Chapter 1

Impact of Credit Risk on Stock Market and Short-Term Financing: Evidence From the U.S. Market

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Abstract

In this study, we examine the impact of two leading credit risk indicators (ABX.HE and CDX.NA.IG indexes) on the U.S. equity market (the Dow Jones Industrial Average index, DJIA) and short-term financing stress (TED spread) through asymmetric causality and Markov Regime-Switching regression analysis. According to the findings, CDX.NA.IG dominates ABX.HE index both in negative and positive returns. Additionally, it appears to be more impactful over the U.S. equity market and short-term financing stress. Markov Regime-Switching regression analysis shows that CDX.NA.IG negatively affects the U.S. equity market returns and escalates the short-term financing stress in expansionary and contractionary regimes. These effects become considerably higher during financial turmoil. Based on our findings, we suggest market participants monitor the CDX.NA.IG index for potential trend reversals in the equity market and liquidity crunch in the debt market. This attention would help in working capital management.

1. Introduction

Credit default swaps (CDS), as a sophisticated credit derivate instrument, became considerably prominent during the Global Financial Crisis (GFC). Besides being a hedging instrument for credit risk, CDS is also utilized in measuring the extent of credit risk for an entity and country. Besides the single-name CDS, some indices utilize CDS spreads as credit risk indicators of an asset portfolio, for instance, CDX and ABX. CDS spreads can be considered as an insurance premium ratio. Therefore, assigned spreads indicate to what extent the investors might be exposed to a default or predetermined credit event.

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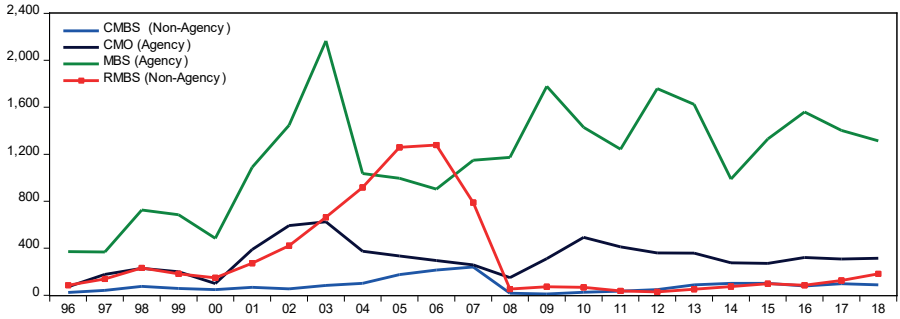
The CDX family, which consists of six different tradable indexes formed by Markit, encompasses North America and emerging markets and operates as a credit risk indicator for the corresponding reference asset portfolio. In this family, each index differs from the other in certain aspects. For example, while North American Investment Grade (CDX.NA.IG) index consists of CDS contracts of 125 corporations from North America, the North American High Yield (CDX.NA.HY) index incorporates 100 constituents that have standard pre-specified features. In case of default in one of the listed entities, the firm is dropped from the list, and the index is updated. These indices roll over every March and September concerning constituents listed in the corresponding series. The previous indexes resume trading even after rolling, although liquidity is intensified in the on-the-run series. Besides updating the index, a fixed coupon rate is determined for existing constituents, and after that, the index is actively traded (Markit, 2018). It is worth mentioning that while most of these indexes trade on the spread, there are also indexes, such as CDX.NA. HY, operates on the price.

As discussed by Bomfim (2015), another credit risk indicator is the ABX family, which Markit introduced in January 2006. The ABX family consists of various indexes, while the most prominent is the ABX.HE. The ABX-HE also has different sub-indexes that are relevant to different credit ratings. The ABX.HE exhibits the credit risk of the 20 largest residential mortgage-backed securities (RMBS), backed by the underlying subprime mortgage pool. The credit risk modeling is executed through the single-name CDS written for these RMBS. The RMBS is a securitized financial instrument and a type of asset-backed security. In this mechanism, the returns and risks of an underlying mortgage portfolio are transferred to the investors of these securitized instruments. In addition to the borrowers' monthly mortgage payments, the default risk of these packages is also transferred to the holders of RMBS, mainly pension funds, hedge funds, and mutual funds (Rhee, 2014). The turmoil in the housing market and subprime mortgage defaults hit this emerging market very hard in 2007 and 2008. Thus, the ABX.HE has rolled only four times so far, although its rolling procedure is akin to its counterpart, the CDX.NA.IG.

