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Asymmetric determinants of CDS spreads: U.S. industry-level evidence through the NARDL approach

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ABSTRACT

This paper investigates the presence of asymmetries in the short- and long-run relationships between the 5-year CDS index spreads at the U.S. industry level and a set of major macroeconomic and financial variables, namely the corresponding industry stock indices, the VIX index, the 5-year Treasury bond yield and the crude oil price, using the NARDL approach. The empirical results provide significant evidence of both short-run and long-run asymmetries in the linkage between ten industry CDS spreads and the potential driving factors common for all industries, confirming the importance of asymmetric nonlinearity in this context. It is also shown that the industry equity prices, the VIX, the 5-year Treasury bond rate and, to a lesser extent, the crude oil price constitute important asymmetric determinants of these U.S. industry CDS spreads. The findings of this study have relevant implications for investors, speculators, arbitrageurs and policy makers interested in credit risk at the industry level.

1. Introduction

The recent global financial crisis, which originated in the U.S. subprime mortgage market in 2007 and later spread around the world, leading to a severe economic downturn in many countries, was primarily caused by a combination of underpricing of credit risk and innovation in derivative products which allowed an explosive growth of leverage. In this context, credit default swaps (henceforth, CDSs) are the most important type of credit derivative and have become one of the most controversial derivative instruments created over the past two decades. [1] They have been the object of fierce criticism because of their critical role in spreading risk across financial markets and countries rather than acting as hedging instruments.[2] A single-name CDS is an over-the-counter credit derivative contract between a seller and a buyer that provides the buyer a protection against default of an underlying entity (corporate or sovereign). The buyer pays the seller a fee called a CDS spread or premium, and in the exchange the buyer will receive compensation from the seller if a default occurs.

A CDS index is a single contract that represents a portfolio of single-name CDSs based on a particular market sector or broad market. As noted by Alexander and Kaeck (2008), the CDS index contracts are very similar to single-name CDS contracts. However, a credit event of a CDS index member does not lead to the termination of the whole contract. Instead, the respective reference entity is removed from the index and the contract continues until expiration, but with a reduced nominal amount. CDS indices are highly liquid and standardized credit instruments that trade at a very small bid-ask spread and allow for the measurement of the credit quality of the reference entities represented in the CDS index. The first CDS indices were created in 2001 by JP Morgan and Morgan Stanley, and these indices were merged in 2003

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[1] The CDS market has existed since the early 1990s and reached its historical high in the last quarter of 2007, with $62.2 trillion of notional amount outstanding of CDS contracts. The notional amount of CDS contracts outstanding at the end of June 2015 was $15 trillion. Despite this sharp drop, the notional amount of the derivatives market is still almost 20 times the global gross domestic product (www.isdacdsmarketplace.com).

[2] For example, Warren Buffett, the legendary U.S. investor, claimed in 2002 that the CDSs were financial weapons of mass destruction, which carry potentially lethal dangers. Similarly, George Soros, the famous hedge fund manager, stated in 2009 that CDSs are toxic instruments whose use should be strictly regulated.

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under the Trac-x name. During the same period, Iboxx launched a series of CDS indices. In 2004, Trac-x and Iboxx merged to form the CDX indices in North America and the iTraxx indices in Europe and Asia. These CDS indices provide a broad-based measurement of the credit markets and the best known indices capture more than 100 reference entities in each market. The industry CDS indices were also launched in 2004 and reflect the average of the single-name CDS spreads of the set of reference entities in each industry. These industry CDS indices are considered efficient measures of the credit risk faced by each industry. The CDS spread of an industry measures the premium on the protections provided by the CDS issuers of the debts generated by the companies in that industry, for example Financials, Utilities, Oil & Gas, etc. Thus, the magnitude of an industry's CDS spread gauges the average level of credit risk exposure of the firms that make up that industry. A widening of a CDS index spread indicates an increase in the level of credit risk in the corresponding industry, while a narrowing of a CDS spread signals a decrease in credit risk.

The analysis of the main factors influencing the behavior of CDS spreads has attracted a great deal of attention in the finance literature over the last few years. The structural model of credit risk introduced by Merton (1974) provides the basic theoretical framework to identify the primary determinants of changes in CDS spreads. The structural model of Merton (1974) offers a very intuitive way of explaining the relationship between economic fundamentals and credit-risky instruments and this model has been broadly utilized to analyze corporate credit spreads. In the Merton model, default occurs when the market value of a firm' assets, which is assumed to be described by a stochastic process, falls below a certain threshold associated with the value of the outstanding debt of the firm. This model implies that the key theoretical determinants of credit default are financial leverage, asset volatility and the risk-free interest rate. However, the problem is that these determinants are not directly observable, which has opened the door to the consideration of a number of macro-finance variables, such as stock prices, implied stock volatility and spot interest rates, which are widely accepted as good proxies for leverage, asset volatility and the risk-free interest rate, respectively. Moreover, these variables have been regarded in many related studies as being important in explaining changes in CDS spreads (see, e.g., Alexander and Kaeck, 2008; Annaert et al., 2013; Chan and Marsden, 2014; Ericsson et al., 2009; Galil et al., 2014).[3] The crude oil price constitutes another potentially relevant driver of CDS spreads due to the significant impact of oil price shocks on the real economy as well as on the probability of default of many firms (e.g., Arouri et al., 2014; Hammoudeh et al., 2013b; Lahiani et al., 2016). Hence, the oil price has been included as an additional determinant of CDS spreads.

Furthermore, the bulk of the research on the explanatory factors of CDS spreads has been conducted in the framework of the linear model. Nevertheless, the linkage between the CDS spreads and the selected macroeconomic and financial risk variables does not necessarily have to be linear, but it may exhibit a more complex nature owing to potential asymmetry and regime shifts caused by unusual changes in financial market conditions. For example, the global financial crisis of 2008–2009 and the subsequent European sovereign debt crisis of 2010–2012 have generated unprecedented levels of fear and risk aversion in stock markets, stress in financial markets and economic uncertainty in policy making. This turbulent situation has materialised in huge increases in CDS spreads of many firms and sovereigns and led to the presence of outliers and structural breaks in the data. Thus, it does not seem unreasonable to think that the extreme market conditions may have induced a change in the type of relationship between CDS spreads and major economic and financial indicators. Concretely, the fact that the participants in the CDS market, including investors, arbitrageurs, speculators and policy makers, are a group of heterogeneous agents with bounded rationality and different preferences, risk tolerance and trading strategies may have played a critical role in this context. This is because each of these agents becomes particularly active under different economic and market conditions, which may give rise to asymmetric responses of CDS spreads to movements of different sign in their main determinants, especially during periods of high financial turmoil. For instance, speculators, including short sellers and market makers tend to be more active during high financial stress times than during normal times and herding is also stronger in such tumultuous times.

An alternative explanation for the asymmetric behavior in the CDS markets has been proposed by Acharya and Johnson (2007) which attribute asymmetry to information revelation that occurs only for negative credit news and for institutions that subsequently experience adverse shocks. Additionally, since asymmetry and nonlinearity are two important stylized facts of many economic and financial time series, it is appropriate to use a nonlinear model to characterize the short- and long-run linkages between CDS spreads and their major determinants in a less restrictive way than a linear specification. Therefore, it is important to model the asymmetric nonlinearity in order to determine whether the actions of short-term traders such as speculators and arbitrageurs and long-term investors such as pension fund managers and institutional investors lead to significant asymmetries in the short- and long-run response of CDS spreads to changes in macroeconomic and financial conditions. Contrarily, assuming a strictly linear relationship in the presence of asymmetries would produce inefficient and biased results.

The aim of this paper is to examine possible asymmetries in the short- and long-run relationships between ten U.S. industry-level CDS index spreads and a group of major macroeconomic and financial variables widely accepted as theoretical drivers of CDS spreads, which include industry stock indices, the VIX index, the U.S. 5-year Treasury yield and the crude oil price. The motivation for conducting an industry-based analysis of the determinants of CDS spreads is the fact that the consideration of the aggregate stock market may induce bias and hide useful information regarding the behavior of the individual industries. The CDS index spreads of different industries may behave in a heterogeneous way in response to changes in economic and financial conditions, depending on the type of business, the cyclical or countercyclical nature and perceived risk of the industry, the structure of balance sheets of firms within the industry and the typical position in the CDS market of firms in the industry. The industry-level analysis is also supported by the results of Narayan (2015) and Narayan et al. (2014), which show notable heterogeneity across industries in terms the relationship between the CDS spreads and equity returns in the U.S.

To that end, the nonlinear autoregressive distributed lag (henceforth, NARDL) methodology recently introduced by Shin et al. (2014) is applied in the current study. This approach allows for modeling simultaneously the asymmetries and cointegration dynamics among the underlying variables and offers various advantages over standard cointegration techniques (e.g., Engle-Granger and Johansen).[4] Industry-level CDS indices, by their very nature, are less affected by firm-specific variables than individual firms' CDSs, and hence more influenced by macroeconomic and financial factors. Therefore, they constitute a very useful instrument for participants in the CDS market which they can use to implement better trading and hedging strategies at the industry level and to exploit possible arbitrage opportunities across industries. The industry CDS indices are also more suitable for investors who use the top-down investing approach. Additionally, it is

[3] A number of authors, such as Cao et al. (2010), Cremers et al. (2008) and Di Cesare and Guazzaroti (2010), argue that implied volatilities extracted from options are superior to historical volatilities and should be used as the proxy for the volatility in the Merton model since the former are forward-looking measures.

[4] To honor the space limitation of the Introduction, see a more detailed discussion of the main advantages of the NARDL model in Subsection 3.3.

worth highlighting that the literature is swamped by firms' CDS studies, and thus the firm-level field is well plowed.

This research contributes to the existing literature in two ways. Firstly, this study is one of the first to address the presence of asymmetric nonlinearity in the short- and long-run relationships between industry CDS spreads and a set of influential macro-finance variables using the NARDL approach. To our knowledge, only the recent paper by Lahiani et al. (2016) has employed the NARDL model within the framework of the nonlinear linkage between sector CDS index spreads and various major macroeconomic and financial indicators. However, it should be noted that there are major differences between the current paper and that of Lahiani et al. (2016) in terms of the industries and the macro-finance variables considered as well as in terms of the sample length and the data frequency. Secondly, unlike several earlier studies exclusively focused on the CDS index spreads of financial sectors (e.g., Arouri et al., 2014; Hammoudeh and Sari, 2011; Hammoudeh et al., 2013a; Lahiani et al., 2016), the current study investigates the relationship between CDS index spreads and a group of selected macro-finance variables from a broader perspective, considering a wide range of industries representative of the U.S. economy as a whole and not only the U.S. financial sectors.

Our empirical results provide evidence of significant short- and long-run asymmetric nonlinearity in the relationship between ten U.S. industry CDS index spreads and the set of influential macroeconomic and financial variables under consideration. Positive and negative changes in the industry stock prices, the VIX index, the 5-year Treasury bond rate and, to a lesser extent, the crude oil price have an asymmetric impact on the industry CDS spreads in the short-run and the long-run. Accordingly, these macro-finance variables should be regarded by the participants in the CDS market as important asymmetric determinants of the CDS index spreads of U.S. industries. It is also shown that the signs and significance of asymmetric effects are robust to the use of different data frequencies (weekly and daily), although better results when using weekly data. Therefore, the presence of asymmetry should not be ignored in future research when studying the response dynamics of industry CDS spreads to changes in economic and financial conditions in order to avoid misleading conclusions.

The remainder of the paper is organized as follows. Section 2 provides a brief review of the related literature. Section 3 presents the data description and the empirical framework used in the study. Section 4 reports and discusses the main empirical findings and Section 5 concludes.

2. Literature review

Given the pivotal role played by CDSs in the making and spreading of the global financial crisis in 2008-2009, the research in this area has grown enormously in recent years. A large strand of the literature has concerned on identifying the primary determinants of CDS spreads (e.g., Alexander and Kaeck, 2008; Annaert et al., 2013; Ericsson et al., 2009; Cremers et al., 2008; Galil et al., 2014). Most of this research is based on the structural credit risk model developed by Merton (1974). The Merton model allows one to establish an explicit link between credit spreads and a number of macroeconomic and financial variables such as stock prices, stock volatility and spot interest rates. It should be also noted that the majority of this body of work has been conducted at the firm level and carried out in a linear framework (e.g., Annaert et al., 2013; Di Cesare and Guazzaroti, 2010; Ericsson et al., 2009; Galil et al., 2014). In view of the crucial importance of oil prices in the modern economy, a few studies have also considered the crude oil price as a possible determinant of CDS spreads (Guo et al., 2011; Hammoudeh et al., 2013b; Sharma and Thuraisamy, 2013). These studies acknowledge that the oil price may significantly influence the probability of default of firms and countries, hence affecting their corresponding CDS spreads.

Additionally, there are various empirical studies investigating the interrelationships among CDS spreads and a number of economic and financial indicators at the industry level. Most of these contributions concentrate on the CDS index spreads of a few selected industries such as the financial and oil-related industries. In this regard, Hammoudeh and Sari (2011) and Hammoudeh et al. (2013a) focus on the CDS spreads of financial sectors, i.e. the banking, financial services and insurance sectors, while Hammoudeh et al. (2013b) focus on CDS spreads of oil-related sectors. The studies by Byström (2006), Narayan (2015) and Narayan et al. (2014) analyze the link between CDS index spreads and equity returns on an industry-wide basis considering a wide array of industries, but these studies still leave out the effect of some important economic and financial variables on the industry CDS spreads. Furthermore, it is worth mentioning that all of the above studies examine exclusively linear relationships without accounting for potential nonlinearity in the dynamics of industry CDS index spreads.

Nonetheless, several recent CDS studies have shown that the linear modeling is not appropriate to capture the potential nonlinearity and asymmetry in the relationship between CDS index spreads and their major determinants, especially in the wake of the onset of the global financial crisis of 2008–2009 and European sovereign crisis of 2010–2012. First, by using Markov regime-switching models, Alexander and Kaeck (2008) and Chan and Marsden (2014) have found that the determinants of European and North American CDS indices, respectively, exhibit regime specific behavior during periods of crisis and tranquil markets. Second, Arouri et al. (2014) have explored the dynamic links between CDS index spreads of three U.S. financial sectors and various macro-finance risk factors using a smooth transition error-correction model that accommodates the presence of nonlinearities in the adjustment process of the financial CDS spreads towards the long-run equilibrium. Lastly, the recent contribution of Lahiani et al. (2016) is so far the only study that has applied the NARDL approach to identify possible asymmetries in the short-run and long-run linkages between financial sub-sector CDS spreads and a group of influential macroeconomic and financial variables. Although closely related to the paper by Lahiani et al. (2016) from a methodological point of view, our study differs from Lahiani et al. (2016) in regard to the following three aspects. First, while the paper of Lahiani et al. (2016) focuses only on the CDS index spreads of the U.S. banking, financial services and insurance sectors, the present study examines a set of ten industries that are good representatives of the U.S. economy as a whole, thus providing a more complete picture of the existence of asymmetries in the dynamics of CDS spreads at the industry level. Second, our study is also different from that of Lahiani et al. (2016) in terms of the macroeconomic and financial variables employed. More precisely, Lahiani et al. (2016) use various short-term interest rates such as the federal funds rate, the 3-month Libor rate and the 3-month Treasury bill rate, as well as the VIX index and the crude oil price as exogenous variables. Instead, the current study utilizes, besides the VIX and the crude oil price, the industry stock indices, which correspond to each of the ten industry CDS spreads, and the 5-year Treasury bond yield, which is better suited to the most liquid maturity (5 years) for CDS index spreads. Third, Lahiani et al. (2016) consider monthly data, whereas weekly and daily data are used in this paper as we check the robustness of the NARDL model by considering these two different data frequencies.

3. Data and methodology

This section introduces the dataset employed in the empirical analysis, describes the macro-finance variables used as explanatory factors of industry CDS index spreads as well as the expected relationship between the industry CDS spreads and each of these variables. Finally, the main features of the NARDL framework are also presented in this section.

3.1. Data overview

The main dataset in this study consists of weekly closing values of the U.S. 5-year industry CDS index spreads, the corresponding industry stock indices, the VIX volatility index, the U.S. 5-year Treasury bond yield and the WTI crude oil price. The time period ranges from December 14, 2007 to September 25, 2015, totaling 407 weekly observations. The beginning of the sample is dictated by the availability of liquid data on industry CDS indices. The weekly data allow for reducing the problem of excessive noise associated with the much higher frequency data and reflect better the long-term trends in the data. Instead, the daily data have lower bid-ask ratios and are best suited to track short-term movements and actions of short-term traders. Taking this information into account, we first do the analysis by using the weekly data and then check the robustness of the obtained weekly results by re-estimating the model using daily data in Subsection 4.4 that focuses on robustness analysis. Following Fung et al. (2008), Hammoudeh and Sari (2011), Hammoudeh et al. (2013b) and Lahiani et al. (2016), among others, the 5-year industry CDS index spreads, which represent the most frequently traded term, are utilized in this study. These industry-wise CDS indices are equally weighted and reflect the average mid-spread calculation of the 5-year CDS of the firms within each industry. These indices are rebalanced every six months to better reflect liquidity in the CDS market. The industry breakdown follows the Industry Classification Benchmark (ICB) developed by Dow Jones and FTSE, which is the most widely used global standard for company classification. Thus, the ICB industries covered are Oil & Gas, Basic Materials, Industrials, Consumer Goods, Health Care, Consumer Services, Telecommunications, Utilities, Financials, and Technology.

