dominance hypothesis with a fixed value of τ, the test statistic to bootstrap is given by:

$$G_{mn}(\tau) = \sup_u |A_m(u) - B_n(u)|, \tag{2.5}$$

where $A_m(u)$ and $B_m(u)$ are the CDFs of the absolute values of $\Delta CoVaR^{system|i}(\tau)$ and $\Delta CoVaR^{system|j}(\tau)$ and m and n are the size of the two samples. Again, bootstrap-based methods are needed to calculate the p-values for the dominance test.

We extend the testing procedure of Bernal et al. (2014) by combining significance or dominance tests corresponding to different values of τ, for instance $\tau \in \{0.01, 0.05, 0.1\}$. Given a set of J possible values for τ, $\{p_l\}_{l=1,\dots,J}$, the test statistic we propose is given by the sum of test statistics for individual values of p_l, i.e.,

$$K_{mn} = \sum_{l=1}^{J} K_{mn}(p_l). \tag{2.6}$$

for the significance test, and

$$G_{mn} = \sum_{l=1}^{J} G_{mn}(p_l). \tag{2.7}$$

for the dominance test.

To determine the p-value associated to (2.6), the strategy is also to use bootstrap-based methods. In particular, at the hth replica of the bootstrap, first the time series of $CoVaRs$ associated to p_1 are sampled with replacement to obtain $K^h_{mn}(p_1)$, then the time series associated to p_2 are sampled with replacement to quantify $K^h_{mn}(p_2)$, and so on until we derive $K^h_{mn}(p_J)$. The hth replica for the bootstrapped test statistic is then given by $K^h_{mn} = \sum_{l=1}^{J} K^h_{mn}(p_l)$. We proceed in a similar manner to obtain the p-value associated to (2.7).

3. Data Description

In our empirical application we apply the tests described in the previous section to $CoVaR$s or $\Delta CoVaR$s estimated for a sample of 35 energy companies entering the S&P500 Energy index[6]. All the considered companies, which belong to the sector "Energy" according to the Global Industry Classification Standard (GICS), are reported in Table 1 and listed by sub-industry group in Table 2. The data consists of daily observations covering the period from 3 October 2005 to 19 June 2013.

In our analysis, the *system* is mirrored by daily returns of the S&P500 ex Energy index[7], while the *institutions* are proxied, by daily returns either of single energy companies (components of the S&P500 Energy index) or of the S&P500 Energy index. In this way, we can characterize both the behaviour to contagion risk of each single energy enterprises (company level) and the behaviour of all companies considered together (sector level).

The stock market data for the single 35 energy companies and in aggregate are taken from S&P website[8].

It should be noted that the emphasis on stock returns is motivated by the desire to include the most recent information for risk measurement; stocks returns reflect information more rapidly than non-trading-based measures such as accounting variables, especially considering that such information is mostly not available on a daily frequency.

The set of M_t and N_t variables includes those factors identified by the literature (Fama and French, 1989; Ferson and Harvey, 1994) as possible drivers of energy and stock market's

[6]Currently, the S&P500 Energy index comprises 40 companies. In this study we exclude five companies due to lack of data at the beginning of the period of analysis.

[7]The index comprises the S&P500 companies that do not belong to the energy sector.

[8]http://us.spindices.com/

returns. Specifically, M_t comprises:

- the CBOE Volatility Index (VIX), which captures the implied volatility of the S&P500 index and reflects stock market expectations of volatility. It is a popular barometer of investor sentiment and often referred to as the "fear index" (Koch, 2014; Bae et al., 2003);
- the Baltic Dry Index proxy for global demand (Kilian, 2013);
- the MSCI Emerging Market Index proxy for the strength of economic growth in emerging economies that determines the commodity demand from emerging markets (Koch, 2014; Tang and Xiong, 2012);
- the S&P500 equity index to control for broad market exposure. Changes in the equity index can also signal shifts in economic activity and real demand for commodities (Tang and Xiong, 2012);
- the dollar effective exchange rate index as risk factor to control for the exposure of energy futures (priced in US dollars) to exchange rate risk (Algieri, 2014; Erb and Harvey, 2013);
- the US three month T-bill (short-term interest rate) used as barometer of global changes in the international monetary policy (Manera et al., 2013; Chevallier, 2009; Bae et al., 2003; Bessembinder and Chan, 1992);
- the spread between Moody's BAA and Moody's AAA Corporate Bond yields – i.e., yield returns of bonds rated BAA and AAA by Moody's – represents the default risk premium (sometimes called the junk bond yield) (Manera et al., 2013; Chevallier, 2009; Sadorsky, 2002);
- TED spread (i.e., the difference between the 3-Month London Interbank Offered Rate (LIBOR) and 3-Month Treasury Bill) provides a measure of stress (or not) in credit markets and, therefore, it is an indicator of world financial and economic health (Manera et al., 2013; Bae et al., 2003).

N_t comprises the same group of variables excluding the S&P500 equity index. All variables included in M_t and N_t are taken from Bloomberg database. Table 3 displays the variables entering the analysis.

4. Empirical Results and Discussion

The empirical analysis is carried out for the whole sample ranging from to 3 October 2005 to 19 June 2013 and for three subsamples[9] labelled pre-crisis (from 3 October 2005 to 1 August 2007), crisis (from 2 August 2007 to 31 December 2011) and post-crisis (from 02 January 2012 to 19 June 2013).

Table 4 reports the results of the significance test when we use the S&P500 Energy Index as the "institution" and the S&P500 ex Energy Index as the system.

It is worthwhile noticing that when energy companies are considered in aggregate, they have a critical impact on the rest of the economy, i.e., the contagion risk contribution of all oil and gas enterprises taken together is significant given that the null hypothesis is rejected. Hence, it can be stated that energy companies produce spillover effects on the whole economy. This holds true for all the considered sample period, 2005–2013.

The situation changes if one analyses the subperiods. It is interesting to observe that while in the pre-crisis period energy companies do not trigger any contagion risk event, their importance increases during the crisis time, and it continues soon after. It also emerges that while 33 out of 35 companies have significantly contributed to contagion risk during the period 2007–2009, a reduced number of enterprises have exerted a systemic effect in other periods of time.

Table 5 reports the results of the significance tests for each company as well as the ranking based on the results of the dominance tests. In particular, for the entire period of analysis, the oil and gas drilling company Transocean dominates in term of riskiness 29 out of the 30 remaining significant companies (corresponding to a percentage share of 96.67%), followed by Hess Corporation, Tesoro Petroleum, and CONSOL Energy. The less risky companies are Cabot Oil & Gas, FMC Technologies, Halliburton, and Marathon Oil Corporation. Totally insignificant companies, i.e., those for which the p-value of the significance test is larger than 5%, are Cameron International Corporation, EQT Corporation, and Range Resources Corporation.

Tables 6, 7, and 8 display the results for the three subperiods considered, i.e., the pre-crisis, crisis, and post-crisis period, respectively. The findings suggest that the energy

[9]The cut-off date for each subperiod has been taken on the basis of the major events that have characterized the world economy, namely we have considered the period of economic growth and prosperity in financial markets until the period of financial turmoil which marked the entry into the second largest economic recession, and the period of slow recovery.

sector and energy companies under study all represented a higher source of risk for the real economy between 2007 and 2012 than during the other periods. This could be due to the fact that during times of financial crisis, losses tend to spread from a single institution/sector across other institutions/sectors, leading to increased system-wide risk and probable deterioration of the whole stock market system. Furthermore, the dynamics of $\Delta CoVaR$ point to the presence of procyclicality which occurs because risk measures tend to be low in booms and high in crises.