Although both display the extent of credit risk, the underlying asset compositions differ in ABX.HE and CDX.NA.IG. While ABX.HE index allows trading credit risk over the RMBS, the CDX.NA.IG index enables investors to trade the index for hedging and speculation purposes for a package of bond portfolios issued by investment-grade corporations. In addition to CDX.NA.IG index, the ABX.HE index was also rigorously monitored both by investors and policymakers during the GFC. However,

due to insufficient new RMBS issues, it does not enjoy its past reputation among market professionals and investors today.



CMBS: Commercial Mortgage-Backed Securities, CMO: Collateralized Mortgage Obligation, MBS: Mortgage-backed securities, RMBS: Residential Mortgage-Backed Securities

Figure 1. U.S. Mortgage-Related Securities Issuance

Figure 1 illustrates the U.S. Mortgage-Related Securities Issuance. According to the SIFMA (n.d.) (Securities Industry and Financial Markets Association), while the RMBS issuance reached a record high in 2005, it declined to a historical low along with the emergence of the GFC in 2007 and 2008. The graph shows that the sharpest decay occurs in RMBS among all issuances. Due to these developments in the mortgage-backed securities market, ABX.HE index also dropped off the radar of the media. As discussed earlier, the ABX.HE did not roll since 2008, however, according to the reported statistics by the International Swaps and Derivatives Association (ISDA), CDX.NA.IG index still has the largest market share among all other CDS indexes, with a traded notional rate of 36.7%. This statistic increased by 106.8% by the end of 2018 compared to the previous year. High liquidity in CDX indexes provides more efficient representativeness regarding the respective market events.

Considering these market developments, in the empirical section of the study, we investigate the efficiency of these two alternative credit risk indicators, ABX.HE and CDX.NA.IG. Following the determination of the index that leads the other, we employ this variable in exploring the credit risk effect on the U.S. equity market and short-term financing stress. Empirical analyses are carried out through asymmetric spillover analysis of Hatemi-J (2012) and Markov Regime-Switching regression (MRSR) analysis. In the following sections of the study, we present the respective literature and our empirical analysis findings for the relationship above.

2. Literature Review

The GFC, which emerged in the U.S. housing market, rapidly became a liquidity crisis for financial and non-financial firms in 2008 and 2009. In its second phase, European economies were also contaminated through trade channels and financial linkages. Eventually, the turmoil induced a global crisis. To date, numerous academic studies have examined the causes of the crisis. In this regard, in this study, we have focused on credit default swap indices and liquidity crunch in financial markets. Aligning with this goal, this section of the study presents the relevant literature studies that examined the housing market and liquidity challenges. In one of the early studies, Althman (2008) states that the reason behind the GFC are excess liquidity and considerably low interest rates not the collapse of the housing market. Chudik and Fratzscher (2012) examine the propagation of the liquidity crisis in global financial markets. Results indicate that the main parameters in distinguishing the extent of exposure are the countries' sovereign rating and institutions' financial vulnerability. Hodson and Quaglia (2009) state that the GFC crisis raises questions and concerns about decentralized decision-making in the European Union. Reinhart and Rogoff (2009) analyze the aftermath of the GFC and find that although the real estate market fell around 35% in six years, the collapse in equity prices was worse as the fall was 55% in three and a half years. Avgouleas (2009) suggests higher supervision in international financial markets, emphasizing the need for rigorous regulations regarding shadow banking operations and investment funds. Likewise, Agarwal et al. (2013) share their concerns about the mortgage market. They examine the impact of manipulative lending operations on mortgage default rates. Results show the significant influence of manipulative transactions over subprime default rates. Duchin et al. (2010) investigate the effect of the GFC on corporate investment decisions. They find that capital expenditures of U.S. companies declined until April 2009 following the crash in the U.S. stock market.

