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Financial Sector Troubles and Energy Markets

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ABSTRACT

Literature shows the dynamics of energy markets impacting a variety of sectors. In response to the 2007/2008 financial crisis, the U.S. Treasury provided financial assistance (bailouts) to hundreds of public and private financial institutions under the Troubled Asset Recovery Program (TARP) and the Targeted Investment Program. Several studies suggest that bailouts alter the risk profile of the receiving companies. Since risk profiles are at the core of volatility transmissions between asset groups, in this study, we evaluate the volatility impacts of energy markets on these financial institutions before and after they received financial assistance. The data used corresponds to daily observation from January 2022 to December 2020. After controlling for systematic components, our findings show no volatility transmission before the financial intervention but suggest robust volatility transmission from oil and natural gas markets to the bailout banks post bailouts.

Keywords: Energy Markets, Volatility Transmission, Bank Bailouts
JEL Classifications: G01, G21, Q43

1. INTRODUCTION

Financial institutions are crucial to the health of an economy. Systemic failures in the financial sector can lead to investor panic and cause a snowball effect with severe repercussions in the long run. The 2007/2008 financial crisis was fundamentally driven by inadequate risk management in the financial sector, and the U.S. government intervened to stop the crisis from further deteriorating the economy. While the scope of this study is not to debate whether an intervention by the government is beneficial to the markets, there is some research that investigates its impacts. For example, Acharya et al. (2014) look at bank bailouts' impact on sovereign credit risk. They find that this intervention essentially triggered the rise of sovereign credit risk in 2008 even after controlling for bank-level determinants of credit spreads. Evaluating the company-level impacts, Berger and Roman (2020) show that TARP recipients gained a competitive advantage after the bailouts. Harris et al. (2013) find that TARP banks' operating efficiency decreased after receiving assistance. Furthermore, Ng et al. (2016) show that the stock returns were lower for TARP banks after the program was initiated. However, they suggest these returns increase later on. Looking at the risk component, Gietl and Kassner (2020) find that government bailouts, in general, result in bank managers taking higher risks. Concurrently, Cuadros-Solas et al. (2021) suggest bailouts to negatively impact sovereign ratings. On the other hand, Berger et al. (2015) suggest that the banks which received bailouts decrease the average systemic risk. They further argue that the decrease is primarily due to TARP institutions becoming safer after receiving financial assistance. Lastly, Norden et al. (2020) find a positive multiplier effect from the borrowers of bailed-out banks in terms of trade credit.

Several outside shocks impact the overall risk structure of stock markets. While some factors have stronger impacts than others, one significant source of shocks comes from the energy markets. Literature has an abundance of studies looking at the impacts of energy price shocks on the equity markets. For example, Zhu et al. (2021) suggest significant volatility spillovers from the stock markets to oil markets. In another study, Sim and Zhou (2015) find large negative oil price shocks to positively impact the stock market-especially in bull markets. Furthermore, Du and He (2015) demonstrate the significant volatility relationship between oil prices and the stock market but suggest the relationship to be stronger after the 2007/2008 financial crisis. Similarly, Bouri and Demirer (2016) observe the ability to predict select international equity markets' volatility using the oil market. In another study, Le and Chang (2015) show several factors to drive the relationship between oil market volatility and the stock market. They argue that the evaluation time-period, among other factors, is a major component of this relationship. From a return transmission perspective, Anand and Paul (2021) find oil shocks significantly impact stock returns. Looking at the reverse interactions, Zhang and Wang (2019) provide evidence of stock markets moving oil prices. Last but not least, Mensi et al. (2017) find strong evidence of tail dependence between oil prices and the stock markets they tested. Xiao et al. (2022) suggest oil price uncertainty increases stock price crash risk. Lastly, Liu et al. (2023), suggest unexpected oil volatility is positively associated with stock returns, but negatively interact with stock volatility.