3.2. Description of explanatory variables

As mentioned earlier, the potential determinants of the industry CDS index spreads considered in this study have been selected according to the structural credit risk model of Merton (1974) and a number of relevant recent empirical studies on the main factors influencing firms' CDS spreads.

There is already an extensive literature on the relationship between CDS spreads and broad measures of the stock market such as the S & P 500 index (see, for example, Di Cesare and Guazzarotti, 2010; Ericsson et al., 2009; Fung et al., 2008). Further, using the S & P 500 index is not an innovative approach and the resulting estimates typically suffer from aggregation bias and from the influence of different weights of the individual sectors in this S & P 500 index. In order to avoid these problems, it is more adequate to examine the link between the individual industry CDS index spreads and the corresponding industry stock indices than using the overall S & P 500 index for all the industries. Thus, the equity market indices of the ten industries under examination, which can be interpreted as a measure of the aggregate health of firms within each industry, are used as explanatory factors of the CDS indices of the respective industries. The linkage between CDS spreads and stock prices can be justified by two major reasons. First, the modern finance theory postulates that in an efficient stock market, share prices reflect information pertaining to the default probability of firms. A rise in the stock price of a firm generally brings about an improvement in business and financial conditions of the underlying firm, which lowers the probability of that firm to default on its debt, and consequently leads to a decline in the firm's CDS spread. Second, the connection between the CDS and stock markets is supported by the structural model of credit risk of Merton (1974). In the Merton model, equity and debt are viewed as contingent claims on the firm's asset value and both debt and equity prices are determined by firm's fundamental data such as the value of its assets, asset volatility and leverage ratio, etc. A key implication of the Merton model is that changes in stock prices and in credit spreads must be closely negatively related to ensure the absence of arbitrage opportunities. Both channels suggest an inverse relationship between equity prices and CDS spreads. A number of previous studies have found that the stock market performance has a strong explanatory power for the behavior of firms' CDS spreads (Byström, 2006; Fung et al., 2008; Galil et al., 2014; Norden and Weber, 2004).

The VIX index is the Chicago Board Options Exchange (CBOE) Volatility index which measures the implied volatility of the S & P 500 index options over the next 30 days. The VIX, also called the fear index, is typically interpreted as a measure of global risk aversion. Higher values of VIX indicate greater fear and uncertainty in the stock market, which is associated with a higher probability of default and leads to higher CDS spreads. A higher VIX also implies a greater degree of risk aversion in the stock market, which may induce a flight-to-quality from stocks in favor of the safer government bonds, with the consequent negative impact on stock prices. Hence, a positive association is predicted between the VIX and industry CDS indices. The influence of this variable on firms' CDS spreads has been examined in several prior papers such as those of Arouri et al. (2014), Chan and Marsden (2014), Galil et al. (2014) and Lahiani et al. (2016).

The U.S. 5-year Treasury constant maturity rate is used as a proxy for the spot interest rate to be consistent with the five-year maturity of the CDS contracts (see Galil et al., 2014; Greatrex, 2009; Hasan et al., 2015). From a theoretical perspective, as pointed out by Longstaff and Schwartz (1995), rising spot interest rates increase the risk-neutral drift of the process that describes firm value and thus reduce the probability of the firm value falling below the default threshold, thus leading to lower credit spreads. Moreover, the relationship between spot interest rates and CDS spreads can also be justified by the well-established predictive power of the yield curve for future real economic activity (Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1996). In this regard, low interest rates are often observed during periods of economic recession where corporate defaults tend to occur more frequently, which also supports the existence of an inverse link between spot interest rates and CDS spreads. It is worth highlighting that we have used in this study the spot interest rates as a determinant of CDS spreads rather than any variable representative of economic activity for two reasons. First, CDS markets react to high frequency information such as that contained in interest rates, while economic activity data such as real GDP growth or some economic activity index tend to be of lower frequency (e.g., monthly, quarterly or even annual). In this context, it seems reasonable to think that the participants in the CDS market base their decisions more on financial variables such as interest rates with information in real time that reflects well future economic trends than on economic activity variables which are usually available at lower frequencies and are more appropriate to describe the past economic performance. Second, spot interest rates, besides their use being directly inspired by the credit risk model of Merton (1974), represent one of the variables most commonly employed as a determinant of CDS spreads in prior empirical research (e.g., Alexander and Kaeck, 2008; Annaert et al., 2013; Galil et al., 2014; Hasan et al., 2015; Raunig, 2015). In a similar vein, Zhu (2013) has documented the presence of a significant effect of surprise changes in the federal funds target rate on credit spread changes of corporate bonds, particularly for short-term bonds. Closely related to those results, Zhu (2015) has also shown a strong predictive power of a common global factor, which is constructed as a linear combination of international forward rates for international bond risk premiums.

The West Texas Intermediate (WTI) oil spot price is employed as a proxy for crude oil prices. It is widely accepted that oil prices can be a major source of instability in the world economy since they play a crucial role in determining activity in many economic sectors. In this sense, it has been well documented that oil price shocks have an important impact on industrial activity, stock market performance and economic growth, even though the effects differ considerably across countries and industries (e.g., Arouri et al., 2011; Gogineni, 2010;

Table 1
Statistical properties of the variables under study.

	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J-B stats
Panel A: Industry CDS spreads							
Oil & Gas	146.31	399.01	54.654	66.866	1.6737	5.7526	1591.7***
Basic Materials	290.07	1417.5	80.853	150.33	2.3957	12.495	9586.8***
Industrials	169.99	843.78	53.462	121.20	3.0470	14.115	13,618.4***
Consumer Goods	143.62	345.10	76.502	46.923	1.0516	4.7256	627.282***
Health Care	324.22	867.36	156.95	136.57	1.4135	5.0472	1032.5***
Consumer Services	290.22	1194.5	132.77	167.68	2.6365	10.765	7467.0***
Telecom	227.79	621.30	107.09	102.01	1.4216	5.1801	1087.8***
Utilities	227.84	828.70	52.864	147.63	1.1072	4.8238	697.47***
Financials	347.20	1099.7	144.66	168.19	1.4988	5.3468	1228.3***
Technology	180.80	722.38	53.043	102.65	2.8222	12.263	9972.0***
Panel B: Industry stock indices							
Oil & Gas	1983.5	2797.7	1116.0	367.73	-0.1386	2.3315	44.388***
Basic Materials	236.65	326.60	108.33	49.811	-0.2478	2.5197	40.364***
Industrials	332.80	498.14	132.83	90.040	0.2011	2.1117	80.581***
Consumer Goods	351.55	520.94	199.80	85.640	0.4178	1.9228	157.52***
Health Care	484.10	892.26	252.84	173.85	0.9199	2.5327	305.37***
Consumer Services	355.25	636.24	125.72	137.13	0.4368	1.9528	157.62***
Telecom	514.50	659.54	323.12	86.802	-0.2120	1.6716	164.79***
Utilities	181.81	251.40	113.81	28.371	0.1130	2.1563	64.656***
Financials	369.47	642.49	130.32	101.93	0.3299	2.2540	84.071***
Technology	455.08	731.61	198.51	133.60	0.4200	2.3381	96.920***
Panel C: Other variables							
VIX	21.852	80.860	10.320	10.399	2.1360	8.6466	4248.8***
SPOT interest rate	1.7083	3.7300	0.5600	0.7129	0.4939	2.6711	91.844***
WTI oil	85.127	144.96	33.170	21.093	-0.3249	2.8842	7.3922**

Note: This table reports the main descriptive statistics, including the mean, maximum, minimum, standard deviation, skewness, kurtosis and Jarque-Bera test statistics of the variables under consideration over the whole sample period from December 14, 2007 to September 25, 2015. The asterisks *** and ** indicate a rejection of the null hypothesis of normality at the 1% and 5% levels of significance, respectively.

Hamilton, 1983). For example, positive oil price shocks lead generally to an economic slowdown in net oil- importing countries and have differential impacts on market participants, while the effect on economic growth tends to be beneficial for net oil-exporting countries. Similarly, crude oil prices may significantly influence industry CDS index spreads, although the sign of the link is likely to depend on the specific industry. Thus, a negative association is expected between the WTI oil price and the CDS spread of the Oil & Gas industry because profits of firms in this industry are directly related to the level of oil prices. Therefore, rising oil prices improve the financial health of Oil & Gas companies, leading to a narrowing of their CDS spreads. In contrast, a positive linkage is predicted between oil prices and CDS index spreads of oil-intensive and most cyclical (non-oil) industries. In this case, higher crude oil prices increase production costs, undermine business and consumer confidence and reduce economic growth, which is reflected in higher CDS spreads. In addition, a non-significant relationship seems the most likely outcome for defensive industries with low sensitivity to oil prices such as the regulated natural monopolies of Utilities and Telecommunications industries. The effect of crude oil prices on CDS spreads has been investigated in several previous studies (see Arouri et al., 2014; Guo et al., 2011; Hammoudeh et al., 2013b; Lahiani et al., 2016).

All variables are expressed in logarithmic form to ensure better distributional properties of the data. As indicated above, the data are weekly and have been sourced from Thomson Reuters DataStream. Table 1 summarizes the descriptive statistics of the ten U.S. industry CDS spreads and their corresponding stock industry indices, the VIX index, the 5-year Treasury yield and the WTI oil price. As expected, the highest average weekly CDS spread and volatility are found for the financial industry, reflecting the tremendous impact of the recent global financial crisis on the financial sector. The great majority of variables are positively skewed, indicating that the corresponding distributions are non-symmetric. Furthermore, the kurtosis exceeds the reference value of the normal distribution (which is equal to 3) for all series, suggesting that the underlying data are leptokurtic (more peaked around the mean and with fatter tails than the Gaussian distribution). This departure from normality is supported by the Jarque-Bera test statistic, which strongly rejects the null hypothesis of normality in all cases.

3.3. Empirical methodology

The NARDL approach, recently developed by Shin et al. (2014), is used in this study to investigate the presence of asymmetric effects in the short- and long-run relationships among the U.S. industry CDS index spreads, the industry stock indices, the stock market volatility, the 5-year Treasury bond yield and the WTI crude oil price. The NARDL model is an asymmetric expansion of the linear autoregressive distributed lag (ARDL) cointegration model of Pesaran et al. (2001). In essence, the NARDL approach consists of a dynamic error-correction representation that allows for capturing asymmetries both in the short- and long-run. This framework enables to jointly model cointegration and asymmetric nonlinearity in a single equation and performs better in small samples than other conventional cointegration techniques (Romilly et al., 2001). Another advantage of the NARDL model is its greater flexibility as this method yields valid results regardless of whether the involved variables are I(0), I(1) or a combination of both (Nusair, 2016). Additionally, the NARDL framework enables testing for hidden cointegration, so that it avoids omitting any relationships which are not visible in a conventional linear setting.[5] Thus, the NARDL modeling approach makes it possible to distinguish between linear cointegration, nonlinear (asymmetric) cointegration and lack of cointegration.

[5] The concept of hidden cointegration was introduced by Granger and Yoon (2002). Hidden cointegration is detected if two time series are not cointegrated in the conventional sense, but there is cointegration between the positive and negative components of these series.

As mentioned above, the NARDL approach relaxes the usual assumption in the cointegration analysis that all variables must be integrated of the same order. However, it is necessary to check the unit root properties of the data series as the NARDL method is not valid in the presence of I(2) variables. The standard Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests have been extensively used in economic applications to determine the order of integration of the variables, but they lack power in the presence of structural breaks in the series. In particular, as pointed out by Perron (1989), ignoring structural breaks can lead to false acceptance of the unit root null hypothesis. In order to account for this possibility and to ensure the robustness of the results, the ADF-type unit root test that allows for two structural breaks in both the level and slope of the series proposed by Narayan and Popp (2010) is conducted in this study. One of the main advantages of the Narayan and Popp (2010) unit root test is that it does not require a priori knowledge about the timing of possible structural breaks because the break dates are endogenously determined within the model. Another distinctive feature of this test is that breaks are allowed under both the null and alternative hypotheses. Two different specifications are considered by Narayan and Popp (2010) to test the order of integration of a series. The first specification allows for two breaks in the level and is denoted as Model 1 or M1, and the second one allows for two breaks in both the level and trend of the deterministic component and is denoted as Model 2 or M2. Based on Monte Carlo simulations, Narayan and Popp (2013) have shown that the Narayan and Popp (2010) unit root test has better size and power properties and identifies the breaks more accurately than its main two-break unit roots rivals, namely the Lumsdaine and Papell (1997) and the Lee and Strazicich (2003) tests. Since the Narayan and Popp (2010) unit root test has already been widely employed in the economic and financial literature, we do not reproduce the details of this test.[6]

Given that the NARDL approach is an asymmetric extension of the ARDL model, it is interesting to start by initially presenting the linear ARDL model. The general form of the unrestricted error-correction model in the ARDL approach is given by:

$$\Delta y_t = \mu + \rho y_{t-1} + \theta x_{t-1} + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-j} + \sum_{j=0}^{q-1} \pi_j \Delta x_{t-j} + \varepsilon_t \tag{1}$$

where Δ is the first difference operator, y_t is the dependent variable,μ denotes an intercept, x_t is a *k x 1* vector of regressors, ρ and θ represent the long-run coefficients, α_j and π_j are the short-run coefficients, p and q are the respective lag orders for the dependent and explanatory variables and ε_t is the error term. The ARDL procedure involves testing the null hypothesis of no cointegration ($\rho = \theta = 0$) against the alternative of linear cointegration ($\rho \neq \theta \neq 0$). To test this hypothesis, Pesaran et al. (2001) propose a non-standard F-test, denoted by F_{PSS}, that takes into account the stationarity properties of the variables. Specifically, they compute bounds for the critical values at any significance level. The lower bound assumes that all variables are I(0), whereas the upper bound assumes that all variables are I(1). If the test statistic is above the upper bound critical value, the null hypothesis of no cointegration is rejected. Instead, if the test statistic is below the lower bound, then this null hypothesis is not rejected, indicating the lack of cointegration. Lastly, the inference remains inconclusive if the test statistic falls within the upper and lower bounds and other cointegration tests such as the Johansen test must be used. The main assumption of the ARDL approach is that all exogenous variables have symmetric effects on the dependent variable.

Following Shin et al. (2014), the NARDL model is built around the following asymmetric long-run equilibrium relationship: [7]

$$y_t = \beta^+ x_t^+ + \beta^- x_t^- + u_t \tag{2}$$

where u_t is a stationary zero-mean error process that represents deviations from the long-run equilibrium, $\beta^+$and β^- are the associated asymmetric long-run parameters and x_t is $_t$he vector of regressors decomposed as:

$$x_t = x_0 + x_t^+ + x_t^- \tag{3}$$

where x_0 is an arbitrary initial value and x_t^+ and x_t^- denote partial sum processes which accumulate positive and negative changes in x_t, respectively, and are defined as follows:

$$x_t^+ = \sum_{j=1}^{t} \Delta x_j^+ = \sum_{j=1}^{t} \max(\Delta x_j, 0) \tag{4}$$

$$x_t^- = \sum_{j=1}^{t} \Delta x_j^- = \sum_{j=1}^{t} \min(\Delta x_j, 0) \tag{5}$$

By combining Eq. (2) with the linear ARDL(p,q) specification in Eq. (1), the following asymmetric error correction model can be obtained:

$$\Delta y_t = \mu + \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{j-t}^-) + \varepsilon_t \tag{6}$$

where all variables are as defined above, $\theta^+ = -\rho\beta^+$ and $\theta^- = -\rho\beta^-$, and the short-run adjustments to positive and negative changes in the explanatory variables x_t are captured by π_j^+ and π_j^- , respectively.