At company level, Exxon is ranked first in terms of risk during the pre-crisis period and during the crisis, but its degree of riskiness has fizzled out after 2011. Exxon's percentage share of dominance is estimated to be 87.5% between 2005-2007 and 100% during the crisis. The companies Chevron and Apache turn out to be risky for all the three subsamples and their degree of dominance is quite strong. In terms of percentage share on the total significant firms, both Chevron and Apache enterprises record higher values in the pre-crisis period (81.25% and 62.50%, respectively), than during (59.38% and 21.88%, respectively), and after the crisis (57.14% and 50%, respectively). These results imply that when high ranking energy companies face distress they can trigger serious problems to the energy market with negative consequences for the whole economy. Conversely, energy companies with a low ranking generate less difficulties for the rest of the economy. In this context, we would expect that among the seven of the S&P 500's top ten losers on the year 2015 there are some companies that can trigger more negative domino effects than others. Given that the worse performances were recorded by Chesapeake Energy Corp and Consol Energy Inc. that went down by 77% respectively, followed by Southwestern Energy Co., that collapsed by 74%, we would expect that these three companies would impact more severely on the energy sector and the economy than other enterprises.

The company Halliburton, which deals with oil and gas equipment and services, is always not significant for the system. It is interesting that a number of companies are significantly risky during the crisis, but not before or after. Companies belonging to this group are Cameron, Anadarko, Consol, EOG, FMC, Helmerich, Hess, Schlumberg, Tesoro, Transocean, and Williams.

5. Conclusions and Policy Implications

After the financial crisis, the policy debate has focused the attention not only on how to mitigate the risk stemming from systemically important financial institutions, but also on the possibility of risks in the non-financial system, including energy markets. This is because in a globalized and financialized economy, economic agents are becoming increasingly more interconnected. This favours the spread of adverse shocks occurring in one or several financial and non-financial institutions not only towards their own sectors, but also to the rest of the economy. Indeed, while rooted in physical markets, non-financial markets are directed impacted by the financial sector and sensitive to spillover effects.

In this paper we have applied the market-based measure, $\Delta CoVaR$ proposed by Adrian and Brunnermeier (2016) to the energy sector, and extended the tests of significance and dominance of $\Delta CoVaR$ implemented by Bernal et al. (2014). The $\Delta CoVaR$ measure has permitted us to evaluate the contribution to contagion risk of each single energy enterprise by measuring the system's minimum loss in market–valued assets (i.e., the financial system's VaR) when the energy enterprise is suffering losses equal to its VaR and when the same energy enterprise is in its median state.

The two tests have allowed determining whether or not an energy enterprises can be classified as being systemically important on the basis of the estimated contagion risk contribution, and whether or not one energy company is more important than another in spreading contagion. We found that important spillover effects take place from the energy sector to the whole economy, and that a high contagion risk has characterized energy markets during the great financial crisis of 2007-2009, and during the period corresponding to the major Eurozone sovereign turmoil. In fact, we found that the conditional value at risk has increased considerably during the financial crisis and remains larger in magnitude after it for the oil and gas companies in the sample. This pattern could be due to the fact that the growth of derivatives and financial contracts has increased contagion risk by expanding linkages among markets and financial institutions. The findings indicate that some energy firms such as Exxon, Chevron and Apache turn out to play a key role for contagion risk management, as they heavily outweigh other firms within the economic network. This feature holds also at the industry level, with industries classified according to the Global Industry Classification Standard. The three companies together with few other energy firms have a significant impact on the whole economy during a period of turmoil and can actually be ranked according to their contagion risk contribution on the basis of $\Delta CoVaR$ at a given point in time.

