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FRA-CDS-VDAX based Credit Crash Model: A German Conundrum

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Abstract: Often credit crash opens up the glaring research warts in finding credit pits. Robust German credit and interest rate derivative market have been under scrutiny to develop credit crash predictor by effective utilisation of a cobbled methodology encompassing various research tools (such as econometric, mathematical and machine-learning etc.) and the logical trio, namely forward rate agreement (FRA), credit default swap (CDS) and volatility index constructed on CBOE methodology (VDAX). Though setting up VDAX predictor is the first objective, yet the cross-dependence of various derivatives, threshold finding for sudden change (steep) in VDAX and linking the results with real life events remain the secondary objectives. The results point out a clear threshold for detecting credit pit and a prominent behavioural trace as well.

Keywords: CDS, FRA, VDAX, Neural Network, Credit Pits, Comonotonicity

JEL Classification Code: G15

INTRODUCTION

When the global economy is standing at the cross-roads of self-contradictions (whether the eventuality of crisis could be predicted or not) and queer situational conditionality (BREXIT, GREXIT, Syria migration etc.), need of the hour is to safe guard the existing economies before eventual derailment. During the detailed study of several literatures, it has been found that most of the works are directed towards cross-correlations of the various complex financial instruments, such as interest rate swaps (IRS), credit default swap (CDS) and forward rate agreement (FRA). Apart from that individual predictions too took place in many a works of eminence. However country specific credit triggers or thresholds were set by only a few works. An Italian econophysicist worked on (M. Bianchetti, 2011) Euribor and Overnight Indexed Swap (OIS) during the global credit fiasco and found that around September 2008 (during Lehman collapse) both Euribor and OIS suddenly diverged, as if some kind of external force have been implied. They found this queer phenomenon quite similar to Zeeman Effect of Physics (where atomic spectral lines split into groups, in the presence of magnetic field). They termed it as "Libor Spectroscopy", where crisis plays the similar role as magnetic field and separates Euribor and OIS. In an extension of this work(Marco Bianchetti & Carlicchi, 2012) provided an explanation of such divergence. The wrong pricing method (classical one, using single yield curve) paved the route for such sudden divergence in September 2008 resulting the chaos. They used the concept of credit support annex (CSA), a bilateral default risk mitigating guarantee followed by the construction of CSA discounting curve using OIS, serving as an efficient proxy of the risk free rate.

An eminent researcher has proven that the "Libor Spectroscopy", or sudden explosion or divergence of OIS and Euribor may be explained within a plausible credit model considering a risky zero coupon bond and a default-free zero coupon bond floated by a vulnerable counterparty (Mercurio, 2009, 2010). US CDS spreads were linked with equity market factors such as DJIA, SP500 and VIX as proxies and credit alert triggers (Gatfaoui, 2017) were set in an innovative study. In a decade long study from 2004 to 2014, a group of researchers(Hkiri, Besma, Hammoudehb, 2016) have found that co-movement of time and frequency in financial sector CDS holds the key, and during the global credit crisis in 2008, the frequency has been observed to take a sudden sharp rise. Most of the studies conducted so far have assumed the CDS spread movements or FRA movements are linear in nature, which itself is under a question mark. One descriptive attempt in late 2011, however(Lindquist, 2011) showed that to hedge a convex interest rate swap (IRS) by a dynamic hedge could be less accurate compared to a static hedge. In the current study, the credit pit trigger is a static point, rather than a dynamic zone to make the calculations more accurate. In real most fluctuations are found to be non-linear.

