Spread, ratings, default probability and all that /

Assessment of banking sector issuers' creditworthiness

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Executive summary

Introduction

- Assessment of CDS spread (senior) and rating for financial institutions using neural networks

- Exploiting different information sources from heterogeneous inputs:
  - Fundamental data from financial statements, specific for each issuer included in the analysis
  - Macroeconomic variables representative of the economic support guaranteed by the country in which issuers are based
  - Market data, proxies for the rationale underlying the market esteem of the creditworthiness of each individual issuer

- In-sample calibration of the model via supervised learning and its validation through an out-of-sample prediction

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Executive summary

CDS - Possible fields of application

- Risk management: Assessment of the creditworthiness for non-quoted issuers with the purpose of managing and hedging credit risk carried by private and institutional portfolios

- Pricing securities: Fair evaluation of credit spread for non quoted debt instruments on the primary and secondary market

- Scenario analysis: Generation of future macroeconomic scenarios

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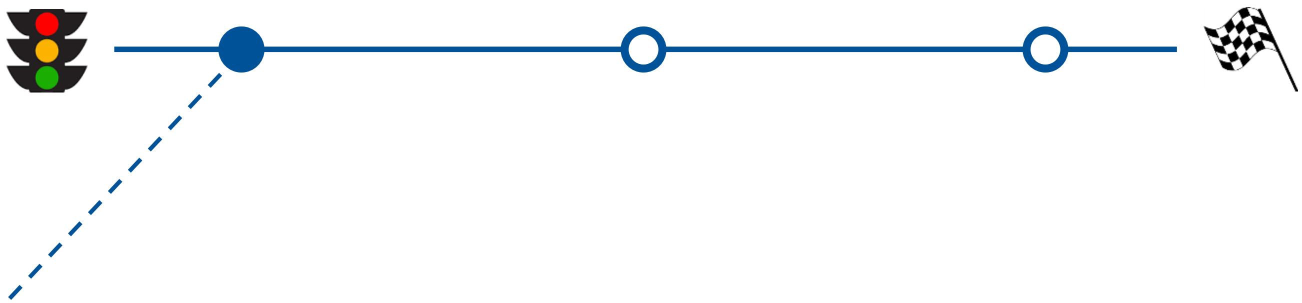
Dataset

Construction - steps followed (1/3)

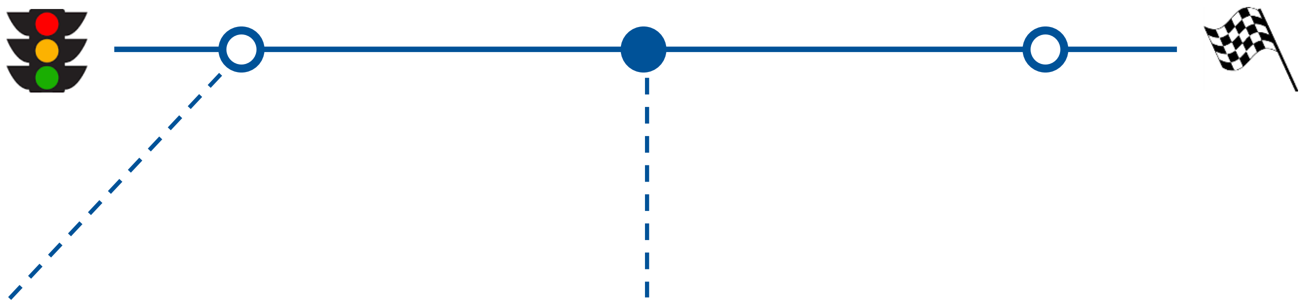


Panel data synchronization

Managing the different frequencies of the variables

Dataset

Construction - steps followed (2/3)



Panel data synchronization

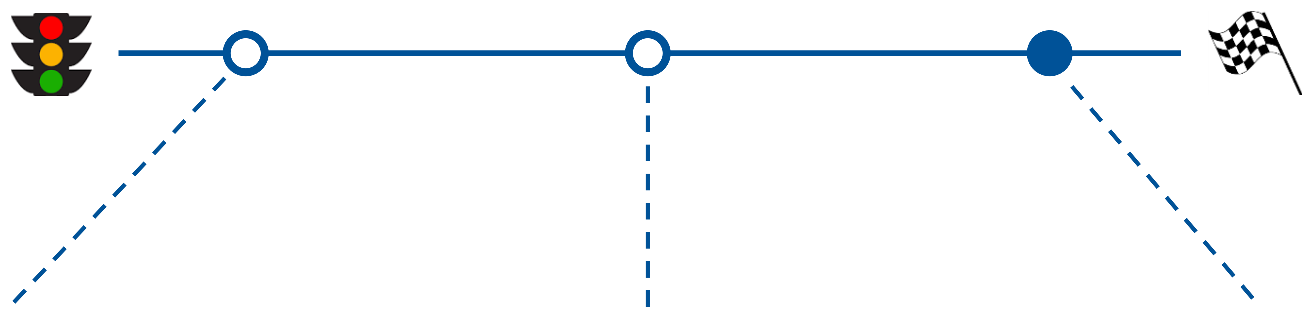
Managing the different frequencies of the variables

Regressor selection

Parametrization of the regressors to be used as input of the model

Dataset

Construction - steps followed (3/3)