There are two possible ways energy price shocks impact the financial sector. One is the indirect impacts through associated industries, and the other is direct spillovers. The energy sector strongly interacts with the financial sector through large loans. In other words, the energy sector's dependence on the financial sector can make the financial sector indirectly susceptible to the energy sector's dynamics. There is some research demonstrating the susceptibility of the energy sector to oil shocks. While oil price shocks impact the overall stock market, the energy sector is especially affected (Hammoudeh and Li, 2005). The direct dependence between the economy and energy commodities seems to drive this significant relationship (Ordu and Soytas, 2015). In particular, Arouri and Nguyen (2010) show that the energy sector presents a high positive sensitivity to oil prices. However, Hammoudeh et al. (2004) point out that the sub-sector component of this industry is important for the direction of the relationship. For example, they showed that oil refineries that use crude oil as their input are negatively impacted by increases in oil prices.

Since banks lend significant funds to energy companies, oil prices are expected to be one of the outside factors influencing their overall business. Literature that evaluate the financial sector in light of energy market shocks find direct information transmission even after controlling for general market components. One of those studies is conducted by Arouri in 2011. Using linear and asymmetric models, the author shows fluctuations in oil prices indirectly impact the financial sector. On a similar note, Lee et al. (2012) test the impacts of oil prices on the sectors of G7 countries' stock markets and find that the financial sector is highly sensitive to oil price shocks. In another study, Bouri et al. (2016) show that oil return shocks significantly impact the financial sector after a political turmoil.

2008 intervention by the U.S. government in the financial industry certainly impacted many aspects of the economy. However, the significance of this intervention for the relationship between financial institutions and energy markets is not clear. In this study, we evaluate the volatility impacts of oil and natural gas markets on the financial sector. In particular, we test those impacts on the institutions that received financial assistance due to the 2007/2008 crisis. Our approach tests for specific volatility information flows before and after the bailouts and demonstrate a robust difference even after controlling for general market dynamics.

The remainder of the paper is structured as follows. In the next section, we explain our econometric methodology and data. Section 3 presents and discusses the results. Section 4 offers a summary and concluding remarks.

2. ECONOMETRIC METHODOLOGY AND DATA

2.1. Volatility Transmission Methodology

In this study, we assess the existence and direction of dynamic volatility transmission between the bailout banks and select energy markets. To achieve this result, we employ a volatility transmission methodology developed by Hafner and Herwartz (2006) (referred to as "HH" going forward). This approach uses a LM-GARCH framework and is shown to be more robust compared to a lot of the popular volatility tests used in literature today. For example, some common volatility transmission tests (e.g. Cheung and Ng, 1996; Hong, 2001 and others) utilize univariate GARCH[1] models and cross-correlation functions of the standard residuals. While this approach can measure volatility accurately in certain situations, it typically suffers from oversizing effects (Gormus, 2016). This is especially true when the volatility processes are leptokurtic and require a selection of lead and lag orders (HH, 2006). To overcome these problems, HH developed the LM-based volatility transmission approach. Their method not only addresses the issues mentioned before but also has an increasing power as the sample size grows.

HH define the initial model as follows:

$$\varepsilon_{it} = \xi_{it}\sqrt{\sigma_{it}^2(1+Z_j^{'}\pi)},\ Z_{jt} = (\varepsilon_{jt-1}^2, \sigma_{jt-1}^2)' \qquad (1)$$

where ξ_{it} and σ_{it}^2 are respectively the standardized residuals and the volatility for the series i. ε_{jt-1}^2 and σ_{ji-1}^2 are the squared disturbance terms and the volatility for the series j respectively. The null hypothesis for no-transmission is $H_0: \pi = 0$ and $H_0: \mu \neq 0$ is the alternative hypothesis which implies that transmission exists. The log-likelihood function of ε_{it} (Gaussian) is used to achieve $x_{it}(\xi_{it}^2 - 1)/2$ where x_{it} are the derivatives of the likelihood function within GARCH parameters. The LM for the volatility transmission is:

$$\lambda_{LM} = \frac{1}{4T}\left(\sum_{t=1}^{T}(\xi_{it}^2 - 1)z_{jt}^{'}\right)V(\theta_i)^{-1}\left(\sum_{t=1}^{T}(\xi_{it}^2 - 1)z_{ji}\right) \qquad (2)$$

1 Since we focus on volatility transmission using the causality-in-variance approach, we do not specify the details of ARCH and GARCH models in order to save space. Please refer to Engle (1982), Bollerslev (1986), and Bollerslev et al. (1992) for derivations of their volatility models.