From a policy perspective these results point to the fact that when energy firms become "distressed" they can be precursor to more defaults and can cause economic havoc. In effect, since the energy sector generates important spillover effects on the economy, it finishes influencing strongly macroeconomic stability. This is particular true during economy's bust phases, when risk measures tend to increase. In fact, $\Delta CoVaR$ measures for the energy sector tends to be pro-cyclical. The empirical evidences bring about the necessity of monitoring energy markets, that have been formerly considered "safe haven", in the attempt to contain contagion risks. This is because risks taken by important energy companies can affect other companies and, via energy prices, spread to the entire energy sector with "negative externalities" for the entire economy. Indeed, the distress of the energy sector may cause higher energy prices volatility, and this would in turn increase uncertainty and impact on growth negatively. Therefore, policymakers should remain vigilant about the possibility of disorderly energy market functioning and scrutinize those companies that have a high risk ranking with the aim to reduce vulnerabilities. In addition, given that historically, corporate defaults in the energy sector have tended to pick up in response to falling oil prices with a lag of about 12 months (Fitch, 2015), aftershocks for the corporate sector may yet remain high. It should be mentioned that the present analysis is one of the first attempts to assess contagion risk in the energy sector and further research is still needed in order to dig into the systemic connections across sectors and broaden the discussion on regulating non-financial sectors.

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Table 1: S&P500 Energy Companies

Companies Included		Companies Excluded	
Ticker	Company	Ticker	Company
APC	Anadarko Petroleum Corp	CPGX	Columbia Pipeline Group Inc
APA	Apache Corporation	KMI	Kinder Morgan
BHI	Baker Hughes Inc	MPC	Marathon Petroleum
COG	Cabot Oil & Gas	PSX	Phillips 66
CAM	Cameron International Corp.	SE	Spectra Energy Corp.
CHK	Chesapeake Energy		
CVX	Chevron Corp.		
XEC	Cimarex Energy		
COP	ConocoPhillips		
CNX	CONSOL Energy Inc.		
DVN	Devon Energy Corp.		
DO	Diamond Offshore Drilling		
ESV	Ensco plc		
EOG	EOG Resources		
EQT	EQT Corporation		
XOM	Exxon Mobil Corp.		
FTI	FMC Technologies Inc.		
HAL	Halliburton Co.		
HP	Helmerich & Payne		
HES	Hess Corporation		
MRO	Marathon Oil Corp.		
MUR	Murphy Oil		
NOV	National Oilwell Varco Inc.		
NFX	Newfield Exploration Co		
NBL	Noble Energy Inc		
OXY	Occidental Petroleum		
OKE	ONEOK		
PXD	Pioneer Natural Resources		
RRC	Range Resources Corp.		
SLB	Schlumberger Ltd.		
SWN	Southwestern Energy		
TSO	Tesoro Petroleum Co.		
RIG	Transocean		
VLO	Valero Energy		
WMB	Williams Cos.		

Table 2: Global Industry Classification Standard (GICS) Sub-industry classification of the companies included in the study.

GICS Sub-industry	N. of Companies	%
Coal & Consumable Fuels	1	2.86%
Integrated Oil & Gas	5	14.29%
Oil & Gas Drilling	4	11.43%
Oil & Gas Equipment & Services	6	17.14%
Oil & Gas Exploration & Production	17	48.57%
Oil & Gas Refining & Marketing & Transportation	2	5.71%

Table 3: Variables Description. M denotes the state variables used in eq. (2.1). The state variables (N) used in eq. (2.3) are the same as those in M excluding the S&P500 index log-returns.

	Description	Ticker
$\boldsymbol{M}$	Market Volatility Index (VIX)	VIX Index
	Baltic Dry Freight	BDIY Index
	MSCI Emerging Markets Index	MXEF Index
	Standard & Poor's 500	SPX Index
	Dollar effective exchange rate	DXY Curncy
	Three month T-bill	USGG3M Index
	Moody's BAA Corporate Bond yield	MOODCBAA Index
	Moody's AAA Corporate Bond yield	MOODCAAA Index
	TED spread	BASPTDSP Index
System	S&P500 Ex Energy	SPXXEGP Index
"Institutions"	S&P500 Energy	SPN Index
	35 Companies of the S&P500 Energy Index (Table 1)	

Table 4: Significance test considering the S&P500 Energy Index as "Institution". Results are for the combined test ($\tau \in \{0.01, 0.05, 0.1\}$) with $\tau_i = 5\%$. P-values have been obtained using a bootstrap procedure with 10,000 replicas.