Panel data synchronization

Managing the different frequencies of the variables

Regressor selection

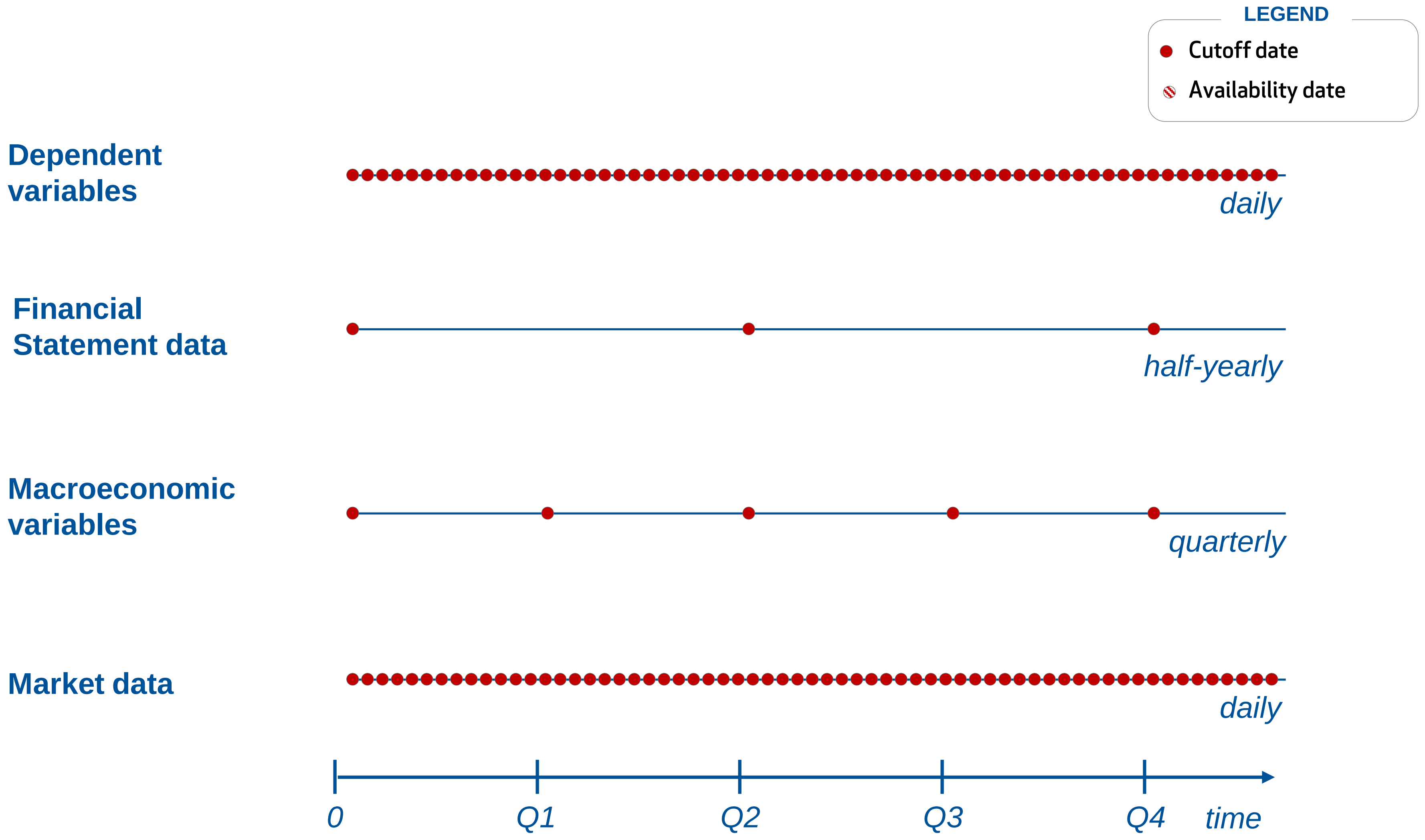
Parametrization of the regressors to be used as input of the model

Issuers selection

Selection of the issuers to be included in the analysis

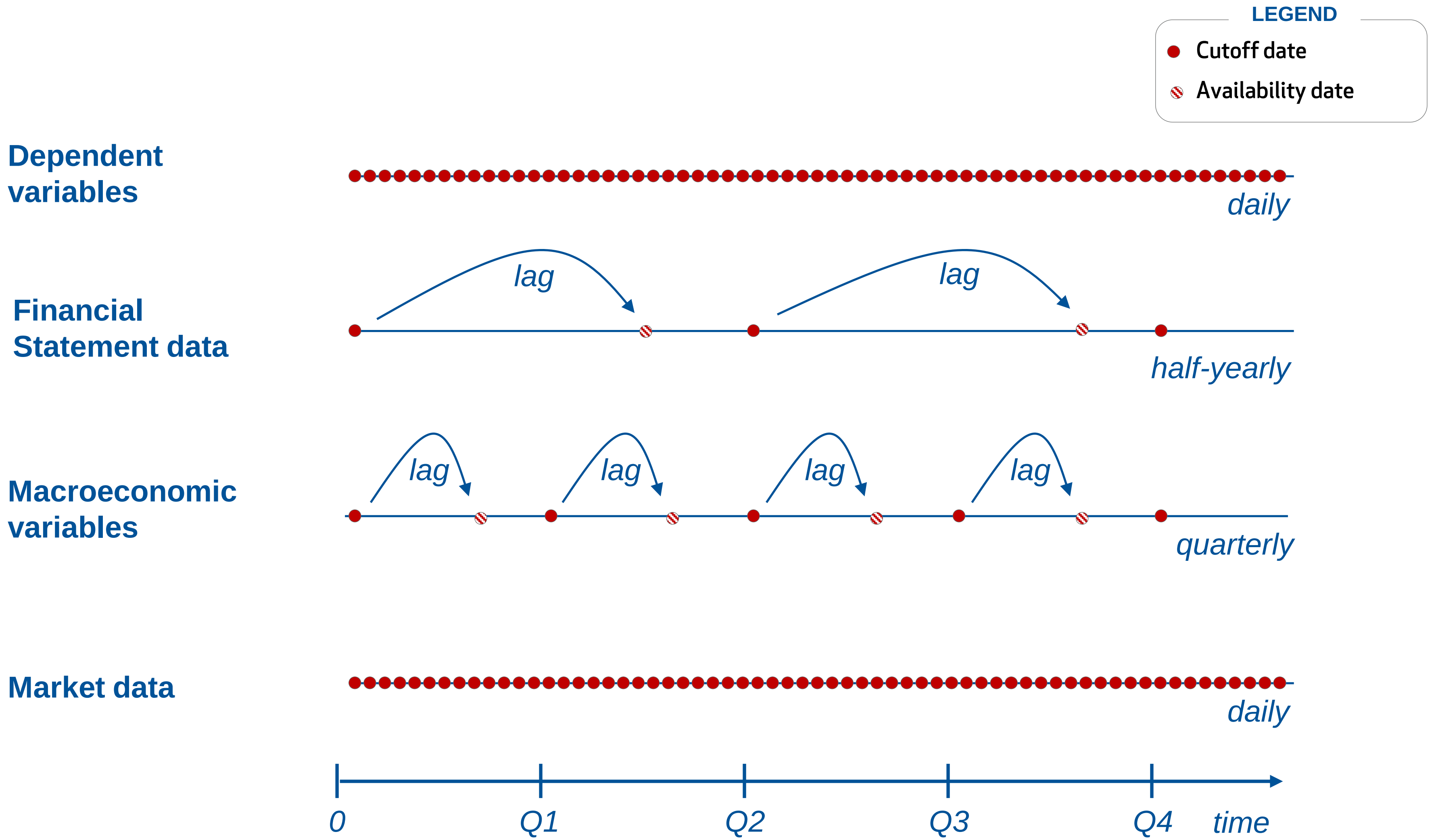
Panel Data Synchronization

Different frequencies (1/2)



Panel Data Synchronization

Different frequencies (2/2)



Panel Data Synchronization

Dataset structure (1/4)

Data frequency	quarterly
Time window	Dec 2011 – Dec 2016
Dependent variables	
CDS	reference quarter average
Rating	last observation over the reference quarter
Independent variables	
Financial statement	last published value
Macroeconomic	last published value
Market	reference quarter average