While the ABX index family was considered one of the early warning signs of the GFC, other Researchers also report that ABX index price developments are not always closely associated with the deteriorations in the U.S. housing market. For example, Balla et al. (2009) utilize an event study to analyze the response of the ABX index to the "teaser freezer" plan announcement of Treasury Secretary Paulson. Results indicate that the plan's effect was positive in investors' perception for the short term. To present evidence from the commercial real estate market, Driessen and Hemert (2012) explored the reaction of the CMBX index to market news announcements and found temporary overreactions in the index during the

crisis. On the other hand, Wachter (2017) discusses the failure of the ABX index during the GFC. According to the author, the index could not reflect the actual value of the reference RMBS. Dungey et al. (2008) examine the reasons behind the declining volume in mortgage-backed securities during the GFC and find that liquidity is the primary factor that affects the performance of ABX.HE index. Stanton and Wallace (2011) state that ABX.HE index underperformed during the GFC and could not display a signal for the mortgage defaults on underlying loans. Fender and Scheicher (2009) analyze the pricing mechanism of subprime mortgages through ABX.HE index and find the parameters behind the collapse of ABX.HE index were the changes in risk appetite and market liquidity crunch. They attribute this to the inappropriate pricing mechanism of the index. Fang and Lee (2011) find stronger interactions between low-rated ABX and CDS indexes than their high-rated counterparts. They also conclude that CDS indexes significantly affect the stock market. Stulz (2010) discusses the weak performance of the ABX index during the GFC. According to the author, while the index is able to incorporate the market events in its price developments, its overreactions against the market news reduce its performance. These findings may also be attributed to the efficiency of these indices, as Gunay and Shi (2016) and Procasky (2023) reported. Cohen-Cole and Sabry (2014) also refer to the same criticism by accounting for its low performance with insufficient deals. The authors state that this constraint induced limited reaction to the developments that affected the overall market. To capture market discrepancies, Imerman et al. (2018) designed information models through the ABX index, Single-name CDS and Cash RMBS. The results show that while the informed traders lead the cash RMBS market, the traders in the ABX market are irrational, and their strategies are not well-founded. Mizrach (2008) seeks the drivers behind the spikes of ABX.HE index and CME housing futures. According to the author, the spikes in the housing futures are more pronounced than the ABX.HE index and they appear to be present even before 2007. The empirical analysis of Longstaff (2010) reveals the role of liquidity and risk premium in the propagation of financial shocks to other markets. Additionally, the author reports that the ABX index governed the bond market returns during the GFC. Gorton (2009) states that the liquidity crunch that emerged in the market distorted the relationship between underlying bonds and credit derivates and induced a crash in the ABX market.

When it comes to the examination of market liquidity, TED (Treasury-EuroDollar) spread comes to the fore with its performance. As stated by González-Hermosillo and Hesse (2011), the TED spread displayed very

high pressure in the interbank market since the spring of 2009 due to the liquidity drain. Boyson et al. (2010) find evidence regarding the impact of liquidity on contagion effects. According to the authors, credit and TED spreads shocks are associated with the likelihood of contagion in the hedge fund market. Cheung et al. (2010) investigate the impact of the subprime mortgage crisis on global stock markets. Results indicate that the influence of liquidity, proxied by the TED spread, is almost 2.5 times greater than the impact of the U.S. stock market developments. More recently, Gunay (2020) also finds that liquidity is a significant element over credit risk, and TED and OIS spreads lead the CDS indexes.

3. Empirical Analysis

In the empirical section of the study, we examine the impact of credit risk on the U.S. equity market and short-term financing stress. We employ CDX.NA.IG and ABX.HE indices to proxy the extent of credit risk in the market for the most liquid investment-grade North American entities and housing market, respectively. DJIA and TED spread[2] are utilized to represent the U.S. stock market developments and short-term financing stress. The analysis period is from July 2007 to February 2013. Using this period, we aim to encompass the most stressful time interval of the GFC. The data has a daily frequency and is obtained through Thomson Reuters Eikon. Econometric tests have been conducted through Matlab, Gauss, and E-views for the following tests: Kapetanios m-Breaks unit root test, asymmetric causality analysis of Hatemi-J (2012), and Markov Regime-Switching regression (MRSR) analysis.