The empirical implementation of the NARDL method entails the same steps as in the linear ARDL model. In the first step, the error-correction model in Eq. (6) is estimated by standard OLS. The second step involves testing for the presence of an asymmetric long-run relationship among the levels of the variables using a bounds testing approach. This can be done using either of the following two statistics (Shin et al., 2014). The first is the F-statistic, introduced by Pesaran et al. (2001) and denoted by F_{PSS}, which tests the null hypothesis of no cointegration ($\rho = \theta^+ = \theta^- = 0$) against the alternative of cointegration ($\rho \neq \theta^+ \neq \theta^- \neq 0$). The second one is the t-statistic, proposed by Banerjee et al. (1998) and denoted by t_{BDM}, which is suitable for testing the null hypothesis of no cointegration against the alternative of cointegration. Since these two statistics have non-standard distributions that depend on the order of integration of the underlying variables, the pragmatic bounds-testing procedure advanced by Pesaran et al. (2001) is also utilized in the NARDL approach. The third step consists of testing for long-run symmetry ($\theta^+ = \theta^-$) and short-run asymmetry ($\sum_{i=0}^{q-1} \pi_{k,i}^+ = \sum_{i=0}^{q-1} \pi_{k,i}^-$) by means of the standard Wald tests. [8] In the fourth step, the asymmetric cumulative dynamic multiplier effect on $y_t$of a unit change in x_t^+ and x_t^- can be derived, respectively, as follows:

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^+},\ m_h^- = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^-},\ h=0,\ 1,\ 2,\ \ldots\ldots \tag{7}$$

Note that as $h \to \infty$, then $m_h^+ \to \beta^+$and $m_h^- \to \beta^-$, where β^+ and β^- are calculated as $\beta^+ = -\theta^+/\rho$ and $\beta^- = -\theta^-/\rho$, respectively. As argued by Fousekis et al. (2016), depicting and analyzing the paths of adjustment and the duration of the disequilibrium following a positive or a negative shock affecting the system provides useful information on the long-run and short-run patterns of asymmetry.

The NARDL model to be estimated in the framework of our study takes the following form:

[6] For a detailed description of the methodology of the Narayan and Popp unit root test, see for example Narayan and Popp (2010 and 2013).

[7] See Shin et al. (2014) for a more detailed derivation of the NARDL model.

[8] In line with previous relevant studies employing the NARDL model (e.g., Jammazi et al., 2015; Katrakilidis and Trachanas, 2012; Nusair, 2016), the less restrictive case of short-run asymmetry, i.e. $\sum_{i=0}^{q-1} \pi_{k,i}^+ = \sum_{i=0}^{q-1} \pi_{k,i}^-$, is considered in this study.

Table 2
Results of the Narayan and Popp (2010) unit root test with two structural breaks (Model M1).

	Level				First Differenced			
	Test Statistics	TB1	TB2	k	Test Statistics	TB1	TB2	k
Panel A: Industry CDS spreads								
Oil & Gas	-3.362	3/23/2012	6/1/2012	10	-23.130***	8/19/2011	3/23/2012	0
Basic Materials	-2.561	4/30/2010	9/23/2011	4	-5.264***	4/30/2010	9/23/2011	9
Industrials	-1.942	12/14/2012	5/3/2013	10	-5.815***	12/14/2012	5/3/2013	12
Consumer Goods	-3.065	5/14/2010	3/29/2013	11	-19.860***	5/14/2010	12/28/2012	0
Health Care	-2.717	4/30/2010	7/29/2011	1	-7.043***	4/30/2010	7/29/2011	9
Consumer Services	-2.800	4/30/2010	9/23/2011	12	-5.983***	4/30/2010	9/23/2011	11
Telecom	-2.492	9/10/2010	7/29/2011	0	-7.649***	9/10/2010	7/29/2011	9
Utilities	-2.979	7/5/2013	11/1/2013	2	-20.820***	7/5/2013	11/1/2013	1
Financials	-2.962	4/26/2013	9/13/2013	3	-11.270***	4/26/2013	9/13/2013	2
Technology	-2.691	9/10/2010	3/25/2011	7	-8.621***	9/10/2010	3/25/2011	6
Panel B: Industry stock indices								
Oil & Gas	-1.984	7/29/2011	9/16/2011	8	-6.048***	7/29/2011	9/23/2011	7
Basic Materials	-3.025	7/29/2011	9/16/2011	6	-7.164***	7/29/2011	9/16/2011	5
Industrials	-3.130	7/29/2011	9/16/2011	0	-7.665***	7/10/2009	7/29/2011	7
Consumer Goods	-2.110	7/10/2009	9/16/2011	10	-7.410***	7/10/2009	5/10/2013	9
Health Care	-2.416	7/17/2009	7/29/2011	1	-22.910***	7/17/2009	7/29/2011	0
Consumer Services	-3.403	4/30/2010	7/29/2011	5	-12.350***	4/30/2010	7/29/2011	2
Telecom	-2.158	7/17/2009	11/25/2011	12	-8.809***	7/17/2009	11/25/2011	11
Utilities	-2.789	7/17/2009	7/2/2010	0	-11.510***	7/17/2009	7/2/2010	3
Financials	-2.889	7/29/2011	9/9/2011	12	-5.758***	7/29/2011	11/25/2011	12
Technology	-3.003	7/10/2009	8/12/2011	0	-21.370***	7/10/2009	4/30/2010	0
Panel C: Other variables								
VIX	-3.565	4/30/2010	12/28/2012	8	-25.790***	1/8/2010	4/30/2010	0
SPOT interest rate	-4.066*	8/5/2011	6/14/2013	0	-9.179***	8/5/2011	6/14/2013	6
WTI Oil	-3.755	7/3/2009	4/29/2011	9	-4.562***	4/30/2010	4/29/2011	8

Note: This table displays the results of the Narayan-Popp unit root test for the model M1 as explained in Narayan and Popp (2010). The model M1 assumes two structural breaks at unknown dates in the level of each series. The test statistics for the null hypothesis of a unit root are presented for both the series in the level and in the first difference. The critical values for the model M1 are -4.67, -4.08 and -3.77 at the 1%, 5% and 10% significance levels, respectively. These critical values have been collected from Narayan and Popp (2010) based on 50,000 replications for a sample size of 500 observations. TB1 and TB2 are the dates of the structural breaks selected according to the sequential procedure discussed in Narayan and Popp (2010) and k stands for the optimal lag length obtained by using the procedure suggested by Hall (1994) and Narayan and Popp (2010). Following Narayan and Popp (2010), a trimming percentage of 20 is used, that is, the breaks are only searched in the interval [0.2T, 0.8T]. As usual, the asterisks *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

$$\begin{aligned}\Delta CDS_{k,t} = {} & \mu + \rho CDS_{k,t-1} + \theta_1^+ STOCK_{k,t-1}^+ + \theta_1^- STOCK_{k,t-1}^- + \theta_2^+ VIX_{t-1}^+ \\ & + \theta_2^- VIX_{t-1}^- + \theta_3^+ SPOT_{t-1}^+ + \theta_3^- SPOT_{t-1}^- + \theta_4^+ WTI_{t-1}^+ + \theta_4^- WTI_{t-1}^- \\ & + \sum_{i=1}^{p-1} \alpha_i \Delta CDS_{k,t-i} + \sum_{i=0}^{q} \pi_{1,i}^+ \Delta STOCK_{t-1}^+ + \sum_{i=0}^{q} \pi_{1,i}^- \Delta STOCK_{t-1}^- \\ & + \sum_{i=0}^{q} \pi_{2,i}^+ \Delta VIX_{t-1}^+ + \sum_{i=0}^{q} \pi_{2,i}^- \Delta VIX_{t-1}^- + \sum_{i=0}^{q} \pi_{3,i}^+ \Delta SPOT_{t-1}^+ \\ & + \sum_{i=0}^{q} \pi_{3,i}^- \Delta SPOT_{t-1}^- + \sum_{i=0}^{q} \pi_{4,i}^+ \Delta WTI_{t-1}^+ + \sum_{i=0}^{q} \pi_{4,i}^- \Delta WTI_{t-1}^- + \varepsilon_t \end{aligned} \tag{8}$$

where $CDS_{k,t}$ stands for the CDS index spread of the kth industry in period t, $STOCK_{k,t}$ is the stock index of the kth industry in period t, VIX_t is the VIX index in period t, $SPOT_t$ represents the 5-year Treasury bond yield in period t and WTI_t denotes the WTI oil price in period t and ε_t refers to the error term. In turn, $STOCK^+$, $STOCK^-$,VIX^+, VIX^-, $SPOT^+$, $SPOT^-$, WTI^+ and WTI^- are the partial sums of positive and negative changes in each of the explanatory variables, respectively.

4. Empirical results

4.1. Unit root and cointegration tests

As indicated earlier, since the low power of the standard unit root tests arises when there are structural breaks in the data series, the unit root test proposed by Narayan and Popp (2010) that allows for two structural breaks at an unknown location in the deterministic components of the series is used in this study to verify the order of integration of each series. Tables 2 and 3 report the results of the Narayan and Popp (2010) unit root test with two structural breaks.[9] Specifically, Table 2 refers to the model allowing two structural breaks only in the level (M1), while Table 3 presents the results for the model with two breaks both in the level and trend of the series (M2). Panels A and B refer to the industry CDS index spreads and the industry stock indices, respectively, while Panel C presents the results for the other variables.

The results of the Narayan and Popp (2010) test reveal that the vast majority of the variables are non-stationary in the level, but stationary in the first difference, irrespective of whether one allows for breaks in the intercept only or breaks in the intercept and trend of each series. In particular, all the time series are I(1) at the usual significance levels, excepting the 5-year interest rate at the 10% level in the model M1 and the Consumer Services and Utilities stock indices at the 5% level in the model M2, which are I(0), i.e. stationary in the level. Therefore, on the basis of the Narayan and Popp (2010) test, it can be stated that the presence of structural breaks is not the key driving factor behind the unit root behavior of the series under examination.[10] In any case, the most important conclusion of the application of the Narayan and Popp

[9] The authors wish to thank Paresh Narayan for kindly providing us his GAUSS code for the calculation of the Narayan and Popp (2010) unit root test with two structural breaks.

[10] The results of the conventional ADF and PP unit root tests in this study fully confirm the evidence of the Narayan and Popp (2010) unit root test but do not provide the dates of structural breaks. For comparison, the unit root test allowing for a single structural break in the intercept and the slope of the trend of the series at an unknown date developed by Perron (1997) is also performed. Its findings are also consistent with those of the Narayan and Popp (2010) test. The results of these tests are omitted here due to the lack of space. However, they are available from the authors upon request.

Table 3
Results of the Narayan and Popp (2010) unit root test with two structural breaks (Model M2).

	Level				1st Diff.			
	Test Statistics	TB1	TB2	*k*	Test Statistics	TB1	TB2	*k*
Panel A: Industry CDS spreads								
Oil & Gas	-3.198	6/1/2012	7/6/2012	10	-22.160***	8/19/2011	9/23/2011	0
Basic Materials	-1.609	4/30/2010	9/23/2011	2	-5.430***	4/30/2010	9/23/2011	9
Industrials	-2.398	12/14/2012	5/3/2013	10	-5.377***	12/14/2012	5/3/2013	12
Consumer Goods	-3.002	5/14/2010	12/28/2012	0	-7.727***	5/14/2010	12/28/2012	9
Health Care	-2.555	4/30/2010	7/29/2011	1	-6.721***	7/15/2011	7/29/2011	9
Consumer Services	-2.153	4/30/2010	9/23/2011	12	-6.509***	4/30/2010	9/23/2011	11
Telecom	-2.455	9/10/2010	7/29/2011	0	-8.235***	9/10/2010	7/29/2011	7
Utilities	-0.875	7/5/2013	11/1/2013	0	-16.010***	7/5/2013	11/1/2013	8
Financials	-3.030	4/26/2013	9/13/2013	3	-25.680***	4/26/2013	9/13/2013	0
Technology	-2.600	9/10/2010	3/25/2011	7	-8.570***	9/10/2010	3/25/2011	6
Panel B: Industry stock indices								
Oil & Gas	-1.510	7/29/2011	9/16/2011	8	-6.390***	4/30/2010	7/29/2011	7
Basic Materials	-3.768	7/10/2009	9/16/2011	6	-7.438***	7/29/2011	9/16/2011	5
Industrials	-4.276	7/10/2009	7/29/2011	5	-7.503***	4/30/2010	7/29/2011	9
Consumer Goods	-5.048	7/10/2009	9/16/2011	8	-7.568***	7/10/2009	7/2/2010	9
Health Care	-3.516	7/17/2009	7/29/2011	1	-6.983***	7/29/2011	9/16/2011	9
Consumer Services	-4.942**	7/10/2009	7/29/2011	5	-8.434***	4/30/2010	7/29/2011	9
Telecom	-1.683	7/17/2009	7/29/2011	12	-8.879***	7/17/2009	11/25/2011	11
Utilities	-4.791**	7/17/2009	7/2/2010	0	-11.520***	7/17/2009	7/2/2010	3
Financials	-3.648	7/10/2009	7/29/2011	12	-5.963***	7/29/2011	9/16/2011	12
Technology	-3.439	7/10/2009	8/12/2011	0	-21.370***	7/10/2009	4/30/2010	0
Panel C: Other variables								
VIX	-4.183	4/30/2010	12/28/2012	1	-25.760***	1/1/2010	4/30/2010	0
SPOT interest rate	-4.293	8/5/2011	6/14/2013	0	-9.289***	8/5/2011	6/14/2013	6
WTI Oil	-3.793	1/1/2010	4/29/2011	9	-4.775***	4/30/2010	4/29/2011	8

Note: This table displays the results of the Narayan-Popp unit root test for the model M2 explained in Narayan and Popp (2010). The model M2 assumes two structural breaks at unknown dates in the level as well as the slope of each series. The test statistics for the null hypothesis of a unit root are presented for both the series in the level and in the first difference. The critical values for the model M2 are -5.29, -4.69 and -4.40 at the 1%, 5% and 10% significance levels, respectively. These critical values have been collected from Narayan and Popp (2010) based on 50,000 replications for a sample size of 500 observations. TB1 and TB2 are the dates of the structural breaks selected according to the sequential procedure discussed in Narayan and Popp (2010) and *k* stands for the optimal lag length obtained by using the procedure suggested by Hall (1994) and Narayan and Popp (2010). Following Narayan and Popp (2010), a trimming percentage of 20 is used, that is, the breaks are only searched in the interval [0.2T, 0.8T]. As usual, the asterisks *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 4
Bounds test for cointegration in the ARDL and NARDL models at the industry level.

Industry	**Linear ARDL Model**		**NARDL Model**	
	$FPSS_{Linear}$	**Lag order**	**$FPSS_{Nonlinear}$**	t_{BDM}
Oil & Gas	8.5750***	(1, 2, 0, 0, 0)	6.4464***	-5.8905***
Basic Materials	1.0125	(4, 3, 1, 0, 0)	4.3938**	-4.6632***
Industrials	3.6122	(1, 0, 0, 2, 4)	5.7211***	-4.3720**
Consumer Goods	4.5782	(2, 3, 4, 4, 3)	6.8106***	-6.5581***
Health Care	8.522***	(2, 2, 3, 1, 4)	9.1764***	-6.9923***
Consumer Services	3.4749	(2, 2, 1, 0, 2)	11.653***	-8.8895***
Telecom	3.9660	(1, 2, 1, 2, 0)	6.1550***	-5.8158***
Utilities	3.0529	(3, 0, 3, 0, 1)	4.6207***	-5.8821***
Financials	5.8898***	(4, 2, 3, 0, 0)	7.4159***	-5.8316***
Technology	6.4124***	(1, 2, 0, 0, 1)	4.0091**	-4.0630**

Note: This table reports the results of the bounds testing procedure for cointegration in the linear ARDL and NARDL models using weekly data. The lag order of the ARDL model is displayed in parentheses, while the exact specification and results of the NARDL model is presented analytically in Table 6. $FPSS_{Linear}$ is the *F*-statistic proposed by Pesaran et al. (2001) for testing the null hypothesis of no cointegration in the ARDL specification. In turn, $FPSS_{Nonlinear}$ and t_{BDM} denote the *F*-statistic and *t*-statistic proposed by Pesaran et al. (2001) and Banerjee et al. (1998), respectively, for testing the null of no cointegration in the NARDL model. The critical values for these statistics have been obtained from Pesaran et al. (2001). ** and *** denote rejection of the null hypothesis of cointegration at the 5% and 1% levels, respectively.

(2010) unit root test in the present study is that none of the variables is found to be I(2), which means that the necessary condition for the use of the NARDL approach is fulfilled. Furthermore, the presence of structural breaks in the time series data gives an early indication of a time series asymmetric behavior over time, and hence the possibility of asymmetric short- and long-run relationships between the variables.