	Test Statistic	P-value	Significant Companies (Out of 35)
All Sample	0.545	0.000	31
Pre Crisis (03/10/2005 to 01/08/2007)	0.082	1.000	17
Crisis (02/08/2007 to 31/12/2011)	0.542	0.000	33
Post Crisis (02/01/2012 to 19/06/2013)	0.545	0.000	15

Table 5: Significance test considering the 35 companies of the S&P500 Energy Index as "Institutions" for the period 2005-2013. Results are for the combined test ($\tau \in \{0.01, 0.05, 0.1\}$) with $\tau_i = 5\%$. P-values have been obtained using a bootstrap procedure with 10,000 replicas. Share is calculated as the ratio between dominated companies and the remaining significant companies.

Company	Ticker	Test Statistic	P-value	Dominated Companies	Share
Transocean	RIG	0.939	0.000	29	96.67%
Hess Corporation	HES	0.928	0.000	28	93.33%
Tesoro Petroleum Co.	TSO	0.808	0.000	26	86.67%
CONSOL Energy Inc.	CNX	0.779	0.000	25	83.33%
Occidental Petroleum	OXY	0.917	0.000	24	80.00%
Murphy Oil	MUR	0.613	0.000	23	76.67%
Newfield Exploration Co	NFX	0.841	0.000	22	73.33%
Baker Hughes Inc	BHI	0.671	0.000	21	70.00%
ConocoPhillips	COP	0.635	0.000	21	70.00%
Exxon Mobil Corp.	XOM	0.501	0.000	21	70.00%
Chevron Corp.	CVX	0.537	0.000	19	63.33%
Devon Energy Corp.	DVN	0.410	0.000	17	56.67%
Pioneer Natural Resources	PXD	0.392	0.000	17	56.67%
Schlumberger Ltd.	SLB	0.423	0.000	15	50.00%
Noble Energy Inc	NBL	0.366	0.000	13	43.33%
Williams Cos.	WMB	0.352	0.000	13	43.33%
Apache Corporation	APA	0.324	0.000	12	40.00%
Anadarko Petroleum Corp	APC	0.301	0.000	9	30.00%
Chesapeake Energy	CHK	0.275	0.000	9	30.00%
Diamond Offshore Drilling	DO	0.304	0.000	7	23.33%
Ensco plc	ESV	0.328	0.000	7	23.33%
Helmerich & Payne	HP	0.267	0.000	6	20.00%
EOG Resources	EOG	0.236	0.000	4	13.33%
National Oilwell Varco Inc.	NOV	0.243	0.000	3	10.00%
ONEOK	OKE	0.250	0.000	2	6.67%
Southwestern Energy	SWN	0.226	0.000	2	6.67%
Cimarex Energy	XEC	0.158	0.000	1	3.33%
Valero Energy	VLO	0.215	0.000	1	3.33%
Cabot Oil & Gas	COG	0.167	0.000	0	0.00%
FMC Technologies Inc.	FTI	0.141	0.000	0	0.00%
Marathon Oil Corp.	MRO	0.208	0.000	0	0.00%
Insignificant Companies					
Cameron International Corp.	CAM	0.106	0.066		
EQT Corporation	EQT	0.074	0.709		
Halliburton Co.	HAL	0.017	0.914		
Range Resources Corp.	RRC	0.107	0.060		

Table 6: Significance test considering the 35 companies of the S&P500 Energy Index as "Institutions" for the period 03/10/2005 to 01/08/2007 (Pre-Crisis). Results are for the combined test ($\tau \in \{0.01, 0.05, 0.1\}$) with $\tau_i = 5\%$. P-values have been obtained using a bootstrap procedure with 10,000 replicas.