Table 1: Descriptive Statistics

	ABX.HE	CDX.NA.IG	DJIA	TED
Mean	-0.00021	0.000167	2.80E-06	-0.00021
Std. Dev.	0.0074	0.015346	0.006376	0.040764
Skewness	-0.05849	0.173357	-0.12846	0.484952
Kurtosis	13.44343	8.664572	10.07499	20.2242
Jarque-Bera	6385.664*	1885.486*	2934.199*	17422.81*

** indicates significance at the 1% level.*

2 TED spread is difference between the 3-month LIBOR and the 3-month Treasury bill rate.

Table 1 populates the results of descriptive statistics of the return series. As seen, the average returns are around zero and have negative values in ABX.HE and TED spread variables. According to the standard deviation statistics, TED spread and CDX.NA.IG index possesses the highest variability among the variables. Negative values of skewness statistics indicate the frequencies of above-mean returns in ABX.HE and DJIA variables are greater than that of below-mean returns. CDX.NA.IG and TED variables, on the other hand, indicate the opposite regarding the shape of their return distributions. Kurtosis statistics, which are greater than the reference number of three, illustrate the presence of fat tails in return distributions. These findings show that all variables have departures from the normal distribution. The statistically significant Jarque-Bera test statistics also verify this conclusion. Figure 1 presents the price series of the variables.

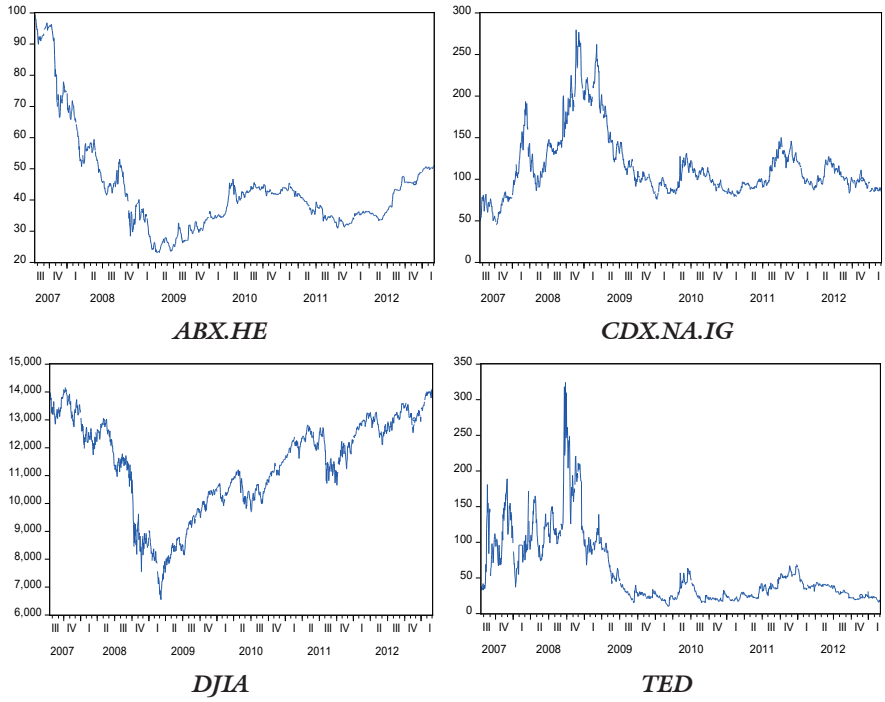


Figure 1. Price Series

The unit root test is a fundamental analysis of financial time series. As Zivot (2006) discussed, economic time series are prone to be nonstationary, meaning their mean and variance might be time-varying. The risk of spurious regression induced by the employment of nonstationary variables can be managed by de-trending procedures, namely, taking the first difference of variables. By following the methodology of Kapetanios (2005) methodology,

we employ the author's m-break unit root test, which is robust against the structural breaks in the analysis period. In the test configuration, we allow breaks of up to five at the 5% significance level. Results are presented in Table 2.