The datasets are built to estimate:

- The average CDS spread over the reference quarter
- The exact rating at the end of the reference quarter

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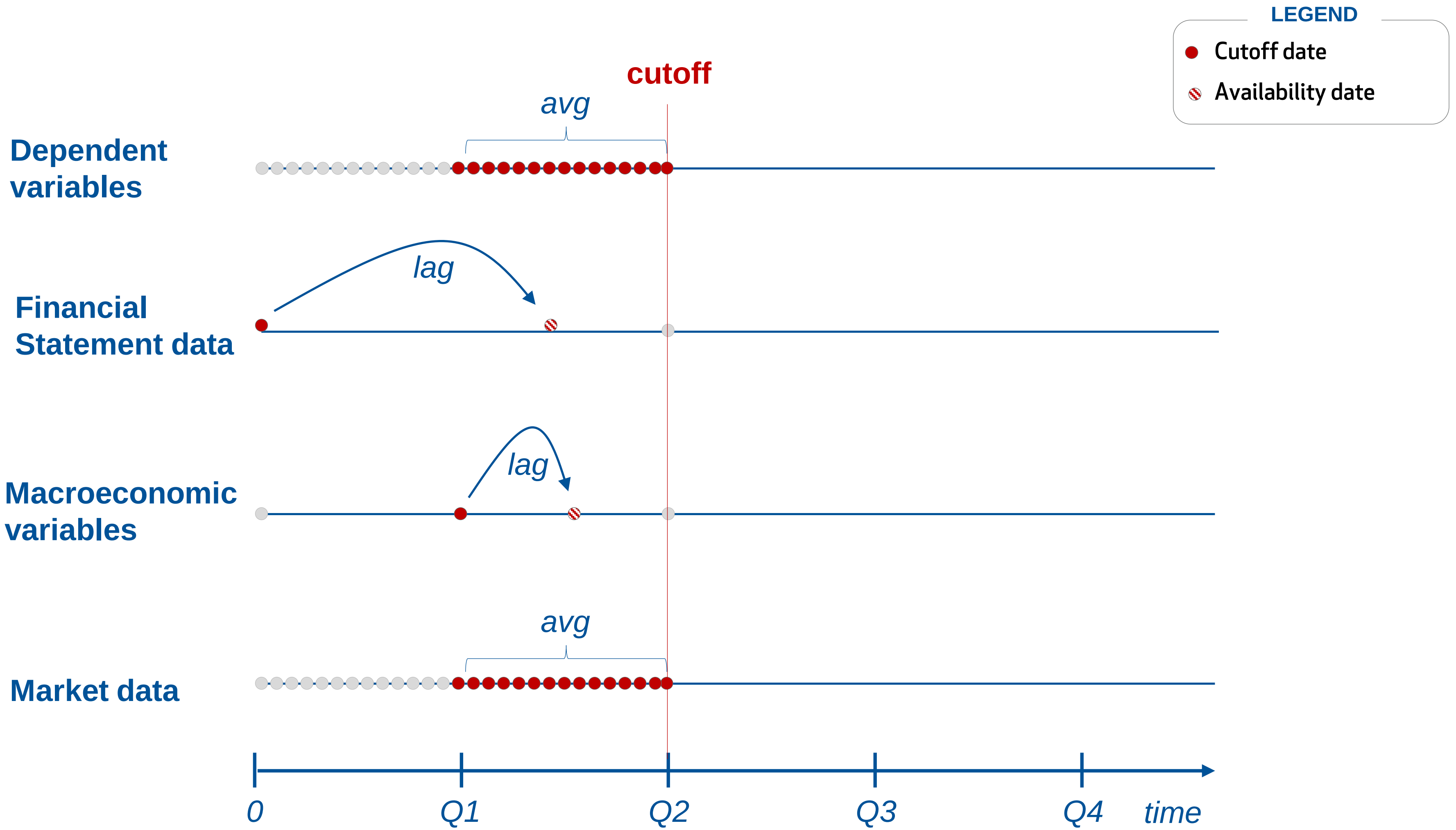
Panel Data Synchronization

Dataset structure (2/4)

PANEL STRUCTURE



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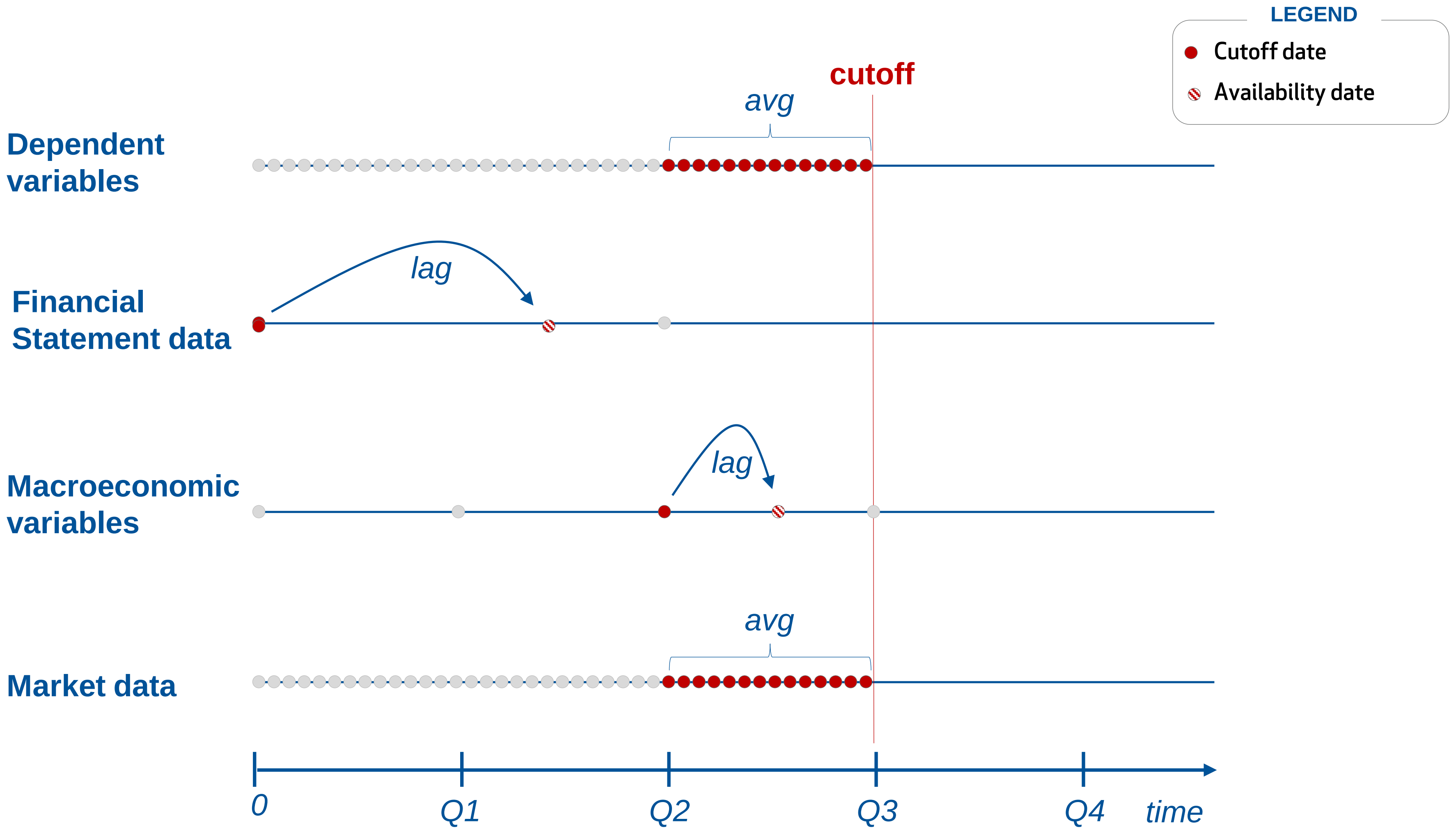
Panel Data Synchronization