Table 4 displays the results of the bounds testing procedure for cointegration between the industry CDS index spreads and the group of influential macroeconomic and financial indicators considered. As a benchmark, the analysis of cointegration using the linear ARDL model is first carried out. The F_{PSS} statistics for the ARDL approach reveal that the null hypothesis of no cointegration can be rejected at the usual levels in favor of linear cointegration only in less than half of the industries. This result implies that there are no long-run linear (symmetric) relationships between CDS spreads and the set of macro-finance variables for most industries. However, it may occur that a linear specification is not the most appropriate functional form because the linkage between the industry CDS index spreads and the economic and financial variables has a more complex nature, such as an asymmetric nonlinearity. In this respect, the F_{PSS} and t_{BDM} statistics for the NARDL model exceed the upper bound critical value at the conventional significance levels in all cases, indicating the existence of asymmetric long-run relationships for all industries. In line with the recommendation of Shin et al. (2014), we have adopted a conservative approach to the choice of critical values in theF_{PSS} and t_{BDM} statistics by taking a maximum of four lags on each first-differenced variable in testing the null hypothesis of no cointegration.

Having established the evidence of asymmetric cointegration for all industries, we proceed to test for asymmetry in both the long-run and the short-run relationships. Table 5 reports the Wald statistics for the tests of long- and short-run asymmetry between the U.S. industry CDS index spreads and our set of macro-finance variables in the framework of the NARDL model. The results indicate that the null hypotheses of

Table 5
Wald tests for long-run and short-run asymmetry at the industry level (weekly data).

Industry	Long-run asymmetry W_{LR}(STOCK)	W_{LR}(VIX)	W_{LR}(SPOT)	W_{LR}(WTI)	Short-run asymmetry W_{SR}(STOCK)	W_{SR}(VIX)	W_{SR}(SPOT)	W_{SR}(WTI)
Oil & Gas	0.807 [0.369]	0.020 [0.885]	0.230 [0.631]	1.319 [0.2515]	11.386*** [0.000]	0.582 [0.445]	21.392*** [0.000]	9.190*** [0.002]
Basic Materials	0.308 [0.579]	5.832** [0.016]	0.319 [0.572]	0.207 [0.648]	0.725 [0.395]	3.544* [0.060]	3.138* [0.077]	8.060*** [0.004]
Industrials	2.211** [0.090]	0.281 [0.169]	4.641** [0.031]	3.422* [0.065]	3.323** [0.028]	7.823*** [0.009]	2.837** [0.038]	9.726*** [0.007]
Consumer Goods	0.286 [0.579]	4.300** [0.016]	1.679 [0.192]	0.331 [0.565]	31.352***[0.000]	0.072 [0.788]	9.454*** [0.002]	10.090*** [0.000]
Health Care	11.570*** [0.000]	1.646 [0.200]	0.718 [0.397]	11.611*** [0.000]	9.182*** [0.002]	9.231*** [0.002]	28.390*** [0.000]	25.420*** [0.000]
Consumer Services	1.229 [0.268]	10.261*** [0.001]	7.040*** [0.008]	0.331 [0.565]	1.660 [0.198]	12.737*** [0.000]	1.538 [0.215]	9.256*** [0.002]
Telecom	0.860 [0.354]	8.260*** [0.004]	0.414 [0.520]	3.512* [0.061]	20.040*** [0.000]	12.641*** [0.000]	4.502** [0.034]	26.912*** [0.000]
Utilities	5.425** [0.033]	3.857* [0.073]	1.066 [0.302]	0.075 [0.784]	15.111*** [0.000]	17.870*** [0.000]	3.487* [0.062]	5.265** [0.022]
Financials	0.066 [0.796]	3.626* [0.083]	0.992 [0.319]	2.988* [0.090]	4.697** [0.019]	0.736 [0.391]	0.971 [0.324]	2.901* [0.089]
Technology	0.029 [0.8648]	4.309** [0.0386]	6.370** [0.012]	0.028 [0.865]	9.183*** [0.002]	2.465 [0.116]	5.138** [0.047]	18.127*** [0.000]

Note: This table reports the Wald statistics of the long- and short-run symmetry tests for the effect of each explanatory variable (the industry stock indices, the VIX, the 5-year Treasury bond yield and the WTI oil price) on each industry CDS spread using weekly data. W_{LR} denotes the Wald statistic for the long-run symmetry, which tests the null hypothesis of $\theta^+ = \theta^-$ for each explanatory variable in Eq. (8). W_{SR} corresponds to the Wald statistic for the short-run asymmetry, which tests the null hypothesis that $\sum_{i=0}^{q-1} \pi_{k,i}^+ = \sum_{i=0}^{q-1} \pi_{k,i}^-$ for each explanatory variable in Eq. (8). The numbers in brackets are the associated *p*-values. *, ** and *** indicate a rejection of the null hypothesis of symmetry at the 10%, 5% and 1% levels, respectively.

long-run symmetry and, mainly, of short-run symmetry can be rejected at the usual levels in a large number or cases for each of the industries. Therefore, it can be stated that in general positive and negative changes in the macroeconomic and financial risk factors under consideration have a differential impact on industry CDS spreads. These asymmetries may be related to the fact that financial markets are complex adaptive systems dominated by incessantly interacting heterogeneous agents with different preferences, investment objectives, time horizons, tolerance of risk and bounded rationality. For example, the participants in the CDS market, which include investors, speculators, arbitrageurs and policy makers, differ in terms of expectations, risk tolerance and trading strategies, in addition to having different information and cognitive abilities during up down markets as well as a diverse availability of time for decision making. In this way, each of these agents may become particularly active at different market and economic conditions, thus leading to asymmetric responses of CDS spreads to changes of different sign in their key explanatory variables. For instance, speculators and policy makers take more aggressive actions during major credit events, while investors show increased interest in holding CDSs during normal times and arbitrageurs try to seize opportunities when they become available.

Overall, the empirical evidence supports the view that a NARDL model allowing for both long- and short-run asymmetries is best-suited to describe the dynamic interactions between the U.S. industry CDS indices and the set of explanatory macro-finance variables under examination than a linear symmetric specification. Accordingly, neglecting the asymmetry in modeling the relationship between the industry CDS index spreads and their driving factors leads to a model misspecification and spurious conclusions.

4.2. NARDL estimation results

Table 6 presents the results of the estimation of the NARDL model as in Eq. (8) for the ten U.S. industries under consideration. The lag order of the NARDL specification has been determined by applying the general-to-specific criterion.[11] In particular, the preferred model is selected by starting with p=12 and q=12 and then dropping all insignificant regressors. Moreover, all the estimated NARDL models are stable as the coefficient of the lagged industry CDS index spread is negative and statistically significant in all cases. In addition, the results of the diagnostic tests are in general quite satisfactory as the null hypotheses of serial correlation and heteroskedasticity can be rejected for most industries, implying that the estimated NARDL models are overall correctly specified.

The estimated long-run coefficients associated with the industry stock prices, L_{STOCK}^+ and L_{STOCK}^-, which capture the relationship between the industry CDS index spreads and the respective industry stock indices in the long-run, are statistically significant at the usual levels for most of the industries (Basic Materials, Consumer Goods, Consumer Services, Telecommunications, Utilities and Financials). Industrials and Health Care also show partial evidence of a significant long-run effect of the industry equity prices on the respective industry CDS indices. The significant long-run coefficients are negative in all cases, implying an inverse relationship in the long-run between the industry stock prices and the industry CDS spreads. This finding is consistent with the argument that higher industry equity prices reflect the strength of current and future earnings of companies in the industry and, hence, indicate a greater capacity to meet their obligations, which results in a narrowing of industry CDS indices. This inverse linkage between the stock market performance and the CDS spreads has also been empirically supported by, among others, Ericsson et al. (2009), Galil et al. (2014), Greatrex (2009) and Hammoudeh and Sari (2011). Furthermore, the long-run effect of increases in the industry stock prices is more pronounced (in absolute value) than the effect of decreases in the industry stock prices for most industries. This asymmetric behavior reveals than in the long-run, the industry CDS index spreads are influenced mainly by rises in the industry stock prices.

The VIX index also has a significant long-run impact on the CDS index spreads of a wide range of industries (Oil & Gas, Financials, Technology, Health Care, Consumer Goods, Consumer Services and Industrials). The estimated long-run coefficients associated with positive (L_{VIX}^+) and negative (L_{VIX}^-) shocks in the VIX are positive in all cases, which implies a direct relationship between this index and the industry CDS spreads. This finding suggests that an increase in the degree of risk aversion in the U.S. equity market causes a widening of CDS spreads as investors are willing to pay a higher premium to buy protection against the higher uncertainty and fear in the stock market. Interestingly, the effect of rises in the VIX is stronger than that of decreases in the VIX for a great majority of U.S. industries, indicating that many industry CDS index spreads are particularly sensitive in the long-run to increased uncertainty about future stock prices. The greater sensitivity to positive shocks in the VIX seems reasonable, taking into account that investors seek protection primarily against higher volatility. In this regard, Cao et al. (2010) and Pan and Singleton (2008) contend that the implied volatility of the U.S. equity market explains the behavior of time series of U.S. corporate CDS spreads and sovereign CDS spreads of three emerging markets (Mexico, Turkey and Korea),

[11] As indicated by Pesaran and Shin (1999), an appropriate selection of the lag order of the NARDL(p,q) model allows for the simultaneous correction of autocorrelation and the problem of endogenous regressors.

Table 6
Estimation results of the NARDL model for the U.S. industries (weekly data).

Oil & Gas		Basic Materials		Industrials		Consumer Goods		Health Care	
Const.	0.5488***	Const.	0.3954***	Const.	0.3769***	Const.	0.7275***	Const.	0.8792***
CDS_{t-1}	-0.1374***	CDS_{t-1}	-0.0862***	CDS_{t-1}	-0.0877***	CDS_{t-1}	-0.1579***	CDS_{t-1}	-0.1764***
Stock^{+}_{t-1}	-0.1536	Stock^{+}_{t-1}	-0.1950**	SP^{+}_{t-1}	0.0285	Stock^{+}_{t-1}	-0.2604**	SP^{+}_{t-1}	0.0411
Stock^{-}_{t-1}	-0.0335	Stock^{-}_{t-1}	-0.1642***	SP^{-}_{t-1}	-0.1655*	Stock^{-}_{t-1}	-0.2027**	SP^{-}_{t-1}	-0.3482***
VIX^{+}_{t-1}	0.0788***	VIX^{+}_{t-1}	0.0428**	VIX^{+}_{t-1}	0.0679**	VIX^{+}_{t-1}	0.0396***	VIX^{+}_{t-1}	0.0731***
VIX^{-}_{t-1}	0.0770***	VIX^{-}_{t-1}	0.0167	VIX^{-}_{t-1}	0.0432	VIX^{-}_{t-1}	0.0240	VIX^{-}_{t-1}	0.0856***
SPOT^{+}_{t-1}	-0.0270	SPOT^{+}_{t-1}	-0.0152	SPOT^{+}_{t-1}	0.0123	SPOT^{+}_{t-1}	-0.0327**	SPOT^{+}_{t-1}	-0.0347**
SPOT^{-}_{t-1}	-0.0361	SPOT^{-}_{t-1}	-0.0074	SPOT^{-}_{t-1}	0.0548**	SPOT^{-}_{t-1}	-0.0178*	SPOT^{-}_{t-1}	-0.0232
WTI^{+}_{t-1}	0.1123	WTI^{+}_{t-1}	-0.0267	WTI^{+}_{t-1}	-0.0613	WTI^{+}_{t-1}	0.0584***	WTI^{+}_{t-1}	-0.0129
WTI^{-}_{t-1}	0.0329	WTI^{-}_{t-1}	-0.0122	WTI^{-}_{t-1}	0.0550*	WTI^{-}_{t-1}	0.0445**	WTI^{-}_{t-1}	0.0961***
ΔCDS_{t-1}	-0.2325***	ΔCDS_{t-5}	0.1138**	ΔCDS_{t-8}	-0.1004**	ΔCDS_{t-7}	0.0991**	ΔCDS_{t-1}	-0.1280***
ΔCDS_{t-2}	-0.0958**	ΔCDS_{t-10}	-0.0941**	$\Delta\text{Stock}^{+}_{t}$	-0.6841**	$\Delta\text{Stock}^{+}_{t-3}$	0.5665**	ΔCDS_{t-4}	-0.0716*
ΔCDS_{t-3}	-0.1189***	$\Delta\text{Stock}^{+}_{t}$	-0.6913***	$\Delta\text{Stock}^{+}_{t-8}$	-0.8378***	$\Delta\text{Stock}^{+}_{t-5}$	0.6768***	$\Delta\text{Stock}^{+}_{t-1}$	-0.5392**
$\Delta\text{Stock}^{+}_{t}$	-0.6059***	$\Delta\text{Stock}^{+}_{t-1}$	-0.5395***	$\Delta\text{Stock}^{-}_{t}$	-0.8765***	$\Delta\text{Stock}^{-}_{t-1}$	-0.5749***	$\Delta\text{Stock}^{+}_{t-3}$	0.5864**
$\Delta\text{Stock}^{+}_{t-1}$	-0.7044***	$\Delta\text{Stock}^{-}_{t-1}$	-0.7120***	$\Delta\text{Stock}^{-}_{t-1}$	-1.0586***	$\Delta\text{Stock}^{-}_{t-5}$	-0.4594**	$\Delta\text{Stock}^{+}_{t-6}$	-0.3915*
$\Delta\text{Stock}^{+}_{t-2}$	-0.6650**	$\Delta\text{Stock}^{-}_{t-4}$	-0.2639**	$\Delta\text{Stock}^{-}_{t-2}$	0.5542**	$\Delta\text{Stock}^{-}_{t-6}$	-0.3904**	$\Delta\text{Stock}^{-}_{t}$	-1.3221***
$\Delta\text{Stock}^{+}_{t-9}$	0.4311*	ΔVIX^{+}_{t}	0.1679***	$\Delta\text{Stock}^{-}_{t-3}$	-0.4894*	ΔVIX^{+}_{t}	0.0786***	$\Delta\text{Stock}^{-}_{t-3}$	-0.4737**
$\Delta\text{Stock}^{-}_{t-1}$	-0.8683***	$\Delta\text{VIX}^{+}_{t-1}$	-0.0992***	$\Delta\text{VIX}^{+}_{t-1}$	-0.1110*	$\Delta\text{VIX}^{+}_{t-1}$	0.0718***	ΔVIX^{+}_{t}	0.1210***
$\Delta\text{Stock}^{-}_{t-3}$	-1.2276***	$\Delta\text{VIX}^{+}_{t-5}$	-0.0779***	$\Delta\text{VIX}^{+}_{t-4}$	-0.0945**	ΔVIX^{-}_{t}	0.1724***	$\Delta\text{VIX}^{+}_{t-4}$	0.0774**
ΔVIX^{+}_{t}	0.2535***	$\Delta\text{VIX}^{+}_{t-7}$	-0.0640**	$\Delta\text{SPOT}^{+}_{t-1}$	-0.2832***	$\Delta\text{VIX}^{-}_{t-1}$	0.0620*	ΔVIX^{-}_{t}	0.1459***
$\Delta\text{VIX}^{+}_{t-8}$	-0.2106***	$\Delta\text{VIX}^{-}_{t-2}$	0.0647*	$\Delta\text{SPOT}^{-}_{t}$	-0.2648***	$\Delta\text{SPOT}^{+}_{t-1}$	-0.0881**	$\Delta\text{VIX}^{-}_{t-3}$	0.0882*
$\Delta\text{VIX}^{-}_{t-2}$	-0.2233***	$\Delta\text{SPOT}^{+}_{t-3}$	0.0905*	$\Delta\text{SPOT}^{-}_{t-2}$	-0.1855*	$\Delta\text{SPOT}^{+}_{t-2}$	0.0954**	$\Delta\text{SPOT}^{+}_{t-2}$	0.1241**
$\Delta\text{VIX}^{-}_{t-7}$	-0.1675***	$\Delta\text{WTI}^{-}_{t-11}$	0.2066***	$\Delta\text{SPOT}^{-}_{t-3}$	0.3543***	$\Delta\text{SPOT}^{+}_{t-8}$	0.1063**	$\Delta\text{SPOT}^{-}_{t-7}$	-0.2167***
$\Delta\text{VIX}^{-}_{t-8}$	0.1454**			$\Delta\text{WTI}^{+}_{t-2}$	0.2745*	$\Delta\text{SPOT}^{-}_{t-3}$	0.1498***	$\Delta\text{WTI}^{+}_{t-1}$	0.1813*
$\Delta\text{SPOT}^{-}_{t-3}$	0.3043***			$\Delta\text{WTI}^{+}_{t-4}$	0.6108***	$\Delta\text{SPOT}^{-}_{t-3}$	0.0910*	$\Delta\text{WTI}^{+}_{t-4}$	-0.3568***
$\Delta\text{SPOT}^{-}_{t-6}$	0.2209**			$\Delta\text{WTI}^{-}_{t-4}$	-0.2456*	$\Delta\text{WTI}^{+}_{t-4}$	0.1352*	$\Delta\text{WTI}^{-}_{t-3}$	0.1923**
$\Delta\text{WTI}^{+}_{t-1}$	0.2952*					$\Delta\text{WTI}^{-}_{t-1}$	-0.1864***	$\Delta\text{WTI}^{-}_{t-5}$	-0.2307***
$\Delta\text{WTI}^{-}_{t-2}$	-0.3865***					$\Delta\text{WTI}^{-}_{t-2}$	-0.1605***		
$\Delta\text{WTI}^{-}_{t-3}$	0.4967***					$\Delta\text{WTI}^{-}_{t-8}$	-0.1980***		
$\Delta\text{WTI}^{-}_{t-4}$	-0.2995**								
$\Delta\text{WTI}^{-}_{t-5}$	-0.3888***								
Long-run asymmetric effects									
L^{+}_{STOCK}	-1.1179	L^{+}_{STOCK}	-2.2626***	L^{+}_{STOCK}	0.3254	L^{+}_{STOCK}	-1.6488***	L^{+}_{STOCK}	0.2334
L^{-}_{STOCK}	-0.2437	L^{-}_{STOCK}	-1.9052***	L^{-}_{STOCK}	-1.8856**	L^{-}_{STOCK}	-1.2835***	L^{-}_{STOCK}	-1.9731***
L^{+}_{VIX}	0.5733***	L^{+}_{VIX}	0.4966**	L^{+}_{VIX}	0.7734**	L^{+}_{VIX}	0.2509***	L^{+}_{VIX}	0.4145***
L^{-}_{VIX}	0.5605***	L^{-}_{VIX}	0.1942	L^{-}_{VIX}	0.4922	L^{-}_{VIX}	0.1524	L^{-}_{VIX}	0.4851**
L^{+}_{SPOT}	-0.1969	L^{+}_{SPOT}	-0.1772*	L^{+}_{SPOT}	0.1409	L^{+}_{SPOT}	-0.2072***	L^{+}_{SPOT}	-0.1970**
L^{-}_{SPOT}	-0.2631	L^{-}_{SPOT}	-0.0863	L^{-}_{SPOT}	0.6250**	L^{-}_{SPOT}	-0.1128**	L^{-}_{SPOT}	-0.1314*
L^{+}_{WTI}	0.8176	L^{+}_{WTI}	-0.3098	L^{+}_{WTI}	-0.6989	L^{+}_{WTI}	0.3697***	L^{+}_{WTI}	-0.0734
L^{-}_{WTI}	0.2395	L^{-}_{WTI}	-0.1419	L^{-}_{WTI}	0.6270*	L^{-}_{WTI}	0.2821**	L^{-}_{WTI}	0.5450***
Statistics and diagnostics									
Adj. R^2	0.4405	Adj. R^2	0.3747	Adj. R^2	0.3094	Adj. R^2	0.3600	Adj. R^2	0.4694
χ^2_{SC}	0.453 [0.900]	χ^2_{SC}	1.553 [0.193]	χ^2_{SC}	0.163 [0.834]	χ^2_{SC}	0.587 [0.527]	χ^2_{SC}	2.295 [0.082]
χ^2_{H}	1.867 [0.072]	χ^2_{H}	3.467 [0.012]	χ^2_{H}	0.849 [0.695]	χ^2_{H}	0.914 [0.586]	χ^2_{H}	1.350 [0.104]