Table 2: Kapetanios m-Break Unit Root Test

Variables	ABX.HE	CDX.NA.IG	DJIA	TED
t statistic	-29.7162*	-34.0294*	-30.3897*	-28.8983*
Break Dates	17.03.2008	10.03.2008	07.01.2008	14.01.2008
	25.09.2008	20.11.2008	07.10.2008	13.01.2009
	01.04.2009	09.06.2010	09.03.2009	10.09.2009
	20.10.2009	03.10.2011	2.07.2010	10.03.2010
	03.05.2010	04.06.2012	19.08.2011	24.08.2010

** indicates significance at the 5% level.*

Before proceeding to MRSR analysis, first, we examine the interactions between the ABX.HE and CDX.NA.IG through the Hatemi-J (2012) asymmetric causality test to ascertain the index that leads the other. Referring to our prior discussion, we know that as ABX.HE index did not roll for its constituents since 2008. Theoretically, it is reasonable that this drawback may reduce the ability of this index to capture credit risk in the respective market. Stulz (2010) presents empirical evidence in this regard. The author states that ABX.HE index only capture market developments partially. Thus, we attempt to present statistical evidence regarding this argument and execute the asymmetric causality analysis for ABX.HE and CDX.NA.IG variables. Results are presented in Table 3. According to the findings, the MWALD test statistics are statistically significant only in the first and second rows, meaning CDX.NA.IG Granger causes ABX.HE both in negative and positive returns. This finding indicates the dominance of CDX.NA.IG over the ABXHE.

Table 3: Asymmetric Causality Analysis of Credit Risk Indicators

Causality Directions					Lag in VAR Model	MWALD Test statistic	CL	CV
+	CDX	→	+	ABX	2 [HJC]	9.869*	99% 95% 90%	10.741 6.682 4.852
-	CDX	→	-	ABX	2 [HJC]	8.301*	99% 95% 90%	9.585 6.062 4.351
+	ABX	→	+	CDX	2 [HJC]	0.441	99% 95% 90%	10.529 5.909 4.442
-	ABX	→	-	CDX	2 [HJC]	0.157	99% 95% 90%	10.181 6.169 4.663

** indicates significance at the 5% level. HJC represents Hatemi-J Criterion*

To further compare the roles of these two indices, we employ the asymmetric causality analysis for another variable set in which we investigate the impact of both credit risk indicators on the U.S. equity market and short-term financing stress. Table 4 accommodates the analysis results. The findings are entirely aligned with the previous observations. Accordingly, CDX.NA.IG appears to be more influential on the U.S. equity market and short-term financing stress than its counterpart, ABX.HE. Results indicate a positive (a negative) shock in CDX.NA.IG index brings about a positive (a negative) shock in TED spread. On the other hand, this effect only holds for positive returns in the equity market. The positive and negative cumulative sums of the variables used in asymmetric causality analysis are displayed in Figure 2.

Table 4: Asymmetric Causality Analysis for Equity Market and Short-Term Financing

Causality Directions					Lag in VAR Model	MWALD Test statistic	CL	CV
+	CDX	→	+	D.J.	2 [HJC]	15.257**	99%	9.503
							95%	6.350
							90%	4.859
-	CDX	→	-	D.J.	2 [HJC]	4.289	99%	13.658
							95%	9.576
							90%	7.761
+	ABX	→	+	D.J.	2 [HJC]	1.883	99%	10.515
							95%	5.857
							90%	4.590
-	ABX	→	-	D.J.	2 [HJC]	1.568	99%	13.950
							95%	9.843
							90%	7.913
+	CDX	→	+	TED	2 [HJC]	16.726**	99%	9.984
							95%	6.067
							90%	4.170
-	CDX	→	-	TED	2 [HJC]	4.842*	99%	8.025
							95%	4.201
							90%	2.655
+	ABX	→	+	TED	2 [HJC]	3.243	99%	10.789
							95%	6.518
							90%	4.678
-	ABX	→	-	TED	2 [HJC]	0.998	99%	11.429
							95%	5.909
							90%	4.506