Dataset structure (3/4)



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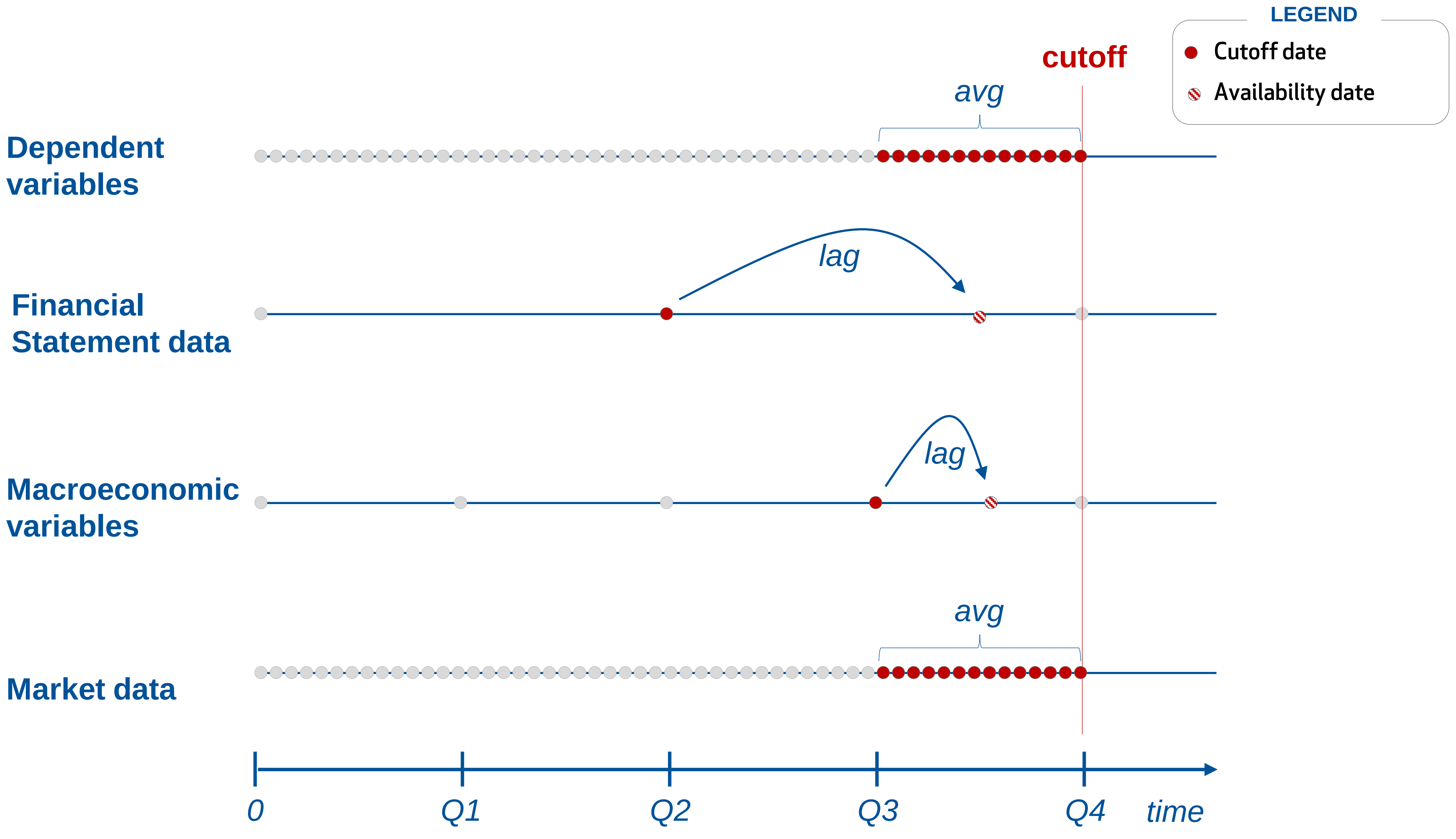
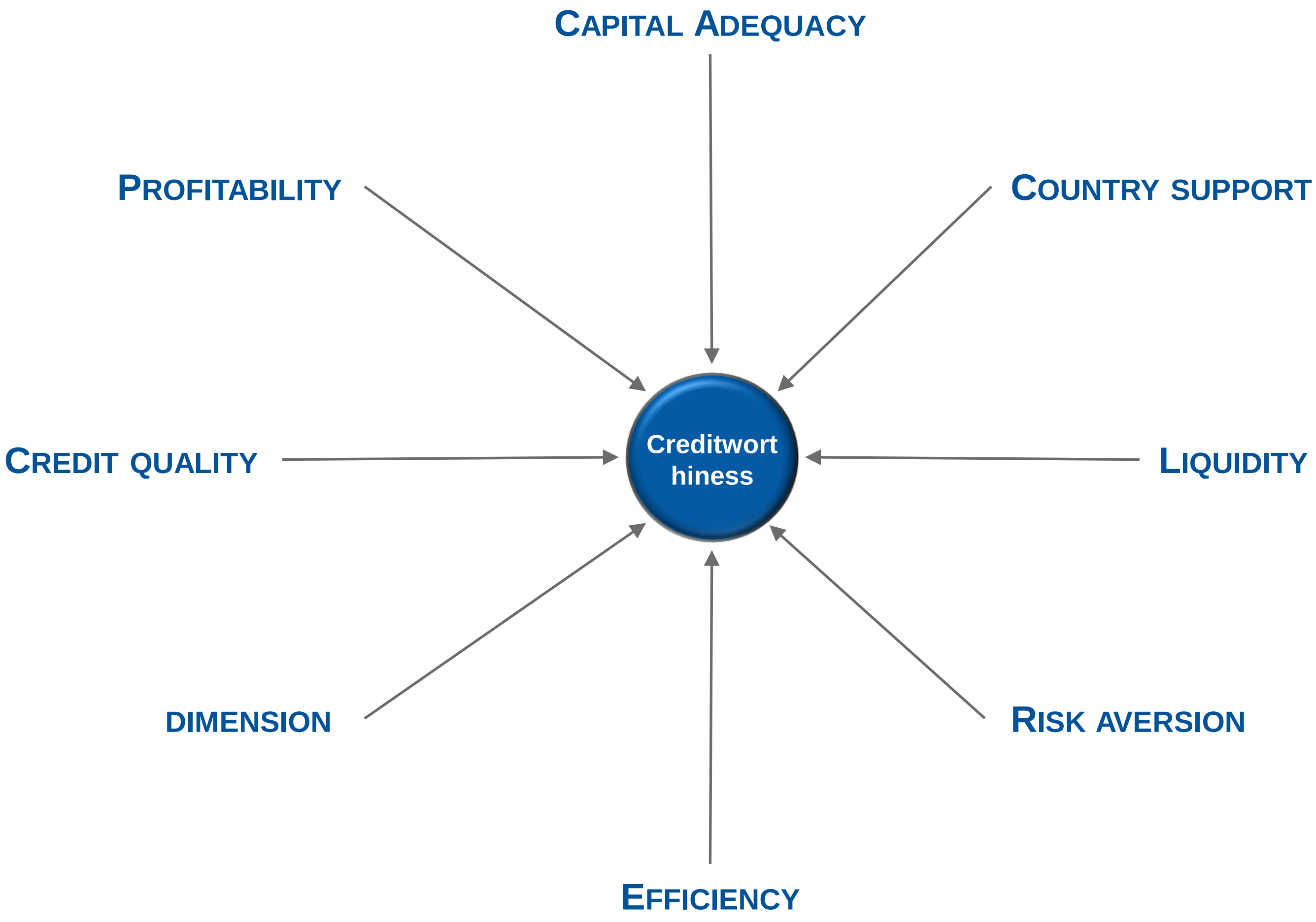
Panel Data Synchronization