Company	Ticker	Test Statistic	P-value	Dominated Companies	Share
Exxon Mobil Corp.	XOM	1.767	0.000	14	87.50%
Chevron Corp.	CVX	1.246	0.000	13	81.25%
Apache Corporation	APA	0.713	0.000	10	62.50%
Newfield Exploration Co	NFX	0.826	0.000	8	50.00%
Devon Energy Corp.	DVN	0.707	0.000	6	37.50%
EQT Corporation	EQT	0.800	0.000	4	25.00%
ONEOK	OKE	1.028	0.000	4	25.00%
Valero Energy	VLO	0.509	0.000	4	25.00%
Chesapeake Energy	CHK	0.507	0.000	3	18.75%
ConocoPhillips	COP	0.478	0.000	2	12.50%
Marathon Oil Corp.	MRO	0.391	0.000	1	6.25%
Cabot Oil & Gas	COG	0.441	0.000	0	0.00%
Cimarex Energy	XEC	0.239	0.015	0	0.00%
Murphy Oil	MUR	0.296	0.000	0	0.00%
Occidental Petroleum	OXY	0.417	0.000	0	0.00%
Pioneer Natural Resources	PXD	0.241	0.013	0	0.00%
Range Resources Corp.	RRC	0.267	0.003	0	0.00%
Insignificant Companies					
Anadarko Petroleum Corp	APC	0.070	1.000		
Baker Hughes Inc	BHI	0.154	0.628		
Cameron International Corp.	CAM	0.098	0.998		
CONSOL Energy Inc.	CNX	0.028	1.000		
Diamond Offshore Drilling	DO	0.130	0.899		
Ensco plc	ESV	0.187	0.230		
EOG Resources	EOG	0.130	0.895		
FMC Technologies Inc.	FTI	0.161	0.537		
Halliburton Co.	HAL	0.126	0.925		
Helmerich & Payne	HP	0.200	0.136		
Hess Corporation	HES	0.037	1.000		
National Oilwell Varco Inc.	NOV	0.089	1.000		
Noble Energy Inc	NBL	0.104	0.996		
Schlumberger Ltd.	SLB	0.083	1.000		
Southwestern Energy	SWN	0.202	0.117		
Tesoro Petroleum Co.	TSO	0.191	0.196		
Transocean	RIG	0.035	1.000		
Williams Cos.	WMB	0.033	1.000		

Table 7: Significance test considering the 35 companies of the S&P500 Energy Index as "Institutions" for the period 02/08/2007 to 31/12/2011 (Crisis). Results are for the combined test ($\tau \in \{0.01, 0.05, 0.1\}$) with $\tau_i = 5\%$. P-values have been obtained using a bootstrap procedure with 10,000 replicas.

Company	Ticker	Test Statistic	P-value	Dominated Companies	Share
Exxon Mobil Corp.	XOM	0.243	0.000	32	100.00%
EQT Corporation	EQT	0.890	0.000	30	93.75%
Ensco plc	ESV	0.258	0.000	29	90.63%
Occidental Petroleum	OXY	0.473	0.000	29	90.63%
Murphy Oil	MUR	0.547	0.000	28	87.50%
Transocean	RIG	0.481	0.000	26	81.25%
Tesoro Petroleum Co.	TSO	1.027	0.000	25	78.13%
Chesapeake Energy	CHK	0.445	0.000	21	65.63%
Schlumberger Ltd.	SLB	0.372	0.000	21	65.63%
ConocoPhillips	COP	1.223	0.000	20	62.50%
Chevron Corp.	CVX	0.353	0.000	19	59.38%
Devon Energy Corp.	DVN	0.504	0.000	18	56.25%
National Oilwell Varco Inc.	NOV	0.189	0.000	18	56.25%
Valero Energy	VLO	0.173	0.003	18	56.25%
EOG Resources	EOG	0.252	0.000	17	53.13%
Pioneer Natural Resources	PXD	0.418	0.000	16	50.00%
FMC Technologies Inc.	FTI	0.179	0.001	15	46.88%
ONEOK	OKE	0.434	0.000	15	46.88%
Hess Corporation	HES	0.466	0.000	14	43.75%
Cameron International Corp.	CAM	0.148	0.028	13	40.63%
Southwestern Energy	SWN	0.432	0.000	12	37.50%
Helmerich & Payne	HP	0.453	0.000	11	34.38%
CONSOL Energy Inc.	CNX	0.505	0.000	10	31.25%
Anadarko Petroleum Corp	APC	0.178	0.002	8	25.00%
Newfield Exploration Co	NFX	0.431	0.000	8	25.00%
Apache Corporation	APA	0.449	0.000	7	21.88%
Williams Cos.	WMB	0.424	0.000	6	18.75%
Diamond Offshore Drilling	DO	0.350	0.000	5	15.63%
Cimarex Energy	XEC	1.087	0.000	4	12.50%
Cabot Oil & Gas	COG	0.323	0.000	2	6.25%
Noble Energy Inc	NBL	0.476	0.000	2	6.25%
Marathon Oil Corp.	MRO	0.412	0.000	1	3.13%
Range Resources Corp.	RRC	0.736	0.000	0	0.00%
Insignificant Companies					
Baker Hughes Inc	BHI	0.122	0.219		
Halliburton Co.	HAL	0.062	0.999		