****and**** *indicate significance at the 5% and 1% levels. HJC represents Hatemi-J Criterion*

Following the evidence obtained regarding the dominance of CDX. NA.IG over ABX.HE index both in positive and negative returns, we seek further signs concerning market regimes. As the patterns of negative and positive returns might be associated with the price developments in bull and bear markets, to account for the price changes of the U.S. equity market and short-term financing stress, we set an MRSR analysis in which CDX. NA.IG index is utilized as an explanatory variable. As a nonlinear time series model, the MRSR analysis contains multiple equations to identify the development of asset prices in different regimes. Switching between these equations allows the model to capture even complex dynamic patterns. The switching mechanism is governed by a Markov process (Hamilton, 2013; Kuan, 2002).

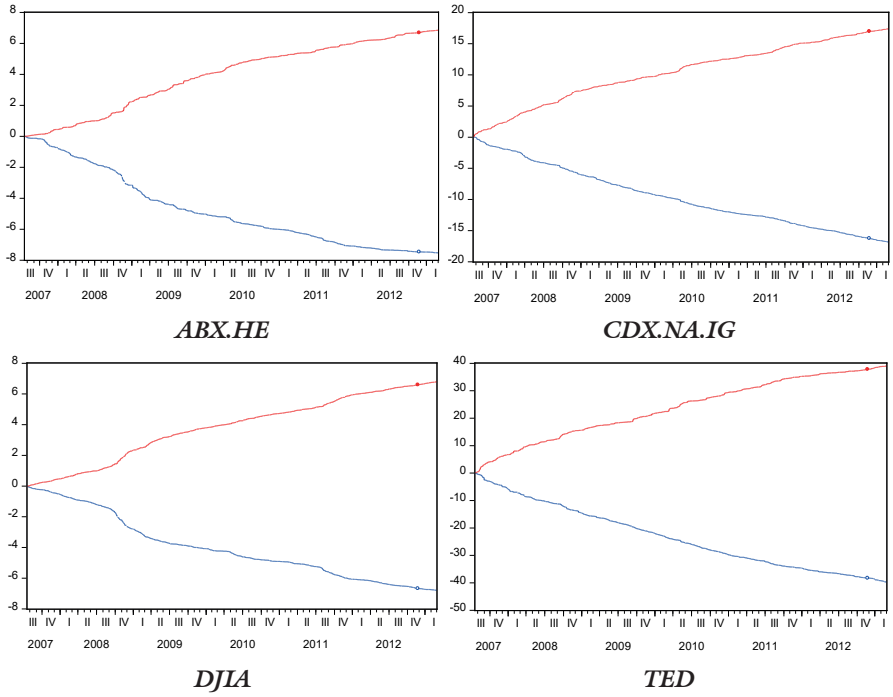


Figure 2. Positive and Negative Cumulative Sums

Besides the nonlinear MRSR analysis, we also present the results of the linear regression model in Table 5. We use a graphical demonstration to identify the regimes in which regime probabilities are plotted along with the corresponding price series. According to the estimated transition probabilities, regime one and regime two display the features of expansionary and contractionary periods, respectively, in the model of the U.S. equity market. The coefficients obtained for CDX.NA.IG variable shows that under each regime, escalations in credit risk reduce the returns of the DJIA. On the other hand, the declines in the returns of the DJIA index appear to be greater in the contractionary period, which aligns with our theoretical expectations.

Table 5: MRSR Analysis Results

Models	Variable	DJIA	TED SPREAD
Linear model	c	0.00005 (0.00012)	-0.00026 (0.00108)
	CDX.NA.IG	-0.27256* (0.00837)	0.30056* (0.07046)
MRSR Regime One	c	0.00017 (0.00012)	0.00007 (0.00124)
	CDX.NA.IG	-0.19835* (0.00866)	0.05228* (0.07908)
MRSR Regime Two	c	0.00015 (0.00033)	-0.00555 (0.01037)
	CDX.NA.IG	-0.66794* (0.02664)	2.49352* (0.32810)
Model Statistics	-2lln	5,675	2,529
	AIC	-8.07	-3.59
	HQ	-8.06	-3.58
Expected Duration	Regime One	53 days	40 days
	Regime Two	11 days	3 days