Dataset structure (4/4)



Regressors selection

Fields of analysis



Regressors selection

Selection process

- Filters have been used for the selection of the regressors, with 5 years senior CDS spread as dependent variable.
- Variables for which there was poor availability of data were excluded ex-ante.

UNIVARIATE REGRESSION

Regression of the dependent variable against each variable in the initial set to explore their significance and expected effect

CHOICE PER FIELD

If two or more variables extracted from the previous point belonged to the same field of analysis and were highly correlated, the most significant one was chosen

MULTIVARIATE REGRESSION

With the set of variables extracted from the previous point, a step-wise regression (backward elimination) is used to extrapolate the subset of significant and coherent variables to be used in the final analysis

Regressors selection

REGRESSORS

Final set of regressors

Regressor	Source	Ref	Methodology	Field
Total assets	Financial Statement	Bank	Logarithm of total assets (Mln €)	Dimension
Return on assets	Financial Statement	Bank	Ratio between net profits and total assets	Profitability
NPL to total loans	Financial Statement	Bank	Ratio between non performing loans and total loans	Credit quality
Liquid assets to total assets	Financial Statement	Bank	Ratio between assets that can be converted into cash within 12 months and total assets	Liquidity
Unemployment rate	Macro	Country	Unemployment rate (source EIU)	Country support
Real GDP growth	Macro	Country	GDP growth rate yoy (source EIU)	Country support
Government CDS spread	Market	Country	5 years CDS spread	Country support
Volatility	Market	Country	Market index implied volatility	Risk aversion

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Issuers selection

Perimeter (1/2)

Sector	Banks, banking groups and financial institutions whose activity is primarily banking-related
Geographical area	World wide
Missing values	excluded
Data count requirements	At least four observations per issuer in order to be included in the dataset

Issuers selection

Perimeter (2/2)

Sector	Banks, banking groups and financial institutions whose activity is primarily banking-related
Geographical area	World wide
Missing values	excluded
Data count requirements	At least four observations per issuer in order to be included in the dataset

= 14 names
= 14 names
= 13 names
= 9 names
= 8 names
= 6 names
= 6 names
= 5 names
= 5 names
= 4 names
= 4 names
= 4 names
= 4 names
= 4 names
= 3 names
= 3 names
= 2 names
= 1 names
= 1 names

names	110 issuers
CDS	1,100 observations
Rating	1,450 observations

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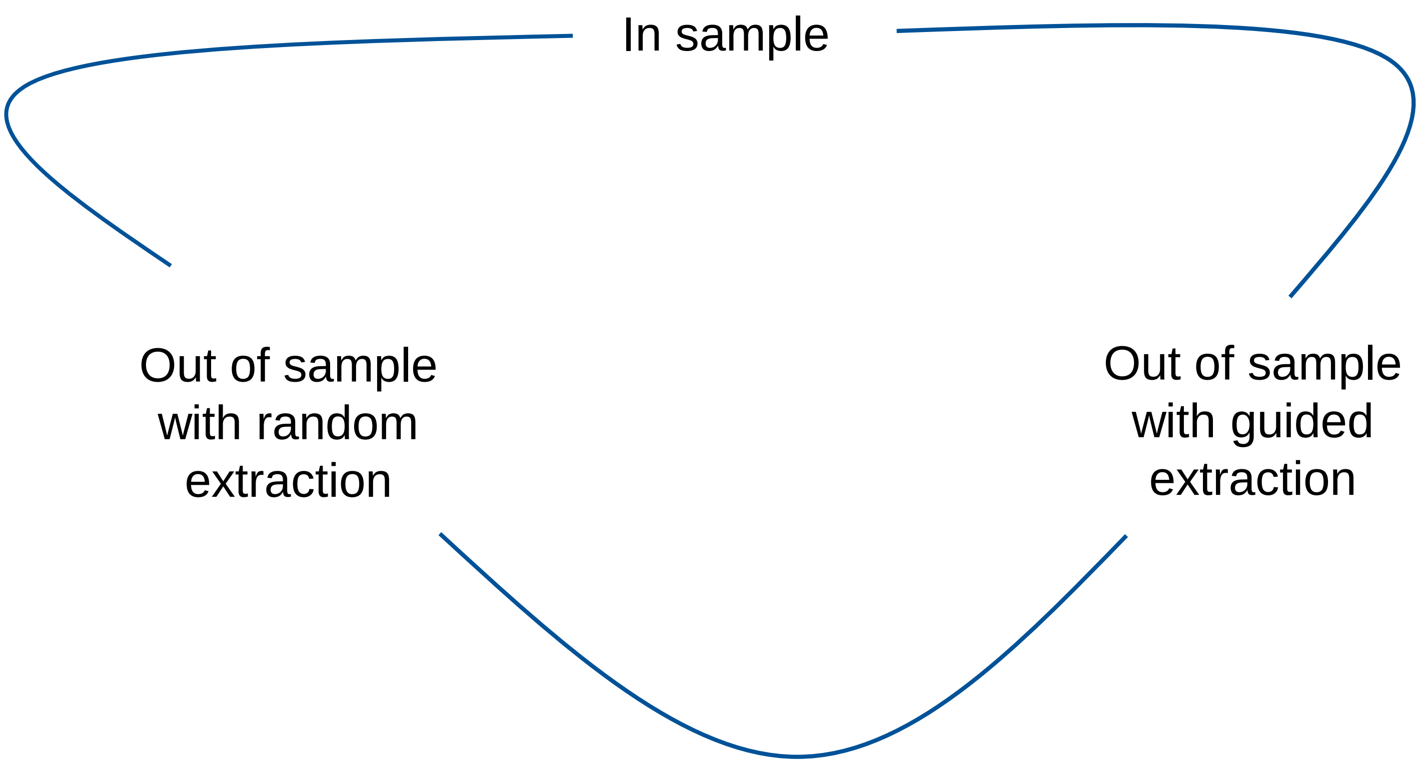
Results