RESEARCH METHODOLOGY

This innovative work has been conducted in four phases. The phases are an innovative mixture of econometrics, machine learning, applied mathematics and behavioural finance. CBOE Volatility index for Germany (VDAX) and many tradable CDS spread, FRA spread, GSEC forward (FWDGSEC), Inflation Swap spread (IfSwap) andvanilla Swapspread (SWAP) has been Granger caused to observe the link in between during the first phase of work. Neural network has been implemented to device a predictor model of future VDAX using the other derivatives (as mentioned above) as independent variables. The next step has been dedicated for finding the credit pits. Regardless of the situation, FRA spread act as an indicator of future interest rates, thus causing the CDS spread to change. Effect of sudden change of CDS spread increases the volatility factor. Hence change of VDAX (dv/dt), along with change of CDS spread (dc/dt) and FRA spread (df/dt) are plotted together to identify the credit pits. Behavioural links have been established with the dates of past credit pits. CDS 12 spread (12 month tenure) and FRA 14 (14 month tenure) is considered as were found to enjoy higher correlations over longer period of time. This work will be able to predict the future value of VDAX with the other allied derivatives, thus the change of VDAX i. e. dv/dt could be calculated and matched with the threshold found in the study.

Variable details

CDS spread - Credit Default Swap acts as insurance in the event of credit default.

FRA spread - A series of interest rate swaps (IRS) construct a Forward Rate Agreement (FRA). Traders observe FRA and on the basis of that CDS premium gets amended.

GSEC Forward- 10 Year GILT of any country serves as a barometer of its risk free rate. The forward of such an instrument indicates towards the future risk free rates.

Inflation Swap Spread- In an inflation swap, fixed rate on a notional principal amount is paid by one party, while a floating rate linked to an inflation index, is paid by the other party. When the spread goes up, it indicates uncertainty over inflation in coming days.

Vanilla Swap Spread-This represents an interest rate swap with a floating interest ratethat is exchanged for a fixed rate. This could also be the other way as well.

VDAX- Similar to CBOE VIX in the US, VDAX serves the same purpose in Germany. VDAX has been constructed by the same mechanism as well.

METHODS

Granger Causality

Granger causality is a prediction based statistical causality method. As per Granger causality, if a stochastic time series X1 "Granger-causes" (or "G-causes") anotherstochastic time series X2, then historical dataset of X1 herald X2 apart from the information embedded in historical dataset of X2 alone. The mathematical formulation however is backed by linear regression modelling of stochastic processes (Granger, 1969).

$$x_1(t) = \sum_{j=1}^{p} A_{11,j}\, x_1(t-j) + \sum_{j=1}^{p} A_{12,j}\, x_2(t-j) + E_1(t) \tag{1}$$

$$x_2(t) = \sum_{j=1}^{p} A_{21,j}\, x_1(t-j) + \sum_{j=1}^{p} A_{22,j}\, x_2(t-j) + E_2(t) \tag{2}$$

Where p is the model order i. e. maximum number of lagged observations embedded in the model. A is a matrix that contains the weightages of the model (the impact of each lagged observation to respective predicted values of X1(t) and X2(t). E1 and E2 are residuals (prediction errors) for respective stochastic time series. In the likely event of the variance of E1 is reduced by the inclusion of the X2 terms in the first equation, it is stated that X2 Granger-(G) -causes X1.

Neural Network

Artificial neural network (ANN) is a replica of the biological nervous system found in human beings. It is complex in nature, overlapping in structures, moves in two or more directions and most importantly improves efficiency over a period of time. Large numbers of interconnected processing entities are present forming layers and loops. They are termed as perceptrons or neurons. Like human being ANN to learn by example, thus become efficient over time. However the memory being artificial, data loss is seldom found. ANN can efficiently perform data classification, pattern recognition and prediction as well. Neurons receive signals; they process the signal and forward it front. Similar to human brain, the functional aspects classify neuron processing into two broad categories. The first category is the learning one whereas the second one is the taught one. Neurons learn to fire signals post processing in the very first mode. In the second mode, they try to identify the input with a reference to their existing learning memory. If, its already stored, they fire accordingly, else they themselves identify the function. If that function is wrong then the information comes back as back-propagation and gets auto-corrected. This feedback mechanism takes neural networks to a position of power and efficiency. These mechanisms are dynamic in nature, and loops start operating till an equilibrium point is reached. This equilibrium is temporary as neural network adopts itself with external inputs and searches for equilibrium on a continuous basis.