Consumer Services		Telecom		Utilities		Financials		Technology	
Const.	1.3775***	Const.	0.7429***	Const.	0.7443***	Const.	1.1471***	Const.	0.3815***
CDS_{t-1}	-0.2556***	CDS_{t-1}	-0.1432***	CDS_{t-1}	-0.1595***	CDS_{t-1}	-0.2017***	CDS_{t-1}	-0.0799***
Stock^{+}_{t-1}	-0.7511***	Stock^{+}_{t-1}	-0.3451***	Stock^{+}_{t-1}	-0.8106***	SP^{+}_{t-1}	-0.1793***	SP^{+}_{t-1}	0.0239
Stock^{-}_{t-1}	-0.6746***	Stock^{-}_{t-1}	-0.2754***	Stock^{-}_{t-1}	-0.4574*	SP^{-}_{t-1}	-0.1896***	SP^{-}_{t-1}	0.0402
VIX^{+}_{t-1}	0.0504***	VIX^{+}_{t-1}	0.0220	VIX^{+}_{t-1}	0.0631	VIX^{+}_{t-1}	0.1112***	VIX^{+}_{t-1}	0.0424**
VIX^{-}_{t-1}	0.0176	VIX^{-}_{t-1}	0.0013	VIX^{-}_{t-1}	0.1217*	VIX^{-}_{t-1}	0.0904***	VIX^{-}_{t-1}	0.0669***
SPOT^{+}_{t-1}	0.0200*	SPOT^{+}_{t-1}	-0.0693***	SPOT^{+}_{t-1}	-0.2186***	SPOT^{+}_{t-1}	-0.0137	SPOT^{+}_{t-1}	-0.0231**
SPOT^{-}_{t-1}	-0.0154	SPOT^{-}_{t-1}	-0.0768***	SPOT^{-}_{t-1}	-0.1766***	SPOT^{-}_{t-1}	0.0094	SPOT^{-}_{t-1}	-0.0618***
WTI^{+}_{t-1}	0.1074***	WTI^{+}_{t-1}	-0.0294*	WTI^{+}_{t-1}	-0.0260	WTI^{+}_{t-1}	-0.0520*	WTI^{+}_{t-1}	0.0138
WTI^{-}_{t-1}	0.1305***	WTI^{-}_{t-1}	0.0245	WTI^{-}_{t-1}	-0.0548	WTI^{-}_{t-1}	-0.0104	WTI^{-}_{t-1}	0.0077
ΔCDS_{t-1}	-0.2561***	$\Delta\text{Stock}^{+}_{t}$	-0.4735***	ΔCDS_{t-1}	-0.2390***	ΔCDS_{t-1}	-0.2137***	ΔCDS_{t-5}	-0.1167***
ΔCDS_{t-5}	0.1306***	$\Delta\text{Stock}^{+}_{t-1}$	-0.5579***	$\Delta\text{Stock}^{+}_{t}$	-2.4783***	ΔCDS_{t-3}	0.0950**	$\Delta\text{Stock}^{+}_{t}$	-0.7080***
ΔCDS_{t-6}	-0.0944**	$\Delta\text{Stock}^{+}_{t-2}$	-0.2709*	$\Delta\text{Stock}^{-}_{t-7}$	1.0869**	ΔCDS_{t-4}	-0.1059**	$\Delta\text{Stock}^{+}_{t-2}$	-0.9613***
ΔCDS_{t-8}	0.0968**	ΔVIX^{+}_{t}	0.1130***	$\Delta\text{VIX}^{+}_{t-1}$	0.2779**	ΔCDS_{t-5}	-0.141038	$\Delta\text{Stock}^{+}_{t-3}$	0.4419**
$\Delta\text{Stock}^{+}_{t}$	-0.8984***	$\Delta\text{VIX}^{+}_{t-1}$	0.0639**	$\Delta\text{VIX}^{+}_{t-2}$	0.1722*	$\Delta\text{Stock}^{-}_{t}$	-0.4879***	$\Delta\text{Stock}^{-}_{t-1}$	-0.4940**
	-0.8304***		0.0567**		0.1882*		0.0932*		0.6426***

(continued on next page)

Table 6 *(continued)*

$\Delta Stock^-_t$		ΔVIX^+_{t-3}		ΔVIX^+_{t-10}		ΔVIX^+_t		$\Delta Stock^-_{t-2}$	
$\Delta Stock^-_{t-2}$	0.5038**	ΔVIX^-_t	0.1138***	ΔVIX^-_{t-3}	-0.3649***	ΔVIX^+_{t-4}	0.1097**	$\Delta Stock^-_{t-3}$	-1.0118***
ΔVIX^+_{t-2}	0.0815*	$\Delta SPOT^+_t$	-0.0992**	$\Delta SPOT^+_{t-3}$	-0.5666***	ΔVIX^+_{t-6}	-0.2077***	$\Delta Stock^-_{t-4}$	-0.3942**
ΔVIX^+_{t-7}	-0.1374***	$\Delta SPOT^+_{t-2}$	0.1053**	$\Delta SPOT^+_{t-12}$	0.3541*	ΔVIX^-_t	0.1832***	$\Delta Stock^-_{t-6}$	-0.5263**
ΔVIX^-_{t-1}	0.0890*	$\Delta SPOT^+_{t-6}$	0.0893*	$\Delta SPOT^-_{t-4}$	0.4130*	ΔVIX^-_{t-1}	0.141350	ΔVIX^+_t	0.1264***
ΔVIX^-_{t-4}	-0.0837**	$\Delta SPOT^-_{t-3}$	0.1623***	ΔWTI^+_{t-1}	-0.7345**	$\Delta SPOT^+_{t-7}$	0.236368	ΔVIX^+_{t-3}	-0.1002**
ΔVIX^-_{t-6}	0.1076**	$\Delta SPOT^-_{t-9}$	0.1627***			$\Delta SPOT^-_{t-2}$	-0.2404**	ΔVIX^+_{t-8}	0.0909***
ΔVIX^-_{t-7}	0.2227***	ΔWTI^+_{t-5}	0.1730**			$\Delta SPOT^-_{t-4}$	0.2065***	ΔVIX^-_{t-3}	0.1329***
$\Delta SPOT^+_{t-1}$	-0.1352**	ΔWTI^+_{t-6}	0.2495***			$\Delta SPOT^-_{t-6}$	-0.2284***	ΔVIX^-_{t-5}	0.1826***
$\Delta SPOT^-_{t-3}$	0.1947***	ΔWTI^-_t	-0.1177**			$\Delta SPOT^-_{t-7}$	-0.2305**	$\Delta SPOT^-_{t-4}$	0.1467**
$\Delta SPOT^-_{t-7}$	-0.1763**	ΔWTI^-_{t-1}	-0.1427**					$\Delta SPOT^-_{t-5}$	0.1480**
ΔWTI^+_{t-3}	-0.3058**							ΔWTI^+_{t-4}	0.2912***
ΔWTI^-_{t-1}	-0.2956***							ΔWTI^+_{t-5}	0.3009***
ΔWTI^-_{t-3}	0.2015**							ΔWTI^+_{t-6}	0.2157**
ΔWTI^-_{t-7}	-0.2308**							ΔWTI^-_{t-1}	-0.1680*
ΔWTI^-_{t-8}	-0.2558***							ΔWTI^-_{t-4}	-0.2801***
Long-run asymmetric effects									
L^+_{STOCK}	-2.9376***	L^+_{STOCK}	-2.4088***	L^+_{STOCK}	-5.0818***	L^+_{STOCK}	-0.8887***	L^+_{STOCK}	0.2997
L^-_{STOCK}	-2.6385***	L^-_{STOCK}	-1.9226***	L^-_{STOCK}	-2.8678**	L^-_{STOCK}	-0.9397***	L^-_{STOCK}	0.5039
L^+_{VIX}	0.1973***	L^+_{VIX}	0.1539*	L^+_{VIX}	0.3957	L^+_{VIX}	0.5512***	L^+_{VIX}	0.5313**
L^-_{VIX}	0.0690	L^-_{VIX}	0.0094	L^-_{VIX}	0.7632*	L^-_{VIX}	0.4483***	L^-_{VIX}	0.8374***
L^+_{SPOT}	0.0788*	L^+_{SPOT}	-0.4839***	L^+_{SPOT}	-1.3708***	L^+_{SPOT}	-0.0679	L^+_{SPOT}	-0.2891**
L^-_{SPOT}	-0.0604	L^-_{SPOT}	-0.5362***	L^-_{SPOT}	-1.1074***	L^-_{SPOT}	0.0468	L^-_{SPOT}	-0.7745***
L^+_{WTI}	0.4202***	L^+_{WTI}	-0.2052*	L^+_{WTI}	-0.1637	L^+_{WTI}	-0.2577*	L^+_{WTI}	0.1737
L^-_{WTI}	0.5105***	L^-_{WTI}	0.1710	L^-_{WTI}	-0.3441	L^-_{WTI}	-0.0519	L^-_{WTI}	0.0972
Statistics and Diagnostics									
Adj. R^2	0.4950	Adj. R^2	0.4096	Adj. R^2	0.2135	Adj. R^2	0.3645	Adj. R^2	0.3550
χ^2_{SC}	0.710 [0.455]	χ^2_{SC}	1.326 [0.235]	χ^2_{SC}	1.453 [0.216]	χ^2_{SC}	0.352 [0.677]	χ^2_{SC}	0.915 [0.405]
χ^2_H	2.889 [0.000]	χ^2_H	0.710 [0.399]	χ^2_H	2.254 [0.036]	χ^2_H	3.621 [0.057]	χ^2_H	1.108 [0.301]

Note: This table reports the results of the estimation of the best-suited NARDL model for the adjustment of the CDS index spread of each U.S. industry over the whole sample period from December 14, 2007 to September 25, 2015 using weekly data. The superscripts "+" and "-" denote positive and negative partial sums, respectively. L^+_x and L^-_x are the estimated long-run coefficients associated with positive and negative changes of the variable x, respectively, defined by $\hat{L}=-\hat{\theta}/\hat{\rho}$. Adj. R^2 represents the value of the adjusted R^2 coefficient of the estimated model. χ^2_{SC} and χ^2_H denote the LM tests for serial correlation and heteroskedasticity, respectively. The superscripts *, ** and *** indicate the 10%, 5% and 1% levels of significance, respectively.

respectively, because it captures a volatility risk premium. The significant role of the VIX index in explaining CDS index spreads is also in agreement with the evidence reported by, among others, Arouri et al. (2014), Greatrex (2009), Hammoudeh et al. (2013b) and Lahiani et al. (2016).

In a similar vein, the U.S. 5-year government bond yield exerts a significant long-run influence on the CDS index spreads of a broad range of industries (Telecommunications, Utilities, Technology, Consumer Goods, Health Care and Industrials). This evidence that the interest rates are a major driver of industry CDS spreads is in line with that of Chan and Marsden (2014), Hammoudeh and Sari (2011) and Lahiani et al. (2016). As expected, the long-run effect of the 5-year Treasury yield is nearly always negative, implying that higher 5-year interest rates signaling a stronger economy reduce industry CDS spreads. It is also shown that the long-run impact of rises in the 5-year government bond yields tends to be more pronounced (in absolute value) than that of falls in the 5-year bond yields for most industries. This result means that U.S. CDS spreads at the industry level are mostly influenced in the long-run by increases in interest rates. This significant long-run asymmetric effect of increases and decreases in interest rates on the industry CDS spreads is consistent with the evidence of Lahiani et al. (2016). However, this finding contradicts the result of Zhu (2013), who does not detect a significant asymmetric response of credit spread changes of corporate bonds to positive and negative surprise changes in the federal funds target rate. Interestingly, the CDS index spread of the Financials industry is immune in the long-run to interest rate fluctuations. This finding is identical to that reported by Alexander and Kaeck (2008) and may be attributed to risk management strategies taken by financial firms to hedge against the interest rate risk inherent to the financial business. In contrast, the most prominent effect of the 5-year Treasury yields on the CDS index spreads in the long-run is found for the Utilities industry. This result is not surprising given that this highly capital intensive industry is widely recognized as one of the most interest rate sensitive (e.g. Sweeney and Warga, 1986; Moya-Martínez et al., 2015). The significant interest rate exposure of Utilities firms is commonly explained by their high level of indebtedness as well as by their regulated nature. On one hand, the financial health of heavily indebted firms such as the Utilities is strongly dependent on interest rate developments, as the cost of their debt is directly related to the level of interest rates. On the other hand, regulated firms such as Utilities adjust the prices of their products and services with some lag after the cost increases due to the constraints imposed by regulators. These two factors contribute to strengthening the impact of changes in interest rates on the earning prospects and the financial health of these companies.