Where

$$V(\theta_i)=\frac{k}{4T}\left(\sum_{t=1}^{T} z_{jt}z_{jt}^{'}-\sum_{t=1}^{T} z_{jt}x_{jt}^{'}\left(\sum_{t=1}^{T} x_{it}x_{it}^{'}\right)^{-1}\sum_{t=1}^{T} x_{it}z_{jt}^{'}\right),$$

$$k=\frac{1}{T}\sum_{t=1}^{T}(\xi_{it}^{2}-1)^{2} \qquad (3)$$

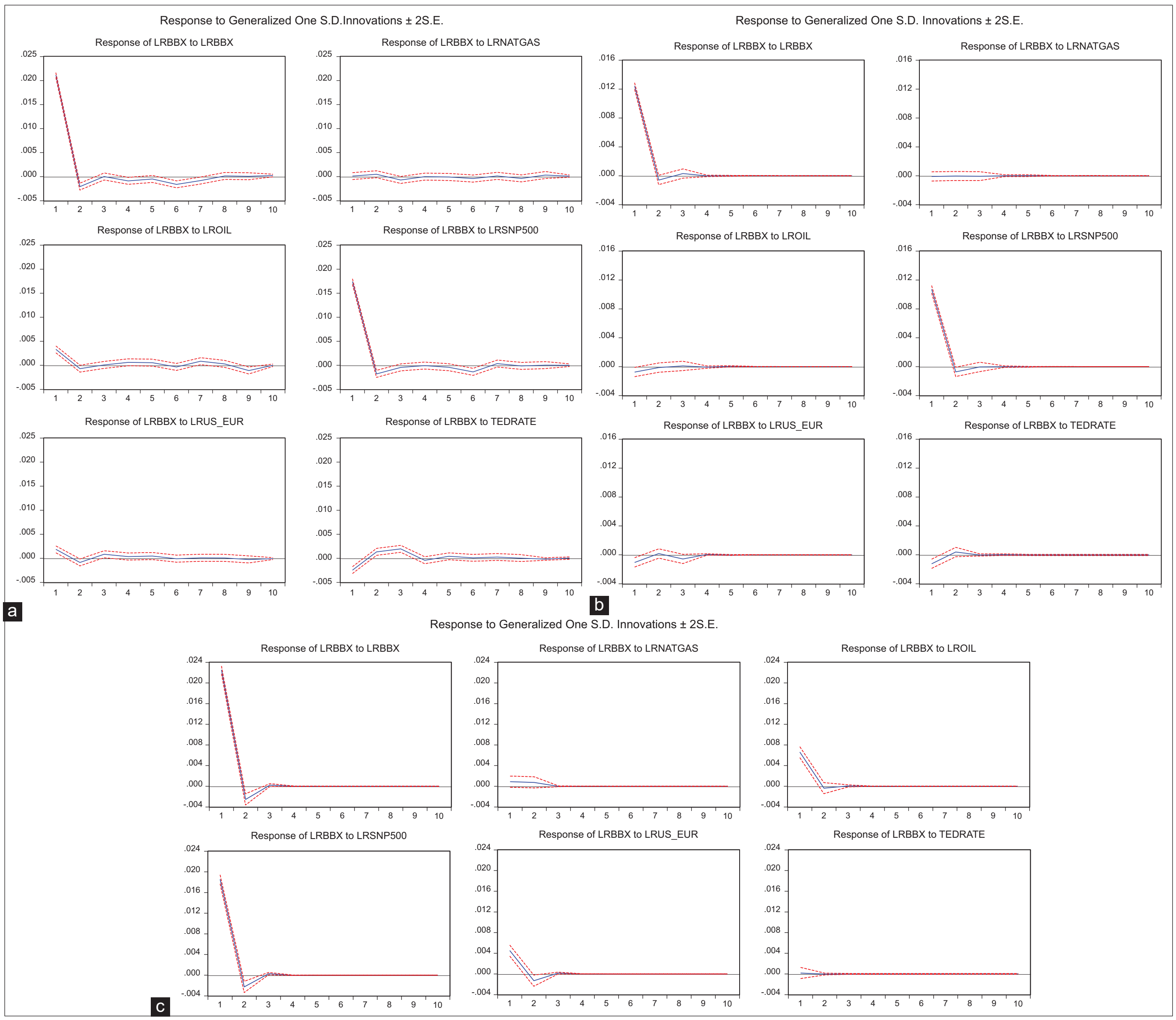
λ_{LM} has asymptotic Chi-square distribution with two degrees of freedom.