In this piece of studythe network structure is [28, 56, 84, 1], where the first layer of 28 input neurons indicate that we are considering 28 input variables. The two middle layers are found as auto-adjustments post the running of the loop for more than 2000 times. The last layer signifies the VDAX (target variable) prediction values. Learning rate in this study is about 0. 5.

First order differential

In this work, x and y are real numbersagain y is a definite function of x. IN simple terms this generate definite values of y for each x. This specific relationship is denoted as y = f(x). Let's say that f(x) represents a linear equation, thus there are two real numbers "m" and" b"so that y can be denoted as y = mx + b. Here, term "m" is called the slope and denoted by

$$m = \frac{Change\ in\ y}{Change\ in\ x} = \frac{\Delta y}{\Delta x} \tag{3}$$

In this case the symbol (Greek letter Delta) is an abbreviation for "change". Hence it will be $\Delta y = m\,\Delta x$. A general function is not a line, so it does not have a slope.

RESULTS AND DISCUSSIONS

Table 1.0
Significant results of Granger Causality between VDAX, CDS12 spread,CDS24 spread,CDS36 spread, CDS48 spread, IfSwap12 spread, IfSwap 24 spread, IfSwap 36 spread, IfSwap 60 spread, IfSwap 120 spread, IfSwap 240 spread, FRA 14 spread, FRA 15 spread, Swap 3 spread, Swap 12 spread, Swap 300 spread and FWDGSEC for a period of 7th May 2015 to 6th April 2017

Accepted Alt Hypothesis	*F-Statistics*	*Occurrence*
IFSWAP24 Granger Cause IFSWAP60	3266.44	100%
FRA15 Granger Cause SWAP12	15.3511	100%
FRA14 Granger Cause SWAP12	14.899	100%
IFSWAP120 Granger Cause IFSWAP60	13.688	100%
FRA14 Granger Cause SWAP3	13.240	100%
FRA15 Granger Cause SWAP3	11.1665	100%
IFSWAP36 Granger Cause IFSWAP24	10.3163	100%
SWAP300 Granger Cause IFSWAP60	9.52549	100%
IFSWAP120 Granger Cause IFSWAP36	9.01747	100%
IFSWAP36 Granger Cause IFSWAP60	8.59749	100%
IFSWAP240 Granger Cause IFSWAP36	7.70536	100%
IFSWAP120 Granger Cause IFSWAP24	7.2698	100%
SWAP300 Granger Cause IFSWAP24	6.5948	100%
IFSWAP240 Granger Cause IFSWAP60	6.0099	100%
IFSWAP240 Granger Cause IFSWAP120	5.0954	99.99%

There has been one set pattern, which could be found as far as the granger causing is concerned. Sometimes, short term swaps are granger causing the longer ones and sometimes the reverse is happening. Out of 15 significant relationships (with 100% occurrence, zero p-value) it has been found that 87% times the long term FRA spread and SWAP spread is the driver and the short term counterpart plays the part of driven.

Table 1.1
Prediction for future volatility (VDAX) by neural network with network structure is [28, 56, 84, 1] along with measures of robustness

Goodness of fit measures		
Post processed Result	*Model Fit*	*Predictions*
Mean Absolute Error (MAE)	1.80747	1.98781
Root Mean Square Error (RMSE)	2.49422	2.66194
R^2	0.778	0.7453

The model seemed quite robust with significant value of R^2 and minimal values of RMSE and MAE.