Lastly, the WTI oil price has a very weak or no significant long-run effect on the CDS index spreads of most industries (Oil & Gas, Basic Materials, Telecommunications, Utilities, Technology, Industrials and Financials). This suggests that the crude oil price is not a key driving factor of the U.S. industry CDS index spreads and is consistent with several prior studies in this field (e.g., Guo et al., 2011; Hammoudeh et al., 2013b; Lahiani et al. 2016). This finding is apparently striking in the case of some industries regarded a priori as especially oil-sensitive such as Oil & Gas and Basic Materials. One possible explanation for this refers to hedging strategies successfully implemented by firms in these two industries to reduce their exposure to crude oil price

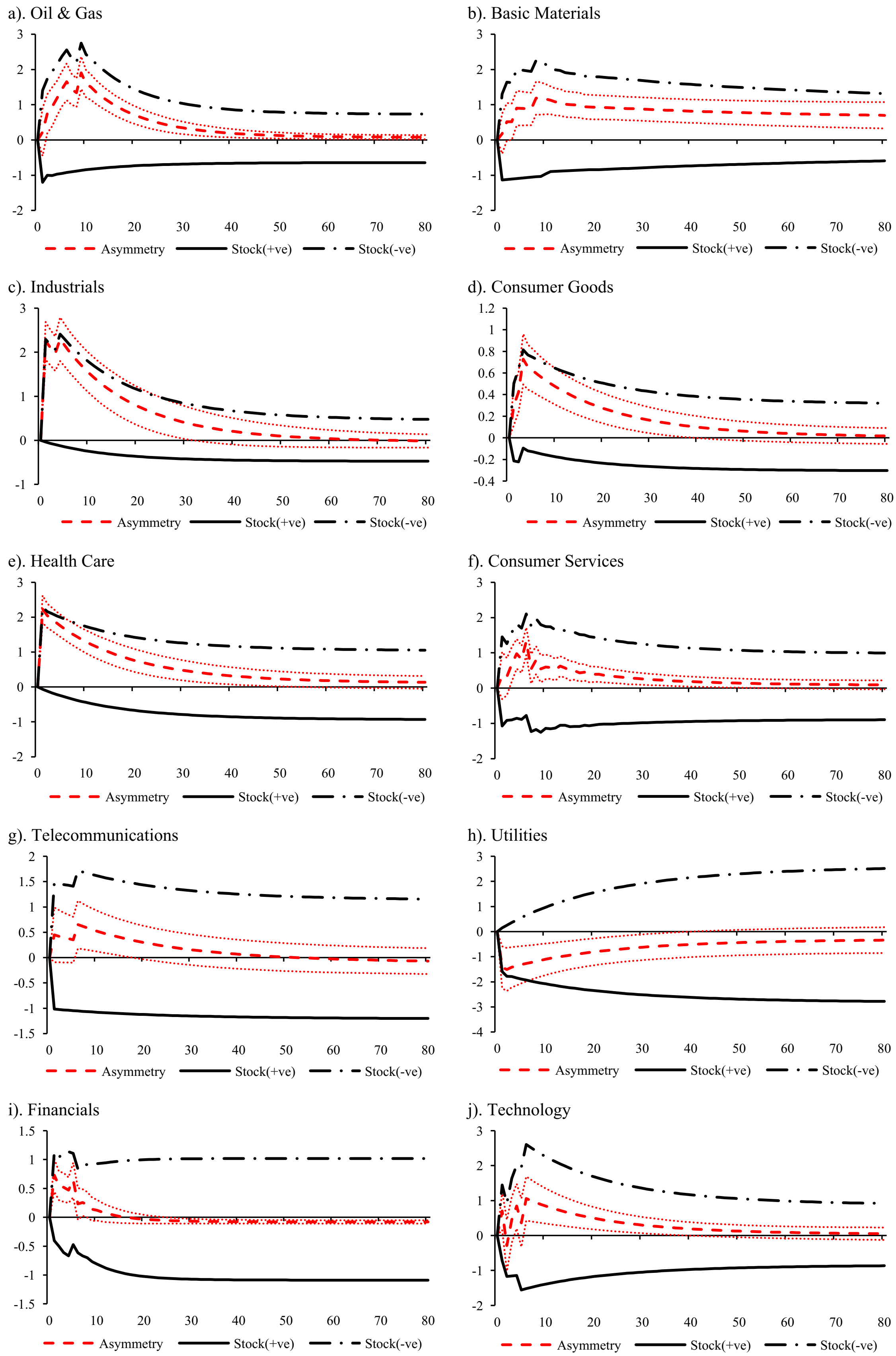

Fig. 1. Dynamic multipliers for the industry CDS index spread–industry stock index link.

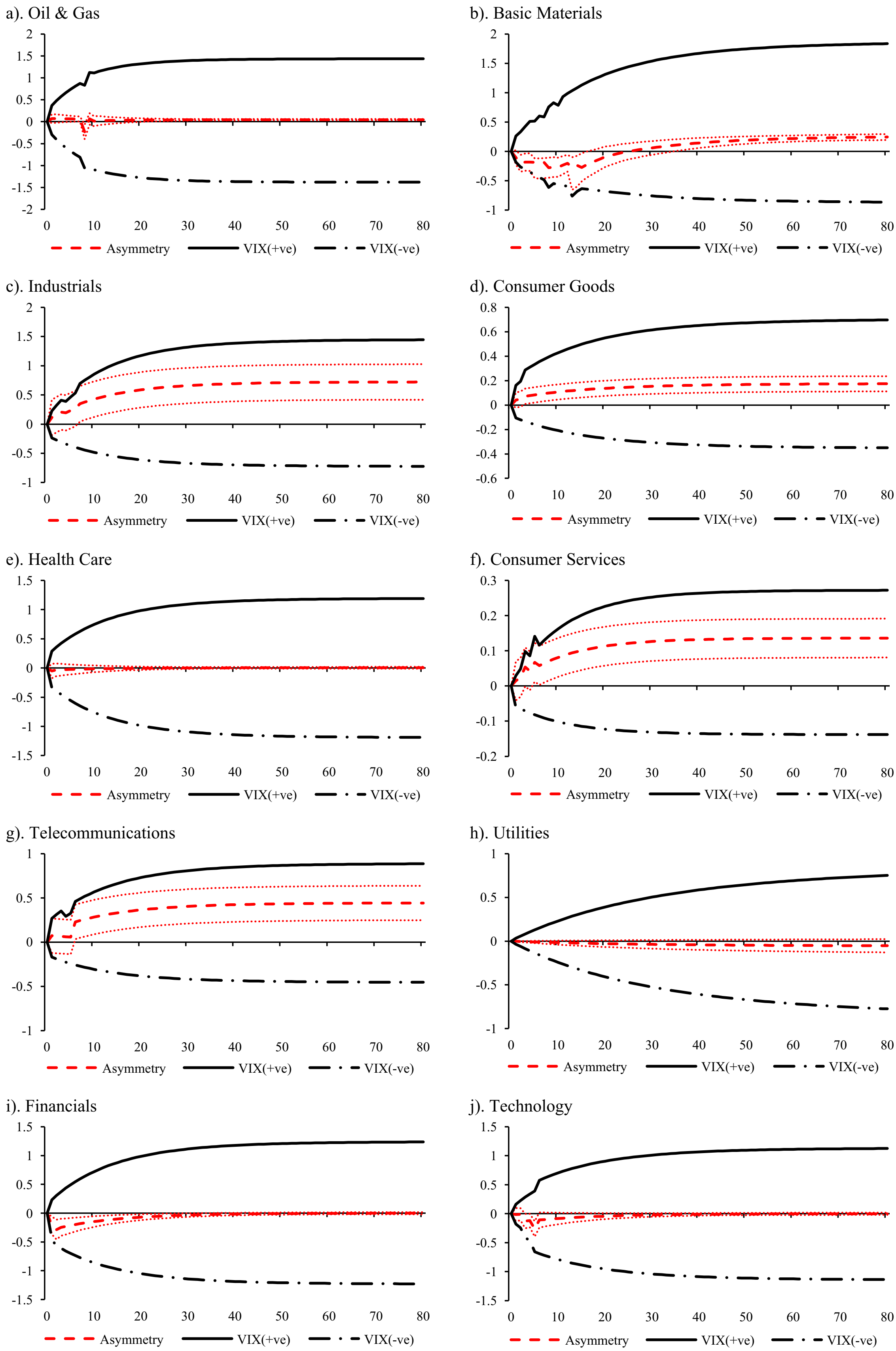

Fig. 2. Dynamic multipliers for the industry CDS index spread–VIX index link.

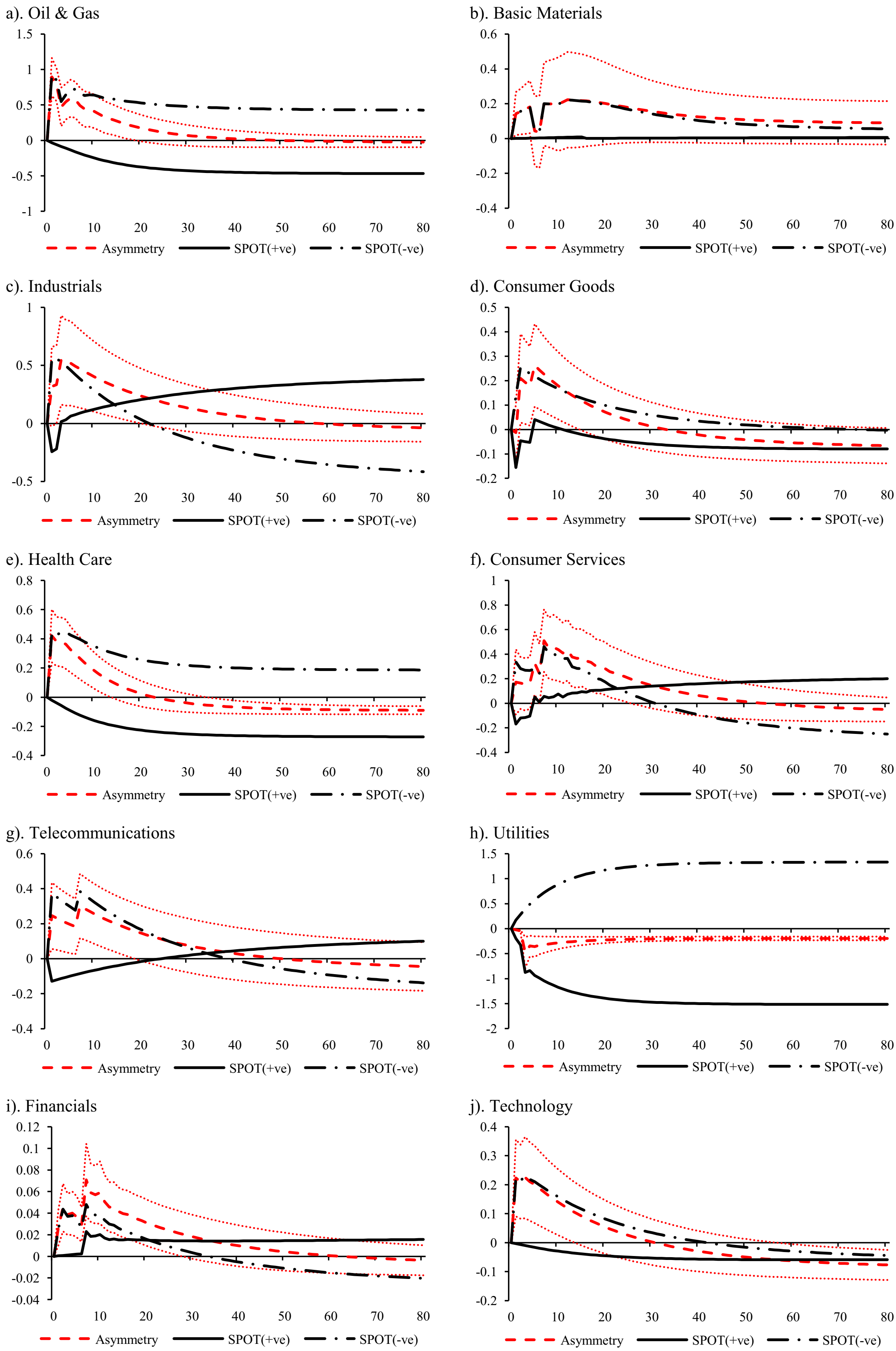

Fig. 3. Dynamic multipliers for the industry CDS index spread–5-year Treasury bond yield link.

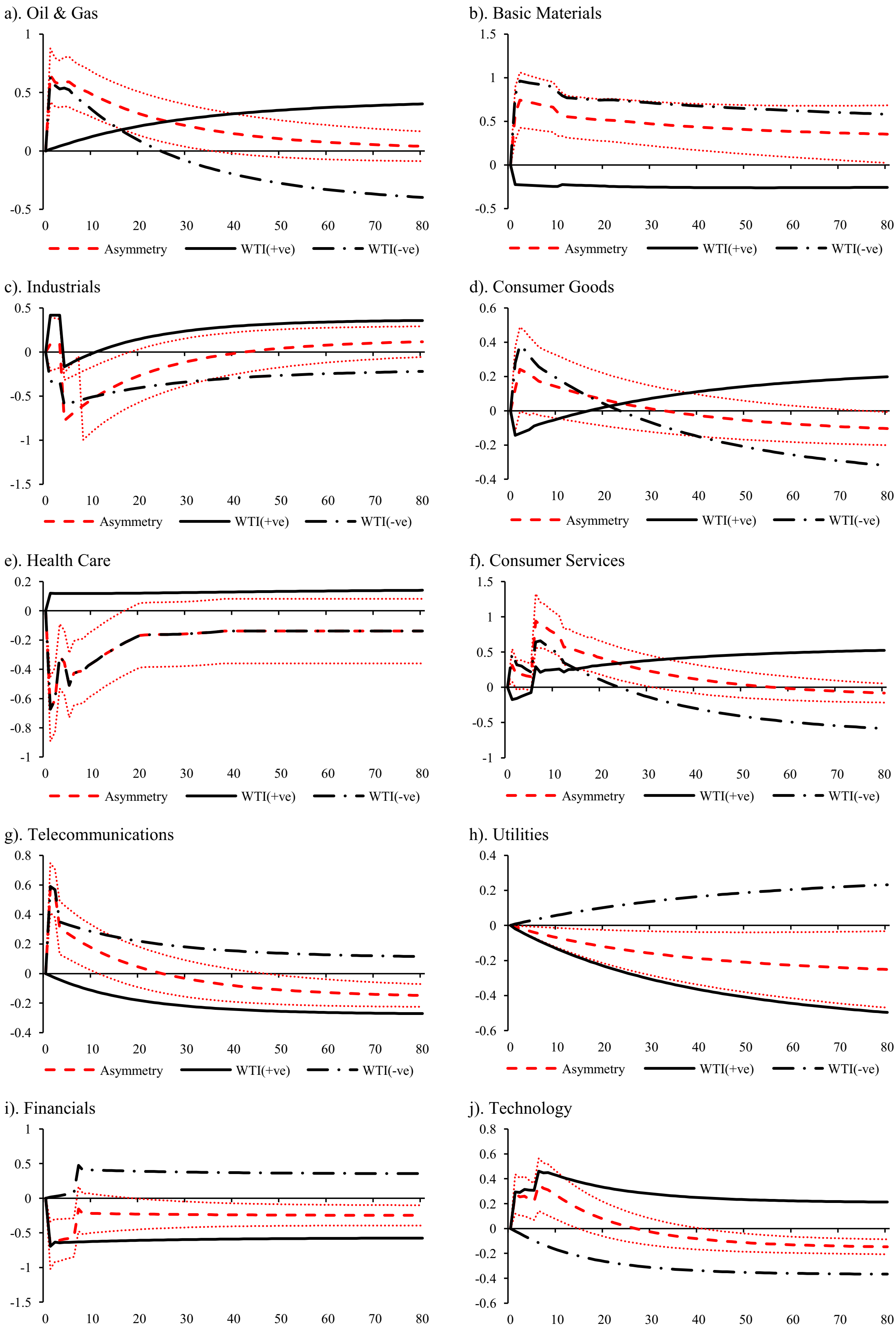

Fig. 4. Dynamic multipliers for the industry CDS index spread–WTI oil price link.

fluctuations. Moreover, the lack of a significant long-run effect of the WTI oil price on the CDS index spread of the Financials industry is in agreement with the findings of Arouri et al. (2014) and Lahiani et al. (2016). On the contrary, the CDS spreads of two non-oil-intensive industries such as Consumer Services and Consumer Goods are the most strongly influenced in the long-run by the oil price development. In fact, the long-run coefficients associated with the WTI crude oil price take positive values in these two industries, although no significant long-run asymmetries are observed. This positive sign may be explained by the fact that rising oil prices dampen consumer confidence and strain spending, which adversely affects profits and future prospects of consumption-related companies resulting in a widening of CDS index spreads of these industries.

4.3. Asymmetric dynamic multipliers

The analysis of the dynamic effects of the explanatory macro-finance variables on the industry CDS index spreads can be complemented with the dynamic multipliers. Figs. 1–4 plot the cumulative dynamic multipliers obtained according to Eq. (8). These multipliers show the pattern of adjustment of the industry CDS index spreads to their new long-run equilibrium following a negative or positive unitary shock in each of the explanatory variables. The dynamic multipliers have been estimated based on the best-suited NARDL models reported in Table 6. The positive (continuous black line) and negative (dashed black line) change curves capture the adjustment of the industry CDS spreads to positive and negative shocks at a given forecast horizon, respectively. The asymmetry curve (broken red line) reflects the difference between the dynamic multipliers associated with positive and negative shocks of each explanatory variable, i.e. $(m_h^+ - m_h^-)$. This curve is displayed together with its lower and upper bands (dotted red lines) at the 95% confidence interval in order to provide a measure of the statistical significance of asymmetry at any horizon h. If the zero line is located between the lower and upper bands, then the asymmetric effects of the explanatory variable in question are not significant at the 5% level.