In the next part of our study, we provide Generalized Impulse Responses generated using a traditional Vector Auto Regression model (VAR). This model is comparatively flexible since it treats every variable as independent in simultaneous regressions. The VAR approach assumes the following model:

$$g_t = A\sum_{i}^{p}\phi g_{t-i}+\varepsilon_t$$

Where g_t is an $m \times 1$ vector of jointly determined endogenous variables, ϕ are m × m matrices of estimated coefficients, A is

Figure 1: Generalized Impulse Responses. (a) Full sample 01/2002-12/2020 (VAR[8]). (b) Before bailout 01/2002-12/2007 (VAR[8]). (c) After bailout 01/2009-12/2020 (VAR[1])



VAR lag lengths are selected based on the majority of BIC, AIC, LR, and HQ criteria and reported in parentheses. All VARs have inverse characteristic roots that lie within unit circle and hence all are stable. LRBBX is the log return of BBX index, LROIL is the log return of spot oil prices, LRNATGAS is the log return of spot natural gas prices, LRSNP500 is the log return of daily S&P 500 index prices, LRUS_EUR is the log return of US/EUR exchange rate and TEDRATE is the TED spread.

a vector of constants, t is time, p is the optimal lag length (we identify the optimal number of lags through appropriate fit criteria such as SIC, AIC, etc.), and ε_t is an $m \times 1$vector disturbances with covariance $\Sigma = \sigma_{ij}$. The term $(K_n \Sigma e_j)(\sigma_{ij})^{-1}$ represents the generalized impulse response (as it is further discussed below) of g_{t+n} with respect to a one standard deviation shock to jth variable at time t. In this equation, $K_n = \phi_1 K_{n-1} + \phi_2 K_{n-2+\ldots} \phi_p K_{n-p,}$ n=1,2…., $K_0 = 0$ for n < 0 and e_j is the $m \times 1$ selection vector with unity as its jth element and zero elsewhere.

In order to test for each variable's response to an abrupt shock to another, we utilize Generalized Impulse Responses (GIR) developed by Pesaran and Shin (1996) and Koop et al. (1996). This approach replaced the common variance decomposition models used in literature before. Although GIR provides similar results to traditional impulse responses, it doesn't suffer from issues related to the ordering of variables.

The results of our GIR tests are provided in Figure 1a-c.

2.2. Data

For this study, we create a capitalization-weighted "Bailout-Bank Index" (referred to as "BBX" going forward). To construct this index, we gather the list of the publically traded financial institutions that received assistance from the U.S. Treasury under the Capital Purchase Program (source: U.S. Department of the Treasury). We then eliminate any firms which do not have data for the entire time frame of this study. The final BBX dataset consists of 252 firms with capitalization-weighted daily observations from January 2002 to December 2020 (source: WRDS database). We also use the daily prices of WTI Oil and Natural Gas provided by the U.S. Energy Information Administration and S&P 500 Index provided by the WRDS database. For our supplemental analysis, we also control for EU/EUR Exchange Rate and TED Spread ("TEDSP") obtained from the Federal Reserve Bank of St. Louis. About half of the financial institutions in our sample were funded in 2008 and the remainder in 2009. We use 2008 as the bailout year for our analysis and look at the relationships before and after 2008. For our robustness checks, we also extend the bailout year from 2007 to 2009 and do not find any significant differences in our results.

3. EMPIRICAL ANALYSIS

Before we analyze the inferences of the volatility tests, we evaluate the descriptive components of the data series we use in this study. Table 1 reports these statistics along with normality