** indicates significance at the 1% level.*

The models for the TED spread show that the credit risk variable (CDX.NA.IG) possesses a positive coefficient under the linear and nonlinear equations. Accordingly, we conclude that rising credit risk brings about a growing TED spread, thus, inflating the short-term financing stress in the U.S. economy. This impact is significantly greater in regime two. It should be noted that unlike the model of DJIA, regime one and regime two refer to the contractionary and expansionary cycles, respectively. Here the expansionary regime is associated with cycles of market turbulence as the soaring TED spreads occur in worsened market conditions, such as periods of liquidity crunches. The coefficient of 2.49 indicates that in an expansionary regime, the impact of credit risk on short-term financing stress becomes considerably severe and more pronounced than that of a contractionary regime. Escalated stress in short-term financing may indicate an evaporated trust among financial institutions. Our empirical findings verify that the U.S. market developments occurred during GFC. Accordingly, we conclude

that worsened market conditions and soaring credit risks induce dramatic expansions in the TED spread. As discussed by Brunnermeier (2009), during periods of market turbulence and economic downturn, increasing demand for risk-free treasury assets, which yields higher prices and lower interest rates, and soaring LIBOR rates due to the panic among financial institutions catalyze the deterioration in short-term financing, thus, brings about a growing TED spread. Finally, expected durations of regimes do not have a significant difference in DJIA and TED models. In both cases, regime one is longer than regime two. Thus, we can conclude that the expansionary regime (in the DJIA model) and contractionary regime (in the TED Spread model) have longer cycles than their counterpart.

4. Conclusion

Credit risk indices associated with the CDS spread are critical indicators for various markets and asset classes. The market developments during the GFC and European debt crisis clearly showed this fact. In the empirical section of the study, we examine the impact of two credit risk indicators (ABX.HE and CDX.NA.IG) on the U.S. equity market and short-term financing stress. We use the Dow Jones Industrial Average (DJIA) index to represent the U.S. equity market. The short-term financing stress is proxied by the TED spread, which is difference between the 3-month LIBOR and the 3-month U.S. Treasury bill rate. To determine the more appropriate variable in proxying the perceived credit risk in the market, we first execute a causality analysis between these two indicators. Results reveal the dominance of CDX.NA.IG over ABX.HE index both in negative and positive return components. Considering this observation, in investigating the impact of credit risk on the equity market and short-term financing stress, we utilize CDX.NA.IG index to represent perceived credit risk in the market. Results show that the CDX.NA.IG index has a significant role in causing the TED spread's negative and positive returns. Regarding the second variable, the U.S. equity market, we only observe Granger causality from positive returns of CDX.NA.IG to positive returns of DJIA index. As the negative and positive return components are associated with the expansionary and contractionary market phases, in the following section of the study, we employed a Markov Regime-Switching regression analysis in which the credit risk indicator, CDX.NA.IG, accounts for the U.S. equity market and short-term financing stress. The results obtained align with our theoretical expectations. We find that credit risk is a significant element for both variables. The model, which investigates this relationship for the U.S. equity market, shows that credit risk has a negative impact on the DJIA index in both regimes. This finding means

that increasing credit risk in expansionary and contractionary cycles reduces the returns in the U.S. equity market. This effect becomes more pronounced in the contractionary regime, with a coefficient three times greater than that of the expansionary regime. The second model that explores the same effect on short-term financing stress reveals that CDX.NA.IG variables' impact on TED is positive. Namely, increasing Credit Default Swap spreads escalate short-term financing stress in the U.S. economy. This effect becomes substantially more apparent in the expansionary regime, which is relevant to the market turbulence cycles. Our results suggest that as a credit risk proxy CDX.NA.IG index is a critical indicator in signaling changes in the U.S. equity market and short-term financing stress. Thus, CDX.NA.IG index can be considered an early warning sign, especially for periods of potential trend reversals in the equity market and liquidity crunches in the debt market. Attention to this index might help in the working capital management.

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