Fig. 1 depicts the adjustment pattern of the industry CDS index spreads to a negative or positive unitary shock in the respective industry stock index. The graphs in this figure confirm the existence of an inverse relationship between industry equity prices and industry CDS spreads both in the short- and long-run for all industries. It is also shown that the effect of a negative shock in industry stock prices dominates that of a positive shock, particularly in the short-run, with the only exception of the Utilities industry. Moreover, a significant asymmetric response to shocks in industry stock prices is observed mainly in the short-run for most industries (Industrials, Telecommunications, Consumer Goods, Consumer Services, Health Care, Utilities and Technology). On the contrary, the CDS spreads of Basic Materials and, to a lesser extent, Oil & Gas and Financials exhibit a significant asymmetric response both in the short- and long-run. Accordingly, the behavior of the dynamic multipliers following a shock in industry stock prices is consistent with the presence of asymmetries mostly in the short-run. In addition, the CDS index spreads of all industries, except the Financials, reach a new equilibrium after approximately 30 to 40 weeks. Instead, the Financials industry seems to attain the new equilibrium more quickly, suggesting that this industry responds much faster to shocks in the stock market than the other industries. This industry is especially supervised by regulators due to its important systematic risk.

The dynamic adjustment of the industry CDS index spreads after a negative or positive unitary shock in the VIX index is illustrated in Fig. 2. The graphs corroborate the presence of a positive link between the CDS spreads and the VIX index in both the short-run and the long-run. However, the pattern of adjustment of CDS index spreads to a unitary shock in the VIX differs largely across industries. In this respect, the effect of a positive unitary shock in the VIX is stronger in the short-run for Industrials, Consumer Goods, Consumer Services and Telecommunications, while the effect of a negative unitary shock in this index is larger in the short-run for Basic Materials and Financials. In contrast, some industries, such as Oil & Gas, Health Care, Utilities and Technology, seem to have a symmetric pattern of adjustment to positive and negative shocks in the VIX in the short- and long-run. Additionally, a significant asymmetric response in the long-run, characterized by the predominance of positive shocks in the VIX, is observed for the CDS index spreads of Consumer Services, Consumer Goods, Industrials, Basic Materials and Telecommunications. This heterogeneous pattern of adjustment to positive and negative shocks in the VIX is consistent with the presence of significant asymmetries in both the short-run and the long-run. Lastly, the CDS index spreads achieve a new equilibrium after approximately 30 weeks.

Fig. 3 depicts the dynamics of convergence to the long-run equilibrium of the industry CDS spreads following a negative or positive unitary variation in the 5-year Treasury yield. In this case, the pattern of adjustment of the CDS index spreads also varies notably across industries. There is a clear negative relationship between the 5-year Treasury bond rate and the CDS index spreads of a large number of industries (Oil & Gas, Consumer Goods, Health Care, Utilities and Technology), while the linkage is more erratic for another group of industries (Financials, Industrials and Telecommunications). It is worth noting that Utilities emerges as the only industry whose CDS index spread is significantly influenced by shocks in the 5-year Treasury bond yield both in the short- and long-run, confirming the special interest rate-sensitive nature of this industry. A significant asymmetric response of the CDS index spreads to changes in the 5-year Treasury yield is observed in the short-run for nearly all industries, where negative shocks in interest rates tend to have a more pronounced effect than positive shocks. However, a significant asymmetric response in the long-run, with predominance of positive interest rate shocks, is found mainly for Utilities, Health Care and Technology industries. This behavior of the dynamic multipliers following interest rate shocks is primarily consistent with the presence of significant short-run asymmetry. Additionally, the CDS spreads of all industries, except Utilities, achieve a new equilibrium after approximately 40 weeks. However, the Utilities' CDS index spread reaches more quickly the new equilibrium as a result of its greater interest rate sensitivity.

Finally, Fig. 4 presents the dynamic multipliers for the transmission of a negative or positive unitary shock in the WTI oil price to industry CDS spreads. A primarily negative relationship between crude oil price and CDS index spreads is found for Basic Materials, Telecommunications, Utilities and Financials, while a mostly positive relationship is observed for Oil & Gas, Industrials, Health Care, Consumer Services and Technology. It should be also mentioned that Consumer Services appears as the industry most significantly affected by oil price shocks. Again, the dynamics of adjustment vary markedly from an industry to another. There is significant evidence of short-run asymmetry in the response of CDS index spreads to positive and negative shocks in the WTI oil price for all industries. In particular, the effect of negative oil price shocks is larger in the short-run for a wide range of industries (Oil & Gas, Basic Materials, Industrials, Health Care, Consumer Goods, Consumer Services and Telecommunications). However, the short-run effect of positive crude oil price shocks on CDS index spreads is more intense in Utilities, Financials and Technology industries. In turn, the CDS spreads of Basic Materials, Utilities, Telecommunications, Financials, and Technology are subject to significant asymmetry in the long-run, although the magnitude of the long-run effect is almost always lower than that of the short-run effect. The negative WTI oil price shocks seem to have a larger effect on the CDS spreads of Basic Materials, Health Care and Technology industries. In addition, the adjustment is in general fast and intense over the first weeks, and the new long-run equilibrium is achieved after about 40-50 weeks for the majority of industries. Overall, we can conclude that the dynamic multipliers further support the asymmetric effect of

Table 7
Wald tests for long-run and short-run asymmetry at the industry level (daily data).

	Long-run asymmetry				Short-run asymmetry			
Industry	W_{LR}(STOCK)	W_{LR}(VIX)	W_{LR}(SPOT)	W_{LR}(WTI)	W_{SR}(STOCK)	W_{SR}(VIX)	W_{SR}(SPOT)	W_{SR}(WTI)
Oil & Gas	12.178*** [0.000]	12.866*** [0.000]	8.570*** [0.000]	14.762*** [0.000]	9.254*** [0.000]	7.873*** [0.000]	1.005* [0.087]	8.762*** [0.001]
Basic Materials	37.486*** [0.000]	6.022** [0.014]	0.028 [0.865]	17.692*** [0.000]	0.394 [0.532]	5.441* [0.019]	– –	8.042*** [0.004]
Industrials	3.249* [0.071]	6.317** [0.012]	5.263** [0.021]	5.850** [0.015]	6.138** [0.008]	8.376*** [0.004]	1.652** [0.061]	8.762*** [0.002]
Consumer Goods	0.124 [0.724]	1.402 [0.236]	0.847 [0.357]	0.042 [0.837]	17.623*** [0.000]	5.765** [0.043]	– –	9.714*** [0.000]
Health Care	1.971 [0.160]	0.106 [0.743]	0.023 [0.609]	3.701* [0.054]	7.653*** [0.001]	5.732*** [0.009]	– –	11.254*** [0.000]
Consumer Services	0.002 [0.998]	7.503*** [0.006]	4.466** [0.034]	9.806*** [0.001]	11.165*** [0.000]	26.285*** [0.000]	– –	13.602*** [0.000]
Telecom	12.475*** [0.000]	2.823* [0.083]	2.197 [0.138]	0.094 [0.759]	2.994* [0.072]	3.873** [0.029]	– –	– –
Utilities	2.818* [0.093]	3.684* [0.093]	0.826 [0.363]	1.802 [0.179]	– –	11.033*** [0.000]	22.502*** [0.000]	– –
Financials	4.473** [0.034]	5.876** [0.015]	5.244** [0.022]	3.525* [0.060]	3.793** [0.041]	23.037*** [0.000]	– –	– –
Technology	4.269** [0.038]	3.233** [0.041]	10.762*** [0.001]	0.577 [0.447]	12.761*** [0.000]	0.132 [0.716]	– –	– –

Note: This table reports the Wald statistics of the long- and short-run symmetry tests for the effect of each explanatory variable (the industry stock indices, the VIX, the 5-year Treasury bond yield and the WTI oil price) on each industry CDS spread using daily data. W_{LR} denotes the Wald statistic for the long-run symmetry, which tests the null hypothesis of $\theta^+ = \theta^-$ for each explanatory variable in Eq. (8). W_{SR} corresponds to the Wald statistic for the short-run asymmetry, which tests the null hypothesis that $\sum_{i=0}^{q-1}\pi_{k,i}^+ = \sum_{i=0}^{q-1}\pi_{k,i}^-$ for each explanatory variable in Eq. (8). The numbers in brackets are the associated p-values. *, ** and *** indicate a rejection of the null hypothesis of symmetry at the 10%, 5% and 1% levels, respectively.

the different macroeconomic and financial variables on the industry CDS spreads previously found in the estimation of the NARDL model.

4.4. Robustness analysis

In this subsection, we briefly assess the robustness of our results by using a different data frequency. There is a growing body of the literature seeking to answer the question of whether the choice of data frequency significantly affects the results of the empirical work in economics and finance research, particularly when examining the relationships among economic and financial variables. For example, Narayan and Sharma (2015) analyze the link between the forward premium and the exchange rate return by asking whether different data frequency matters in that relationship. In turn, Narayan et al. (2015) investigate whether the data frequency holds a difference for the profitability of momentum-based trading strategies in a large set of commodity futures markets. In a very recent contribution, Yildirim (2016) explores whether the transmission of global financial risk shocks to the asset markets of five fragile emerging economies varies across different data frequencies. However, the evidence of this strand of research is mixed, depending on the specific variables included in each case. Thus, while the empirical findings of Narayan and Sharma (2015) and Narayan et al. (2015) strongly support data frequency dependence, the results of Yildirim (2016) remain unchanged with different data frequencies.

Following this emerging literature, we examine whether the presence of asymmetry in the short- and long-run relationships between the U.S. industry CDS index spreads and the selected macroeconomic and financial variables depends on the data frequency considered. To this end, we re-estimate the NARDL model specified in Eq. (8) using daily data, which are also commonly utilized in the literature. Table 7 presents the Wald statistics for the tests of short- and long-run asymmetry in the NARDL model estimated using daily data. The results are very similar to those obtained from weekly data, confirming the existence of significant short-run and long-run asymmetries in the adjustment of industry CDS spreads in a large number of cases for the different industries. However, the number of significant asymmetries is slightly higher when using daily data, mainly in the long-run. This finding is not surprising taking into account the higher levels of noise and variability in daily data compared to weekly data. [12]

Table 8 displays the results of the estimation of the NARDL model as specified in Eq. (8) for the ten U.S. industries considered using the daily data. The Newey-West standard errors have been employed in the estimation to correct for heteroskedasticity and serial correlation issues associated with daily data. Again, the best fitted model is chosen applying the general-to-specific procedure as discussed in Subsection 4.2. The F_{PSS} and t_{BDM} statistics of the cointegration bound testing approach conducted in the framework of the NARDL model on the daily basis, reported in the bottom panel of Table 8, are greater than the respective upper bound critical values at the conventional levels for all industries. This implies the existence of asymmetric long-run relationships between the U.S. industry CDS index spreads and the set of the major macroeconomic and financial variables under study regardless of the industry, as was the case under the NARDL specification with the weekly data. The results in terms of the signs

[12] The empty cells in Table 7 simply reflect that the Wald statistics for the test of short-run asymmetry could not be calculated in some cases. This is because when estimating the NARDL model using the daily data, the short-run lags (in the first difference) of some variables are not statistically significant at the usual levels. Thus, in the absence of significant short-run estimates for any variables, the corresponding Wald tests for the short-run asymmetry cannot be applied.

Table 8
Estimation results of the NARDL model for the U.S. industries (daily data).

Oil & Gas		Basic Materials		Industrials		Consumer Goods		Health Care	
Const.	0.2916***	Const.	0.1820***	Const.	0.0895***	Const.	0.1365***	Const.	0.2719***
CDS_{t-1}	-0.0671***	CDS_{t-1}	-0.0396***	CDS_{t-1}	-0.0201***	CDS_{t-1}	-0.0285***	CDS_{t-1}	-0.0484***
$Stock^{+}_{t-1}$	-0.0496*	$Stock^{+}_{t-1}$	-0.1226***	$Stock^{+}_{t-1}$	-0.0363*	$Stock^{+}_{t-1}$	-0.0389**	$Stock^{+}_{t-1}$	-0.0276
$Stock^{-}_{t-1}$	-0.0940***	$Stock^{-}_{t-1}$	-0.0843***	$Stock^{-}_{t-1}$	-0.0550***	$Stock^{-}_{t-1}$	-0.0360**	$Stock^{-}_{t-1}$	-0.0440**
VIX^{+}_{t-1}	0.0555***	VIX^{+}_{t-1}	0.0093*	VIX^{+}_{t-1}	-0.0078	VIX^{+}_{t-1}	0.0090***	VIX^{+}_{t-1}	0.0325***
VIX^{-}_{t-1}	0.0445***	VIX^{-}_{t-1}	0.0045	VIX^{-}_{t-1}	-0.0143*	VIX^{-}_{t-1}	0.0078**	VIX^{-}_{t-1}	0.0331***
$SPOT^{+}_{t-1}$	-0.0095	$SPOT^{+}_{t-1}$	-0.0098***	$SPOT^{+}_{t-1}$	0.0015	$SPOT^{+}_{t-1}$	-0.0057**	$SPOT^{+}_{t-1}$	-0.0115***
$SPOT^{-}_{t-1}$	0.0055	$SPOT^{-}_{t-1}$	-0.0103***	$SPOT^{-}_{t-1}$	0.0106**	$SPOT^{-}_{t-1}$	-0.0042**	$SPOT^{-}_{t-1}$	-0.0126***
WTI^{+}_{t-1}	-0.0038	WTI^{+}_{t-1}	0.0216***	WTI^{+}_{t-1}	-0.0089	WTI^{+}_{t-1}	0.0088***	WTI^{+}_{t-1}	-0.0058
WTI^{-}_{t-1}	0.0322**	WTI^{-}_{t-1}	0.0038	WTI^{-}_{t-1}	0.0065	WTI^{-}_{t-1}	0.0083***	WTI^{-}_{t-1}	0.0015
ΔCDS_{t-1}	-0.3670***	ΔCDS_{t-1}	-0.1481***	ΔCDS_{t-1}	-0.1877***	ΔCDS_{t-1}	-0.0915***	ΔCDS_{t-1}	-0.1533***
ΔCDS_{t-2}	-0.1250***	ΔCDS_{t-2}	-0.1991***	ΔCDS_{t-2}	-0.1066***	ΔCDS_{t-7}	0.0425*	$\Delta Stock^{-}_{t-2}$	-0.2782**
ΔCDS_{t-3}	-0.1341***	ΔCDS_{t-3}	-0.1008***	ΔCDS_{t-3}	-0.0551**	$\Delta Stock^{-}_{t}$	-0.2461**	ΔVIX^{+}_{t}	0.1140***
ΔCDS_{t-4}	-0.1100***	ΔCDS_{t-4}	-0.0628***	ΔCDS_{t-4}	0.0914***	$\Delta Stock^{-}_{t-2}$	-0.3894***	ΔVIX^{-}_{t}	0.0782***
ΔCDS_{t-6}	0.0678***	ΔCDS_{t-11}	0.0675***	ΔCDS_{t-8}	0.0434**	$\Delta Stock^{-}_{t-3}$	-0.2060**	ΔVIX^{-}_{t-1}	0.1071***
ΔCDS_{t-8}	-0.0590***	$\Delta Stock^{+}_{t-6}$	-0.3411***	ΔCDS_{t-12}	-0.0482**	ΔVIX^{+}_{t}	0.0447***	ΔWTI^{+}_{t-8}	-0.1510***
ΔCDS_{t-9}	-0.0934***	$\Delta Stock^{-}_{t-3}$	-0.2273***	$\Delta Stock^{+}_{t-5}$	-0.2372**	ΔVIX^{+}_{t-7}	0.0224**		
ΔCDS_{t-11}	-0.0805***	$\Delta Stock^{-}_{t-5}$	-0.2070***	$\Delta Stock^{+}_{t-6}$	-0.3736***	ΔVIX^{-}_{t}	0.0334**		
ΔCDS_{t-12}	-0.1039***	ΔVIX^{+}_{t}	0.0761***	$\Delta Stock^{-}_{t}$	-0.5266***	ΔVIX^{-}_{t-1}	0.0772***		
$\Delta Stock^{-}_{t-2}$	-0.4769***	ΔVIX^{+}_{t-1}	0.0991***	$\Delta Stock^{-}_{t-1}$	-0.6010***	ΔVIX^{-}_{t-4}	0.0459***		
ΔVIX^{+}_{t}	0.1099***	ΔVIX^{-}_{t}	0.0930***	$\Delta Stock^{-}_{t-2}$	-0.4585***	ΔVIX^{-}_{t-7}	-0.0255**		
ΔVIX^{-}_{t-1}	0.1179***	ΔVIX^{-}_{t-4}	0.0556***	$\Delta Stock^{-}_{t-3}$	-0.2723**	ΔVIX^{-}_{t-8}	-0.0264**		
		ΔVIX^{-}_{t-6}	-0.0901***	ΔVIX^{+}_{t-4}	0.0543**	ΔWTI^{+}_{t-9}	-0.0661**		
		ΔWTI^{+}_{t-8}	-0.1519***	$\Delta SPOT^{+}_{t-6}$	-0.1068**	ΔWTI^{-}_{t-5}	-0.0834***		
				$\Delta SPOT^{-}_{t}$	-0.1197**				
				$\Delta SPOT^{-}_{t-3}$	-0.1024**				
				$\Delta SPOT^{-}_{t-8}$	-0.1012**				
				ΔWTI^{+}_{t}	-0.1456**				
				ΔWTI^{+}_{t-6}	0.1936**				
				ΔWTI^{-}_{t-4}	0.2497***				
				ΔWTI^{-}_{t-6}	-0.2012***				
				ΔWTI^{-}_{t-11}	0.1402**				
Long-run asymmetric effects									
L^{+}_{STOCK}	-0.7387*	L^{+}_{STOCK}	-3.0984***	L^{+}_{STOCK}	-1.8048**	L^{+}_{STOCK}	-1.3666**	L^{+}_{STOCK}	-0.5699
L^{-}_{STOCK}	-1.4016***	L^{-}_{STOCK}	-2.1288***	L^{-}_{STOCK}	-2.7326***	L^{-}_{STOCK}	-1.2636**	L^{-}_{STOCK}	-0.9094**
L^{+}_{VIX}	0.8273***	L^{+}_{VIX}	0.2344*	L^{+}_{VIX}	-0.3888	L^{+}_{VIX}	0.3167***	L^{+}_{VIX}	0.6719***
L^{-}_{VIX}	0.6639***	L^{-}_{VIX}	0.1127	L^{-}_{VIX}	-0.7082*	L^{-}_{VIX}	0.2727**	L^{-}_{VIX}	0.6829***
L^{+}_{SPOT}	-0.1416*	L^{+}_{SPOT}	-0.2473***	L^{+}_{SPOT}	0.0745	L^{+}_{SPOT}	-0.1991**	L^{+}_{SPOT}	-0.2371***
L^{-}_{SPOT}	0.0815	L^{-}_{SPOT}	-0.2603***	L^{-}_{SPOT}	0.5244**	L^{-}_{SPOT}	-0.1477***	L^{-}_{SPOT}	-0.2603***
L^{+}_{WTI}	-0.0561	L^{+}_{WTI}	0.5457***	L^{+}_{WTI}	-0.4421	L^{+}_{WTI}	0.3080***	L^{+}_{WTI}	-0.1200
L^{-}_{WTI}	0.4793**	L^{-}_{WTI}	0.0964	L^{-}_{WTI}	0.3218	L^{-}_{WTI}	0.2905***	L^{-}_{WTI}	0.0316
Bound tests, Statistics and Diagnostics									
FPSS	8.9784***	FPSS	8.0658***	FPSS	6.3804***	FPSS	5.8547***	FPSS	9.3404***
BDM	-7.1961***	BDM	-6.5780***	BDM	-4.2950***	BDM	-5.5210***	BDM	-7.5510***
Adj. R^2	0.2007	Adj. R^2	0.1353	Adj. R^2	0.1176	Adj. R^2	0.0969	Adj. R^2	0.1127
χ^2_{SC}	3.021 [0.038]	χ^2_{SC}	4.183 [0.003]	χ^2_{SC}	4.132 [0.001]	χ^2_{SC}	5.263 [0.000]	χ^2_{SC}	2.217 [0.009]
χ^2_{H}	3.130 [0.031]	χ^2_{H}	1.607 [0.237]	χ^2_{H}	2.253 [0.046]	χ^2_{H}	9.458 [0.000]	χ^2_{H}	4.360 [0.000]