Table 1: Descriptive statistics and unit root test results

Panel A. Full sample 01/2002–12/2020						
Statistics	**BBX**	**NGAS**	**OIL**	**SNP500**	**US_EUR**	**TEDSP**
Mean	0.0002	0.0000	0.0002	0.0002	0.0001	0.4346
Median	0.0003	0.0000	0.0007	0.0007	0.0000	0.2600
Maximum	0.1916	0.5767	0.1641	0.1096	0.0462	4.5800
Minimum	−0.2289	−0.5682	−0.1519	−0.0947	−0.0300	0.0900
SD	0.0216	0.0448	0.0239	0.0125	0.0063	0.4674
Skewness	0.1072	0.7591	−0.0847	−0.2177	0.1029	3.5966
Kurtosis	20.5900	28.4900	7.5800	12.3300	5.4400	20.3500
Jarque-Bera	45430.3***	95762.8***	3086.4***	12817.3***	880.2***	51818.4***
DFGLS int.	−2.97***	−16.03***	−7.58***	−1.83	−2.10**	−2.06**
DFGLS trend	−5.34***	−3.17**	−7.06***	−6.25***	−4.02***	−2.44***
Panel B. Before bailouts 01/2002–12/2007						
Statistics	**BBX**	**NGAS**	**OIL**	**SNP500**	**US_EUR**	**TEDSP**
Mean	0.0003	0.0007	0.0010	0.0002	0.0003	0.4121
Median	0.0004	0.0000	0.0015	0.0006	0.0002	0.3000
Maximum	0.0784	0.5767	0.1244	0.0557	0.0194	2.4200
Minimum	−0.0563	−0.5682	−0.1519	−0.0424	−0.0211	0.1000
SD	0.0124	0.0506	0.0221	0.0101	0.0055	0.3598
Skewness	0.3600	0.5200	−0.3979	0.1194	−0.1505	2.9781
Kurtosis	7.9392	30.1017	6.3180	5.8282	3.6612	12.5232
Jarque-Bera	1566.5***	46249.7***	732.0***	506.5***	33.2***	7938.1***
DFGLS int.	−3.34***	−13.19***	−2.54**	−3.85***	−4.44***	−2.72***
DFGLS trend	−6.15***	−49.24***	−4.65***	−6.83***	−7.05***	−3.04**
Panel C. After bailouts 01/2009–12/2020						
Statistics	**BBX**	**NGAS**	**OIL**	**SNP500**	**US_EUR**	**TEDSP**
Mean	0.0005	−0.0005	−0.0001	0.0005	−0.0001	0.2921
Median	0.0005	0.0000	0.0001	0.0007	0.0000	0.2300
Maximum	0.1916	0.3901	0.1330	0.0684	0.0462	1.3300
Minimum	−0.2289	−0.2784	−0.1274	−0.0690	−0.0269	0.0900
SD	0.0227	0.0411	0.0224	0.0113	0.0065	0.1880
Skewness	0.3078	1.1428	0.0141	−0.2688	0.1672	2.8184
Kurtosis	22.0900	21.3800	7.2700	7.4500	5.4100	11.4500
Jarque-bera	26788.8***	25176.1***	1338.4***	1474.0***	434.2***	7577.2***
DFGLS int.	−0.57	−5.81***	−2.00**	−4.63***	−4.28***	−0.2
DFGLS trend	−1.87	−33.00***	−4.18***	−14.45***	−7.34***	−0.98

***, **, and *Statistical significance at 1%, 5%, and 10% respectively. All variables except TED are in log returns. The mean, median, maximum, minimum, standard deviation, skewness, kurtosis and observation numbers are given in the table. Jarque-Bera normality tests statistics reveal non-normality in all panels. DFGLS unit root tests in levels with intercept only and intercept and trend are also reported. Non-normality in all periods is observed. All variables are stationary in all periods except for BBX and TED after the bailouts. SD: Standard deviation, BBX: Bailed out bank index, NGAS: Natural gas, OIL: Crude oil, SNP500: Standard and poor's 500 index, US_EUR: Dollar-euro parity, TEDSP: Ted spread and unit root test results. All returns are comparable across panels, but a slight increase in the standard deviations of the BBX, oil, stock market, and currency market returns is observed. The BBX and S&P 500 mean returns and standard deviations seem to have increased following the bailout year, whereas the mean returns in energy and currency markets have gone down. The average Ted spread and its standard deviation seem to have decreased after 2008. There is clear evidence of non-normality based on a visual inspection of the skewness and kurtosis statistics and the formal Jarque-Bera test for normality in all panels. The DFGLS unit root test results also do not change much across samples, except for BBX and TEDSP in the last period. BBX and TEDSP appear to be non-stationary after the bailouts. As mentioned earlier, about half of the financial institutions in our study received their funding in 2008 (and most others were announced to receive it). To evaluate the before and after impacts of the bailouts, we use 2008 as the "event year." Although we use 2008 as the bailout year for the descriptive analysis, we also extend this window from 2007 to 2009 for our volatility transmission robustness checks.