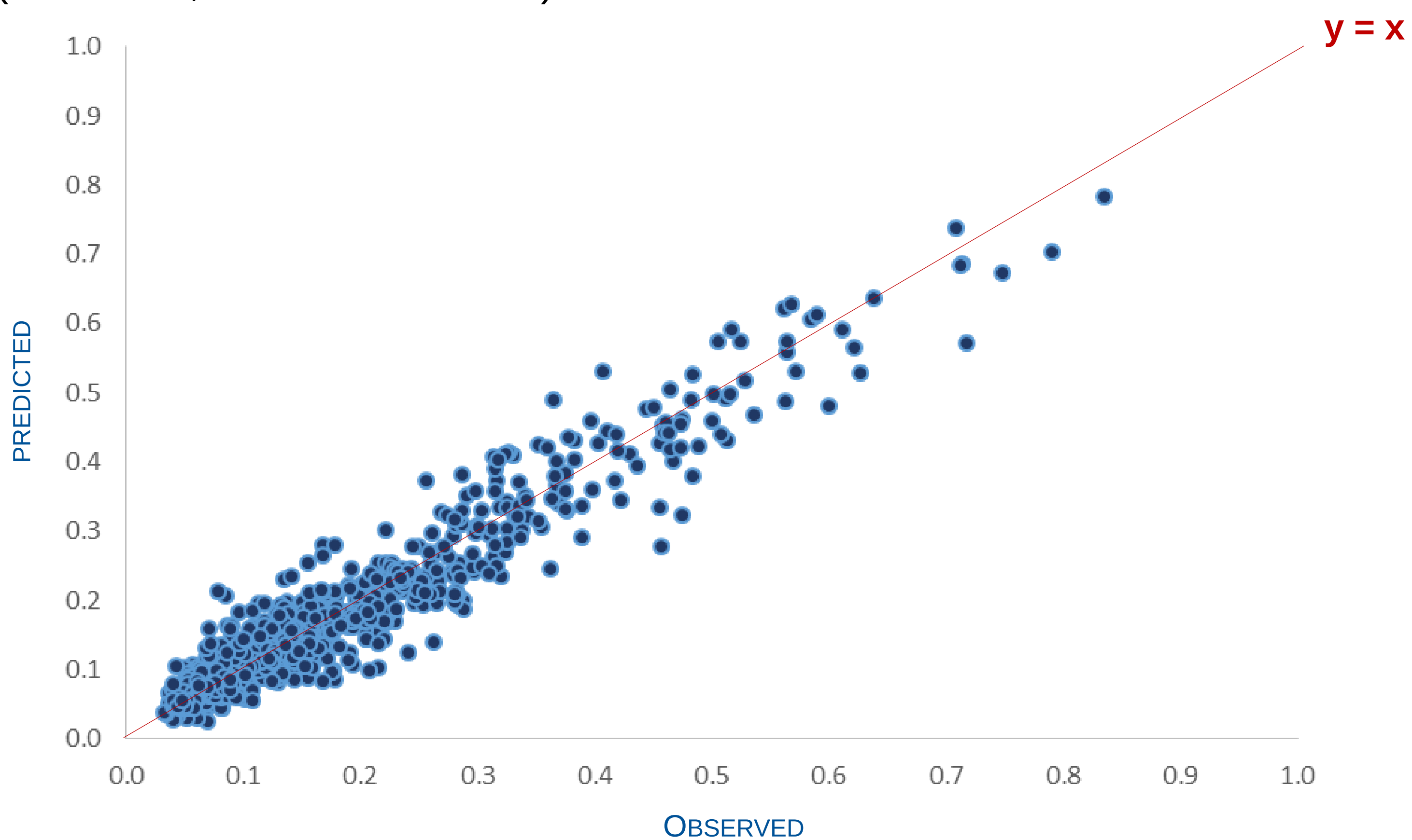
Exercises



CDS prediction

In sample

On a sample of about 1.100 observations, the neural network is able to obtain very good results (R2 = 0.93, Correlation = 0.96)*.