Consumer Services		Telecom		Utilities		Financials		Technology	
Const.	0.4643***	Const.	0.2271***	Const.	0.1539***	Const.	0.4428***	Const.	0.1425***
CDS_{t-1}	-0.0867***	CDS_{t-1}	-0.0412***	CDS_{t-1}	-0.0309***	CDS_{t-1}	-0.0804***	CDS_{t-1}	-0.0275***
$Stock^{+}_{t-1}$	-0.2150***	$Stock^{+}_{t-1}$	-0.0797***	$Stock^{+}_{t-1}$	-0.0987**	$Stock^{+}_{t-1}$	-0.0691***	$Stock^{+}_{t-1}$	-0.0535***
$Stock^{-}_{t-1}$	-0.2150***	$Stock^{-}_{t-1}$	-0.0622***	$Stock^{-}_{t-1}$	-0.0586	$Stock^{-}_{t-1}$	-0.0592***	$Stock^{-}_{t-1}$	-0.0364***
VIX^{+}_{t-1}	0.0113**	VIX^{+}_{t-1}	0.0111***	VIX^{+}_{t-1}	0.0041	VIX^{+}_{t-1}	0.0342***	VIX^{+}_{t-1}	0.0155***
VIX^{-}_{t-1}	0.0063	VIX^{-}_{t-1}	0.0099***	VIX^{-}_{t-1}	0.0004	VIX^{-}_{t-1}	0.0409***	VIX^{-}_{t-1}	0.0177***
$SPOT^{+}_{t-1}$	-0.0003	$SPOT^{+}_{t-1}$	-0.0132***	$SPOT^{+}_{t-1}$	-0.0447***	$SPOT^{+}_{t-1}$	-0.0007	$SPOT^{+}_{t-1}$	-0.0015
$SPOT^{-}_{t-1}$	-0.0063**	$SPOT^{-}_{t-1}$	-0.0157***	$SPOT^{-}_{t-1}$	-0.0392***	$SPOT^{-}_{t-1}$	-0.0106**	$SPOT^{-}_{t-1}$	-0.0102***
WTI^{+}_{t-1}	0.0106	WTI^{+}_{t-1}	-0.0016	WTI^{+}_{t-1}	0.0102	WTI^{+}_{t-1}	-0.0066	WTI^{+}_{t-1}	-0.0033
WTI^{-}_{t-1}	0.0262***	WTI^{-}_{t-1}	-0.0008	WTI^{-}_{t-1}	-0.0045	WTI^{-}_{t-1}	-0.0180**	WTI^{-}_{t-1}	-0.0062
ΔCDS_{t-1}	-0.0638***	$\Delta Stock^{+}_{t-3}$	-0.3180***	ΔCDS_{t-4}	-0.3283***	ΔCDS_{t-1}	-0.3432***	ΔCDS_{t-1}	-0.1158***
ΔCDS_{t-2}	-0.1754***	$\Delta Stock^{-}_{t-1}$	-0.2271***	ΔCDS_{t-8}	-0.1066***	ΔCDS_{t-2}	-0.2290***	ΔCDS_{t-2}	0.0767***

(continued on next page)

Table 8 *(continued)*

Consumer Services		Telecom		Utilities		Financials		Technology	
ΔCDS_{t-5}	-0.1239***	$\Delta Stock^{-}_{t-8}$	-0.2241***	ΔVIX^{+}_{t}	0.1258***	ΔCDS_{t-3}	-0.0582***	ΔCDS_{t-8}	0.0768***
ΔCDS_{t-6}	-0.0838***	ΔVIX^{+}_{t}	0.0872***	$\Delta SPOT^{+}_{t-3}$	-0.4514***	ΔCDS_{t-6}	0.0707***	ΔCDS_{t-9}	-0.0688***
ΔCDS_{t-7}	0.0653***	ΔVIX^{-}_{t}	0.0653***	$\Delta SPOT^{-}_{t-3}$	0.2522***	ΔCDS_{t-8}	0.0655***	$\Delta Stock^{+}_{t}$	-0.2989***
$\Delta Stock^{+}_{t}$	-0.3493***	ΔVIX^{-}_{t-1}	0.0584***			ΔCDS_{t-11}	0.0572***	ΔVIX^{+}_{t}	0.0744***
ΔVIX^{+}_{t}	0.0979***					$\Delta Stock^{+}_{t}$	-0.2113***	ΔVIX^{-}_{t-1}	0.0662***
ΔWTI^{-}_{t-4}	-0.2223***					$\Delta Stock^{-}_{t-1}$	-0.3012***		
Long-run asymmetric effects									
L^{+}_{STOCK}	-2.4805***	L^{+}_{STOCK}	-1.9373***	L^{+}_{STOCK}	-3.1897**	L^{+}_{STOCK}	-0.8597***	L^{+}_{STOCK}	-1.9429***
L^{-}_{STOCK}	-2.4807***	L^{-}_{STOCK}	-1.5100***	L^{-}_{STOCK}	-1.8945	L^{-}_{STOCK}	-0.7355***	L^{-}_{STOCK}	-1.3214***
L^{+}_{VIX}	0.1299**	L^{+}_{VIX}	0.2706***	L^{+}_{VIX}	0.1328*	L^{+}_{VIX}	0.4258***	L^{+}_{VIX}	0.5618***
L^{-}_{VIX}	0.0722	L^{-}_{VIX}	0.2397**	L^{-}_{VIX}	0.0119	L^{-}_{VIX}	0.5090***	L^{-}_{VIX}	0.6420***
L^{+}_{SPOT}	-0.0035	L^{+}_{SPOT}	-0.3214***	L^{+}_{SPOT}	-1.4439***	L^{+}_{SPOT}	-0.0086	L^{+}_{SPOT}	-0.0534
L^{-}_{SPOT}	-0.0721**	L^{-}_{SPOT}	-0.3814***	L^{-}_{SPOT}	-1.2654***	L^{-}_{SPOT}	-0.1314**	L^{-}_{SPOT}	-0.3690***
L^{+}_{WTI}	0.1228	L^{+}_{WTI}	-0.0389	L^{+}_{WTI}	0.3283	L^{+}_{WTI}	-0.0815	L^{+}_{WTI}	-0.1196
L^{-}_{WTI}	0.3026***	L^{-}_{WTI}	-0.0202	L^{-}_{WTI}	-0.1442	L^{-}_{WTI}	-0.2234***	L^{-}_{WTI}	-0.2252
Bound tests, Statistics and Diagnostics									
FPSS	14.6616***	FPSS	9.3076***	FPSS	6.1417***	FPSS	9.1982***	FPSS	10.6867***
BDM	-10.3770***	BDM	-7.8920***	BDM	-5.1330***	BDM	-8.5240***	BDM	-7.5730***
Adj. R^2	0.1483	Adj. R^2	0.1323	Adj. R^2	0.1339	Adj. R^2	0.1926	Adj. R^2	0.0967
χ^2_{SC}	1.483 [0.122]	χ^2_{SC}	1.492 [0.119]	χ^2_{SC}	1.601 [0.081]	χ^2_{SC}	1.776 [0.044]	χ^2_{SC}	1.492 [0.115]
χ^2_{H}	24.014 [0.000]	χ^2_{H}	1.456 [0.098]	χ^2_{H}	4.736 [0.000]	χ^2_{H}	4.880 [0.000]	χ^2_{H}	1.473 [0.001]

Note: This table reports the results of the estimation of the best-suited NARDL model for the adjustment of the CDS index spread of each U.S. industry over the whole sample period from December 14, 2007 to September 25, 2015 using daily data. The superscripts "+" and "-" denote positive and negative partial sums, respectively. L^{+}_{x} and L^{-}_{x} are the estimated long-run coefficients associated with positive and negative changes of the variable x, respectively, defined by $\hat{L}=-\hat{\theta}/\hat{\rho}$. FPSS and BDM are the *F*-statistic and *t*-statistic proposed by Pesaran et al. (2001) and Banerjee et al. (1998), respectively, for testing the null of no cointegration in the NARDL model. Adj. R^2 represents the value of the adjusted R^2 coefficient of the estimated model. χ^2_{SC} and χ^2_{H} denote the LM tests for serial correlation and heteroscedasticity, respectively. The superscripts *, ** and *** indicate the 10%, 5% and 1% levels of significance, respectively.

and significance of the long-run asymmetric coefficients of the four selected macro-finance variables estimated using the daily data are also broadly consistent with those of the initial analysis based on the weekly data. Instead, it is found that at the daily frequency the CDS index spreads of several industries are mainly explained by their own lagged first differences, so that the short-run effect of the macro-finance variables on industry CDS spreads tends to be less significant on the daily basis as compared to the weekly estimates. The lower explanatory power in the short-run of the major risk factors and the lesser presence of significant short-run asymmetries when using the daily data may be related to the fact that at the daily frequency the new information is processed very fast by the most active participants in the CDS market. As a result, industry-level CDS index spreads are primarily driven by their own past behavior, while the influence of economic fundamentals, such as industry stock indices, the VIX, the spot interest rate and the crude oil price, in the short-run is very limited. Moreover, the daily data have generally lower bid-ask ratios than weekly data and more liquid assets tend to exhibit less asymmetry than the less liquid assets. More importantly, the adjusted R^2 values obtained when using daily data are substantially lower (i.e., less than half on average) for all industries than those based on the industry-level NARDL model with weekly data. This finding means that the NARDL specification applied on the weekly basis allows capturing better the influence of the major macroeconomic and financial variables on the dynamics of U.S. industry CDS spreads than when using the daily data.

To sum up, our robustness check using the daily data shows that the long-run asymmetric effects of the macroeconomic and financial variables on U.S. industry CDS spreads are consistent with the theoretical expectations of the credit risk model of Merton (1974) and also coincide with the principal results obtained when using weekly data. However, the NARDL model estimated with the weekly data seems to be more appropriate to analyze the asymmetric relationships in the short-run and long-run between the major risk factors and the U.S. CDS index spreads at the industry level.

5. Concluding remarks

The global financial crisis of the period 2008-2009 has sparked an interesting debate about possible asymmetries in the linkage between CDS spreads and their main determinants, particularly in times of major financial turmoil. In this context, this paper investigates the presence of asymmetries in the short- and long-run relationships between ten U.S. industry CDS index spreads and a set of influential macroeconomic and financial variables selected on the basis of the structural credit risk model of Merton, i.e. the corresponding industry equity indices, the VIX index, the 5-year Treasury bond yield and the WTI crude oil price, using the NARDL approach estimated on weekly and daily data to check for robustness. These factors incorporate the information on the risk and prospects in stock, government bond and oil markets that may influence the market perception of credit risk and may be passed on to the CDS spreads of industries. The NARDL model, which was recently developed by Shin et al. (2014), provides a flexible and efficient framework that allows for quantifying the transmission of positive and negative shocks in each of these variables to the industry CDS index spreads, accounting for asymmetries in both short-run and long-run time horizons.

The empirical results show significant evidence of asymmetries in the short-run and long-run relationships between CDS index spreads and the explanatory factors under examination for all U.S. industries using both weekly and daily data, suggesting that positive and negative shocks in the selected macroeconomic and financial variables have a differential impact on the industry CDS spreads. This means that linear modeling is not appropriate to adequately capture the short- and long-run asymmetries in the adjustment process of the U.S. industry CDS index spreads to changes in several major economic and financial indicators and may lead to misspecified and biased results. Overall, the signs of the long-run effect of the macro-finance variables on industry CDS spreads are as expected. In particular, a significantly negative long-run impact of industry stock prices and the 5-year Treasury yield on the CDS index spreads is found for most industries, indicating that higher equity prices and rising 5-year interest rates signal a stronger economy, which results in declining industry CDS spreads. In turn, the VIX has a significantly positive effect in the long-run on the CDS spreads of a wide range of industries, implying that greater risk aversion and fear in the stock market leads to a widening of CDS index spreads for many industries. However, the WTI crude oil price does not exert a significant long-run influence on the CDS spreads of most industries. Therefore, the industry equity prices, the implied volatility of the stock market, the 5-year Treasury bond yield and, to a lesser degree, the crude oil price should be regarded by market participants as important nonlinear asymmetric drivers of the U.S. industries' CDS index spreads.

The empirical evidence presented in this study has relevant implications for CDS market participants. For example, investors, speculators and arbitrageurs may use their better understanding of the existence of asymmetries in the link between industry CDS spreads and a number of influential macro-finance variables to improve their asset allocation, portfolio diversification, credit risk management and trading decisions at the industry level. Thus, they can take the most appropriate actions depending on their objectives, risk profile and position in CDS contracts for each industry and the expected evolution, either upwards or downwards, of macroeconomic and financial indicators. In addition, the measures adopted by policy makers aimed at minimizing any destabilizing effects of crises in the financial system during turbulent times might also be different depending on the expected sign of changes in major risk factors.

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