VDAX Predictor model

VDAX = 132619 + SWAP3^2*686. 973 + IfSwap12*”CDS12, cubert”*10. 1869 + IfSwap240*”CDS48, cubert”*48. 5198 + FRA15*SWAP12*1960. 19 + “FRA15, cubert”^2*20. 8874 + CDS48*”SWAP12, cubert”*22. 4223 + IfSwap240*”CDS36, cubert”*(-12. 0078) + CDS36*”SWAP12, cubert”*(-44. 8523) + FRA14*SWAP12*(-1288. 36) + CDS48*SWAP12*(-31. 9889) + FRA15*SWAP3*(-943. 289) + SWAP3*”CDS48, cubert”*61. 7266 + IfSwap12*FRA14*(-46. 7467) + CDS36^2*(-0. 37379) + CDS36*FRA14*92. 2649 + SWAP3*”SWAP3, cubert”*(-335. 47) + CDS48*FRA14*(-59. 0458) + CDS48*IfSwap12*(-2. 75551) + “SWAP3, cubert”^2*50. 8511 + “CDS48, cubert”*”SWAP12, cubert”*(-18. 1729) + IfSwap240*”SWAP12, cubert”*1845. 55 + “IfSwap240, cubert”*”SWAP12, cubert”*(-8729. 18) + “SWAP12, cubert”*7150. 1 + IfSwap240*”CDS12, cubert”*(-16. 1474) + CDS12*SWAP3*(-25. 9993) + CDS12*”SWAP3, cubert”*(-4. 84693) + SWAP12*”CDS24, cubert”*196. 46 + FRA14^2*604. 143 + FRA15*”FRA14, cubert”*(-178. 851) + “IfSwap240, cubert”*(-250443) + IfSwap240^2*12904. 5 + “FRA14, cubert”*24. 444 + IfSwap240*SWAP12*(-60. 562) + SWAP3*”FRA15, cubert”*86. 2528 + “CDS36, cubert”*”SWAP12, cubert”*129. 432 + CDS36*SWAP12*19. 6023 + IfSwap12*”FRA14, cubert”*(-11. 8056) + IfSwap240*”IfSwap240, cubert”*(-154053) + IfSwap240*259709 + “IfSwap12, cubert”*”IfSwap240, cubert”*2. 21496 + CDS12*”FRA15, cubert”*2. 16302 + CDS24*IfSwap240*(-0. 545188) + SWAP12^2*(-92. 2168)

Table 1. 2. 1

Correlations between dc/dt and df/dt	-0. 066114834
Correlations between dc/dt and dv/dt	-0. 035609493
Correlations between df/dt and dv/dt	-0. 088994354

Table 1.2.2

Correlations between CDS spread and FRAspread-0. 658849749
Correlations between CDSspread and VDAX-0. 553423653
Correlations between FRAspread and VDAX0. 451017611

Interesting to note that, correlations between variables (CDS spread, FRA spreadand VDAX) are medium however correlations between changes in them are insignificant. CDS and FRA spreads follow inverse relationship. CDS spreadand VDAX too follow inverse relationship. Hence, when volatility increases CDS spread diminishes. In this case the context plays the role. In the expectation of good news at the anvil, market grows. Valuations are stretched by hope among the participants. Sharp rise of market takes VDAX to higher zones. It could be termed as positive volatility. In such condition uncertainty over the market decays quite fast. These results in lowering of CDS spread rapidly. Following this very premise, whenever CDS spread and VDAX correlation goes significantly negative, bourse is expected to experience an unprecedented bull rally for a significant length of time. German bourse DAX,formerly known as Deutscher Aktien Index 30, gained over 4% in an absolute basis in two months (April and May 2017). Furthermore taking a one year view, it has been found that DAX gained more than 35% in an absolute basis. Again, from May 2016 to April 2017, the correlation between CDS spread and VDAX is -0. 55, however from May 2016 to February 2017, the correlation between CDS spread and VDAX is -0. 25. Hence, February 2017 onwards the movement should ideally be sharp. In reality, DAX gained 6. 7% in an absolute basis in nearly 4 months.