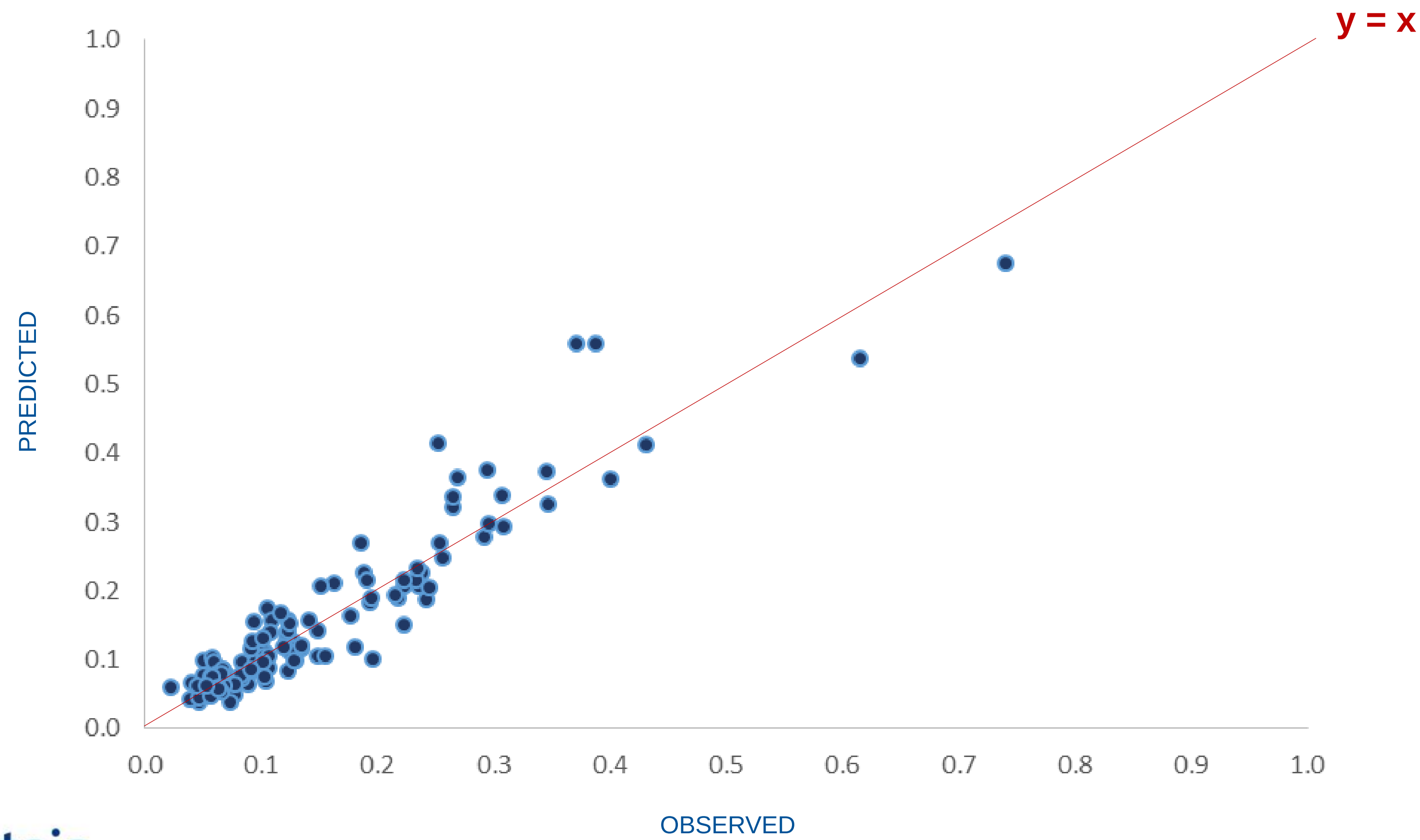


*Figures show the CDS spread 5 years senior predicted against CDS spread 5 years senior observed

CDS prediction

Out of sample – 90% vs 10%

Randomly extracted a 10% of the sample (about 110 observations), the exercise consists in training the network on the remaining 90% of the sample and predict the initial 10% extracted. The results are still very good (R2 = 0.87, Correlation= 0.94).



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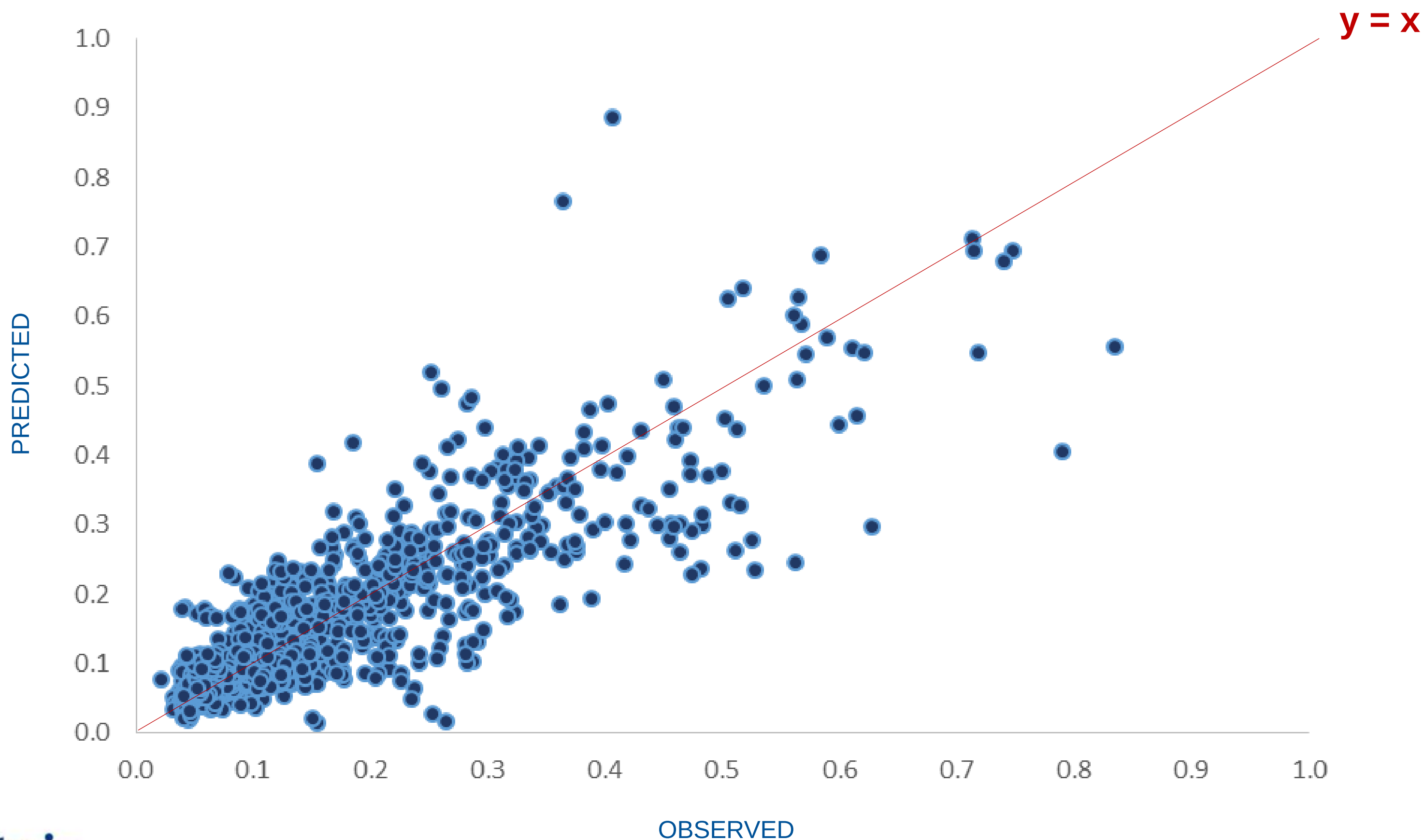
CDS prediction