Table 2 presents our findings for the volatility transmission tests. The existence of a volatility transmission implies that information from one market improves the volatility forecasts of the other (Gormus, 2016). When the full sample is analyzed, we see a strong volatility transmission from oil and natural gas markets to the stock market. This finding confirms studies in the literature that suggest similar results. However, we do not see any volatility interactions between the energy markets and BBX. Since 2008 was a crucial year for financial intervention (about half of the institutions were funded in 2008, and others' funding was announced the same year), we divide the sample into two sections around that year[2]. Significant differences are observed when the full-sample results are compared with the split-sample results. In other words, the full sample results seem to be misleading when we consider the bailout period.

One statistically robust and interesting outcome is that S&P500 volatility spilled over to the oil market before the bailouts. However, the direction of these transmissions is reversed after the bailouts. It is important to note that these time-frames also overlap with the overall financial crisis. Therefore, the relationship between oil and the stock market can be interpreted as transmissions before and after the financial crisis (and not related to the bailout itself).

When we look at the volatility interactions for BBX, we see a different form of reversal in the pattern. While no significant interactions were observed before the bailout period, the results suggest significant volatility transmissions from both oil and natural gas markets to BBX after the bailouts. These findings confirm the results of studies on various financial markets. For example, Turhan et al. (2013) find a reversal pattern in the relationship between emerging markets' exchange rates and oil. Along the same lines, Ordu and Soytas (2015) observe similar reversals in information transmission patterns between the stock market indexes in Turkey, oil and natural gas prices. Both studies argue that energy markets have become more important for market performances of financial assets after 2008. More on reversal patterns, Nazlioglu et al. (2015) report oil prices

2 Results do not change when we extend the bailout horizon from 2008 to 2009. Please see Table 3.

Table 2: Risk transmission test results

Panel A. Full sample 01/2002–12/2020				
Series	**From OIL to**	**P**	**To OIL from**	**P**
BBX	5.4294**	0.0662	4.1243	0.1272
NGAS	1.9266	0.3816	1.9059	0.3856
SNP500	12.4798***	0.002	5.9432*	0.0841
Series	**From NGAS to**	**P**	**To NGAS from**	**P**
BBX	3.7249	0.1553	2.1826	0.3358
OIL	2.3435	0.3098	1.7006	0.4273
SNP500	10.0091***	0.0067	2.0531	0.3582
Panel B. Before bailout 01/2002-12/2007				
Series	**From OIL to**	**P**	**To OIL from**	**P**
BBX	1.9162	0.3836	3.6456	0.1616
NGAS	5.3738**	0.0681	2.9981	0.2233
SNP500	4.5587	0.1024	14.9742***	0.0006
Series	**From NGAS to**	**P**	**To NGAS from**	**P**
BBX	2.1662	0.3386	4.8653*	0.0878
OIL	2.9981	0.2233	5.3738*	0.0681
SNP500	3.6807	0.1588	4.0734	0.1305
Panel C. After bailout 01/2009–12/2020				
Series	**From OIL to**	**P**	**To OIL from**	**P**
BBX	12.0588***	0.0024	2.415	0.2989
NGAS	1.6869	0.4302	3.144	0.2076
SNP500	13.9585***	0.0009	3.1742	0.2045
Series	**From NGAS to**	**P**	**To NGAS from**	**P**
BBX	11.0425***	0.004	1.5235	0.4669
OIL	3.144	0.2076	1.6869	0.4302
SNP500	12.9967***	0.0015	0.5751	0.7501

***, **, and *Statistical significance at 1%, 5%, and 10% respectively. All variables are in log returns. Columns represent the direction of transmission. NGAS: Natural gas, BBX: Bailed out bank index, NGAS: Natural gas, OIL: Crude oil, SNP 500: Standard and poor's 500 index