It has been observed that change of FRA (df/dt) with time (equal intervals, as the observation is daily) if shows sudden hike, the change of CDS (dc/dt) with time (equal intervals, as the observation is daily) too follows as the CDS spread increases in the fear of uncertainty. Change of volatility index (dv/dt) or VDAX (equal intervals, as the observation is daily) thus takes a sharp move. It has been found that out

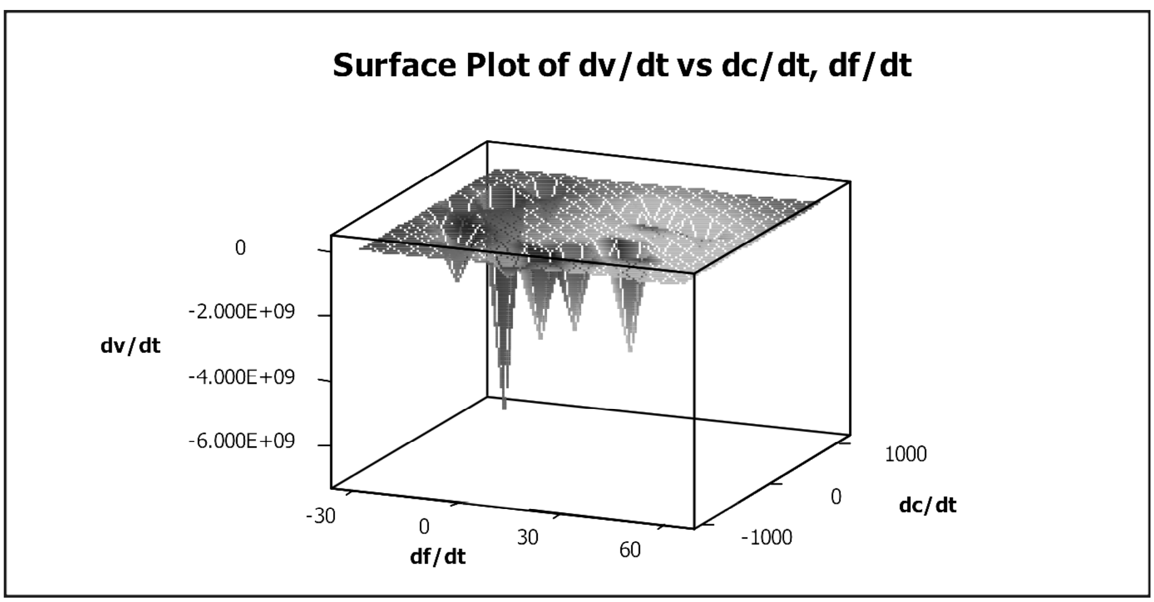

Diagram 1.0: Crash Predictor diagram identifying several Credit Pits

of 491 observations 13 observations of dv/dt are below -1500 zones, qualifying for those prominent credit pits. This is about 2. 6% times in this zone of global turmoil, including BREXIT and Greek Bailout saga. Those 13 observations could be linked to some major events in EU zone and across the globe (reference Table 1. 3). Hence, German bourses are picking out, and this could signal the beginning of credit fallout.

Regardless of the dates, if we observe those 13 days, we found dv/dt and df/dt are inversely correlated and the correlation is medium to strong in nature (-66%). Hence we can conclude that change of FRA (which is a series of interest rate swaps) holds the key for change of volatility index. In each of these cases the absolute value of df/dt was found to be from 0. 5 to 13. 7.

Table 1.3
Past Credit Pit Timeline, generated from our model threshold (dv/dt < -1500)

Dates	*Events*
22-Jun-15	Greece announces a referendum on bailout agreement
13-Jul-15	Greece and EU creditors finalise deal for 86 billion euros bailout for three years
25-Aug-15	Greek Prime Minister Alexi Tsipras resigns
27-Aug-15	Greece opts for a caretaker PM in Vassiliki Thanou
3-Sep-15	Migrant issue becomes serious as EU follow UN principle of "non-refoulement"
19-Jan-16	German industrial production growth has crashed to zero per cent
22-Jan-16	Greek credit rating has been upgraded by S&P's to B"
17-Feb-16	Schengen Agreement modification due to large migrant-influx
11-Mar-16	'German Geopolitics' on the Syrian Migration issue
20-Jun-16	New SME-financing pact signed between Germany and Croatia
23-Jun-16	Polling day for the EU referendum for BREXIT
28-Jun-16	Purdah (final four weeks) started on EU referendum on BREXIT
9-Nov-16	Donald Trump became President-elect post US elections