Table 8: Significance test considering the 35 companies of the S&P500 Energy Index as "Institutions" for the period 02/01/2012 to 19/06/2013 (Post-Crisis). Results are for the combined test ($\tau \in \{0.01, 0.05, 0.1\}$) with $\tau_i = 5\%$. P-values have been obtained using a bootstrap procedure with 10,000 replicas.

Company	Ticker	Test Statistic	P-value	Dominated Companies	Share
National Oilwell Varco Inc.	NOV	0.837	0.000	14	100.00%
Noble Energy Inc	NBL	0.706	0.000	11	78.57%
ONEOK	OKE	0.752	0.000	10	71.43%
Apache Corporation	APA	0.589	0.000	8	57.14%
Chevron Corp.	CVX	0.534	0.000	7	50.00%
Ensco plc	ESV	0.559	0.000	6	42.86%
Occidental Petroleum	OXY	0.597	0.000	6	42.86%
Diamond Offshore Drilling	DO	0.520	0.000	5	35.71%
Chesapeake Energy	CHK	0.343	0.000	4	28.57%
Cabot Oil & Gas	COG	0.379	0.000	2	14.29%
Murphy Oil	MUR	0.313	0.001	2	14.29%
Valero Energy	VLO	0.425	0.000	2	14.29%
Baker Hughes Inc	BHI	0.262	0.021	0	0.00%
ConocoPhillips	COP	0.319	0.001	0	0.00%
Southwestern Energy	SWN	0.283	0.006	0	0.00%
Insignificant Companies					
Anadarko Petroleum Corp	APC	0.071	1.000		
Cameron International Corp.	CAM	0.057	1.000		
Cimarex Energy	XEC	0.044	1.000		
CONSOL Energy Inc.	CNX	0.049	1.000		
Devon Energy Corp.	DVN	0.054	1.000		
EOG Resources	EOG	0.087	1.000		
EQT Corporation	EQT	0.046	1.000		
Exxon Mobil Corp.	XOM	0.180	0.526		
FMC Technologies Inc.	FTI	0.054	1.000		
Halliburton Co.	HAL	0.052	1.000		
Helmerich & Payne	HP	0.155	0.821		
Hess Corporation	HES	0.074	1.000		
Marathon Oil Corp.	MRO	0.074	1.000		
Newfield Exploration Co	NFX	0.063	1.000		
Pioneer Natural Resources	PXD	0.095	1.000		
Range Resources Corp.	RRC	0.221	0.144		
Schlumberger Ltd.	SLB	0.202	0.286		
Tesoro Petroleum Co.	TSO	0.041	1.000		
Transocean	RIG	0.174	0.589		
Williams Cos.	WMB	0.044	1.000		