Table 3: Risk transmission test results with extended bailout period

BEFORE 2007				
Series	**From OIL to**	**P**	**To OIL from**	**P**
BBX	2.999332	0.223205	1.487229	0.475393
NGAS	3.283309	0.193659	2.383345	0.303713
SNP500	8.972024**	0.011265	11.4804***	0.003214
Series	**From NGAS to**	**P**	**To NGAS from**	**P**
BBX	3.171345	0.20481	1.882126	0.390213
OIL	2.383345	0.303713	3.283309	0.193659
SNP500	7.254534**	0.026589	1.902347	0.386287
AFTER 2009				
Series	**From OIL to**	**P**	**To OIL from**	**P**
BBX	7.120983**	0.028425	1.586008	0.452483
NGAS	6.394856**	0.040867	1.881233	0.390387
SNP500	10.58879***	0.00502	2.987374	0.224543
Series	**From NGAS to**	**P**	**To NGAS from**	**P**
BBX	7.774205**	0.020505	4.33274	0.114593
OIL	1.881233	0.390387	6.394856	0.040867
SNP500	11.28651***	0.003541	3.141629	0.207876

***, **, and *Statistical significance at 1%, 5%, and 10% respectively. All variables are in log returns. Columns represent the direction of transmission. NGAS: Natural Gas, BBX: Bailed out bank index, NGAS: Natural gas, OIL: Crude oil, SNP 500: Standard and Poor's 500 index influenced financial stress before the global crisis in 2008, but this relationship changed direction after the crisis. They argue that the financial stress index reported by Cleveland Fed is an aggregate measure of vulnerability in all financial markets (ranging from stock, real estate, exchange rate, credit, and other markets), and the aggregation may be driving their results. As for our findings, we further elaborate on their significance under the "discussion and conclusion" section below.

In addition to our volatility analysis, we also perform price-level tests. For this analysis, in addition to oil, gas, and market prices, we also control for the Dollar exchange rate and the Ted rate. We present our findings for the generalized impulse response analysis in Figure 1a-c below. These results support our risk transmission findings. Before the bailout year 2008, a negative but statistically insignificant response to a shock in oil is observed. BBX is more sensitive to natural gas shocks, but responses are still insignificant. After the bailout, a positive shock in oil seems to trigger a significant and positive response in BBX. This response dies off after one period.

To check the robustness of our volatility results, we extend the bailout window from 2007 to 2009 (Table 3 below). We do not observe significant differences in the results between the original tests and the robustness checks.

4. DISCUSSION AND CONCLUSION

During the 2007/2008 financial crisis, the U.S. government intervened in the financial markets and bailed-out hundreds of financial institutions in an attempt to ease the turmoil. In this paper, we are interested in testing the impact of this bailout on the volatility relationship between those financial institutions and the energy markets. In particular, we test the existence and direction of volatility transmissions between the bailed-out banks, oil and natural gas markets.

Our results show that breaking the sample into two (before and after the financial intervention) is very important. When we evaluate the full sample, we do not observe any significant volatility information transmission between BBX and the energy markets. However, when we divide the sample, we see a significant volatility spillover from both oil and natural gas markets to BBX after the bailout. From the entire stock market's perspective, we find the risk in the stock market transmitting to oil prices before the 2008 period, but this relationship reversed afterward. As we previously mentioned, some studies in the literature show reversal patterns around the financial crisis period. Our tests suggest similar results. However, the fact that BBX shows volatility interactions only after the 2008 period further suggests the crisis elevated the importance of energy markets regarding the financial sector.

In addition to the increased influence of energy markets on the financial markets, our results can be interpreted in several ways. BBX is a stock price index and there are two major components that move stock prices: fundamental factors and investor sentiment. Banks hold a significant amount of energy debt in their portfolios. Since the volatility in energy prices increased during the financial crisis, this most likely caused fundamental fluctuations in the energy sector's balance sheets. These fluctuations could have indirectly spilled over to the financial sector. Another explanation would be from the investor sentiment perspective. While we don't see any risk relationship between BBX and energy markets before the 2008 period, the stock market and BBX show similar interactions with the energy markets after the crisis. This could be due to financial sector investors being more watchful of the energy markets, especially after these institutions' risk *mismanagement* before the crisis.

In this paper, we conclude that the financial sector is more prone to volatility impacts from the energy markets than ever before. Our results suggest that any investor who holds a financial sector portfolio or a general portfolio, including financial sector stocks, should pay close attention to the energy markets.

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