CONCLUDING REMARKS

Germany has plenty of investments in Greece, so German Bond's yield went up during the phase of Greek crisis in a sudden jerk. Couple of years post the infamous credit fiasco in the US, German financial institutions were reported to have an exposure of around 28 billion euros (Dealbook, 2010) in Greek Bonds. Close to half of that Greek GSECwas declared junk by S&P around the fall of 2009. This significant direct exposure to Greek debt forced the intrinsically strong economy like Germany to develop credit pits. Long term spread was found to be strong indicator (reference Table 1.0) instead of short term spread. This works quite similar to the bond yield curve, where long term yields hold the key. Another proxy could possibly be insurance as demand for long term risk taking is higher compared to demand for short term risk taking. Hence, long term risk swap enjoy considerably higher spread over its short term counterpart.

We observed definite herd behaviour (reference Table 1.3) as majority of the market participants are following FRA movements, and surprisingly not so much CDS movements and VDAX experience certain sudden steep downfall. Regardless of the mechanism of prediction and zone definition herd takes over in extreme eco-political circumstances (here it's about 2.6% of the total observations). This finds a strange resemblance in comonotonicity, where random variables move in a secular way for a defined period of time. Hence capturing the comonotonicity gap (Laurence, 2008) by herd behaviour holds the key. Incidentally herd behaviour detection (Linders, Dhaene, & Schoutens, 2015) has been predominantly successful in CBOE VIX methodology. This work echoes the current attempt.

REFERENCES

Bianchetti, M. (2011), The Zeeman Effect in Finance. *SSRN Working Paper, 2011*. Retrieved from http://ssrn. com/abstract=1951578.

Bianchetti, M., & Carlicchi, M. (2012), Markets Evolution after the Credit Crunch. *SSRN Electronic Journal*, (SSRN). https://doi. org/10. 2139/ssrn. 2190138.

Dealbook. (2010), German Banks Have Big Investment in Greece. *The New York Times*. New York, USA.

Gatfaoui, H. (2017), Equity market information and credit risk signaling/: A quantile. *Economic Modelling*, *64*(September 2016), 48–59. https://doi. org/10. 1016/j. econmod. 2017.03.012.

Granger, C. W. J. (1969), Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*, 424–438.

Hkiri, Besma, Hammoudehb, S. and C. A. H. (2016), Strength of co-movement between sector CDS indexes and relationship with major economic and financial variables over time and . . . Strength of co-movement between sector CDS indexes and relationship with major economic. *Economics, Applied*, (May), 1–20. https://doi. org/10. 1080/00036846. 2016. 1161723

Laurence, P. (2008), A new tool for correlation risk management: The market implied comonotonicity gap. Paris: Global Derivatives, Paris, Invited Talk, May 2008.

Linders, D., Dhaene, J., & Schoutens, W. (2015), Option prices and model-free measurement of implied herd behavior in stock markets. *International Journal of Financial Engineering*, *2*(2), 1550012–35. https://doi. org/10.1142/S2424786315500127.

Lindquist, M. (2011), *An investigation of the price setting of illiquid interest rates swaps and the perfect hedging portfolios*. KTH, VETENSKAP OCH KONST.

Mercurio, F. (2009), "Interest Rates and The Credit Crunch: New Formulas and Market Models." *SSRN Working Paper, 2009*.

Mercurio, F. (2010), "Modern Libor Market Models: Using Different Curves for Projecting Rates and for Discounting. " *International Journal of Theoretical and Applied Finance*, *13*(1), 113–137.