Out of sample – extracting single issuers

After removing all of the observations for a single issuer, the network is trained on the remaining subset. The trained network is then used to predict the selected issuer. This was done for all of the issuers in the original set. The results remain good (R = 0.69, Correlation = 0.84)



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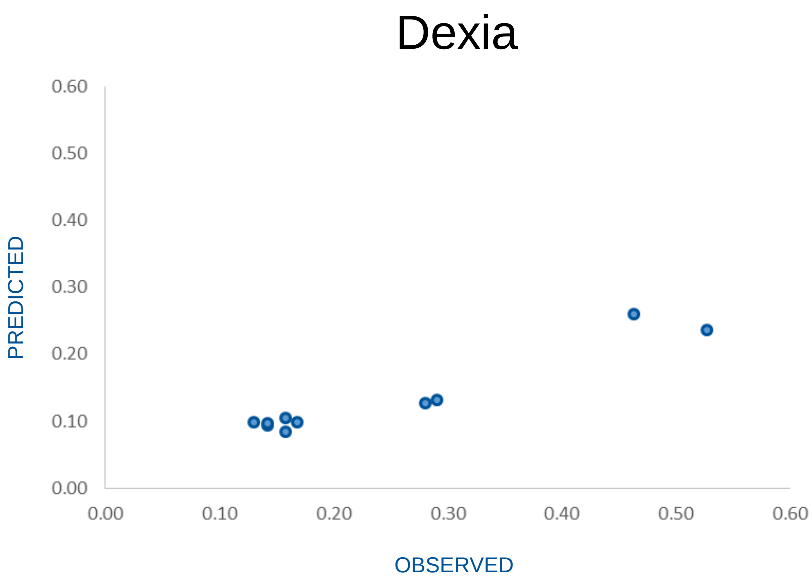
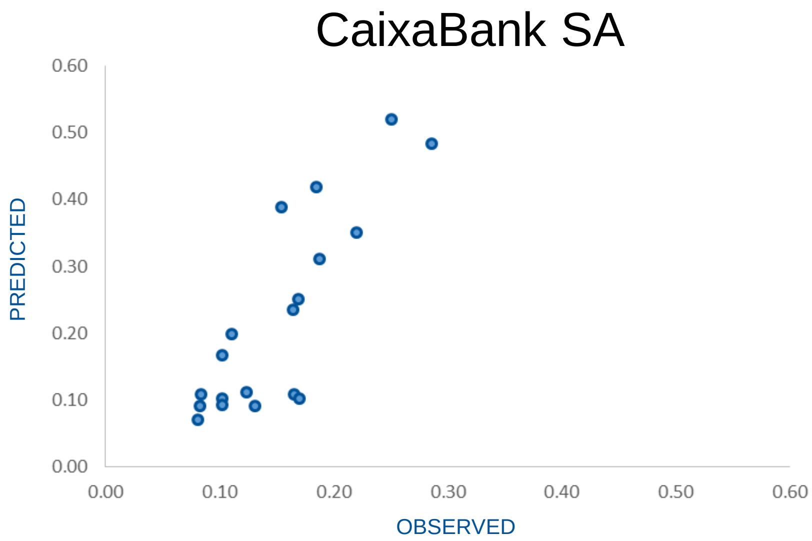
CDS prediction

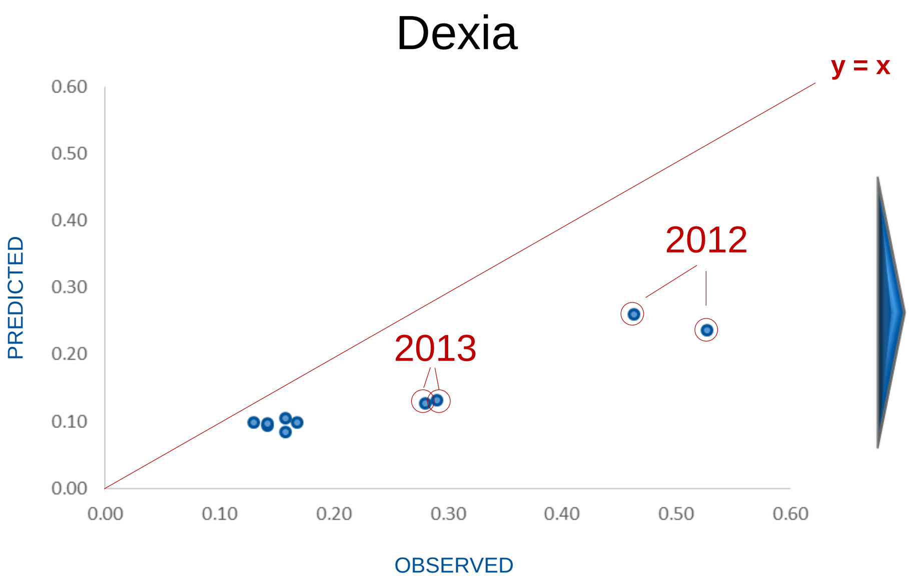
Extracting single issuers – some evidences





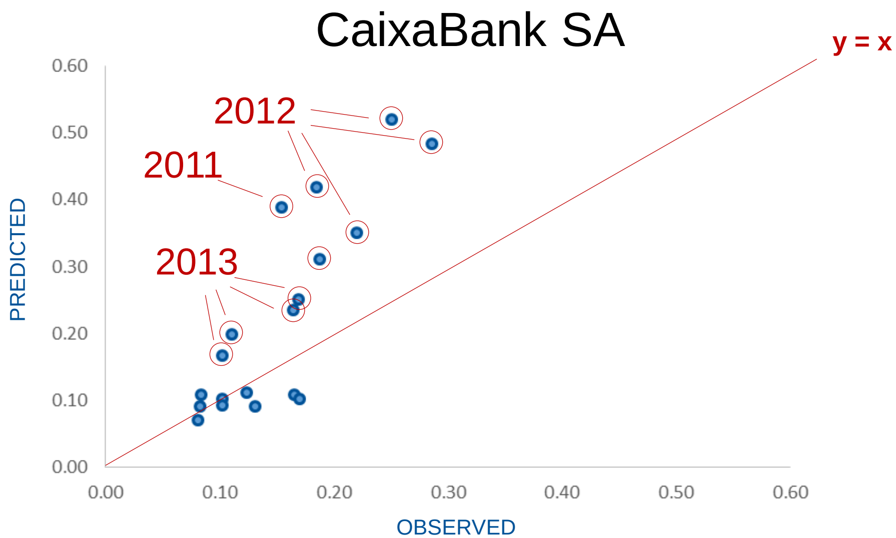
CDS prediction

Extracting single issuers – some evidences



Dexia creditworthiness is always underestimated by the model. The mispricing is greater during 2012 and 2013 when the markets seems to penalize the bank due to its **restructuring process**.

CaixaBank SA creditworthiness is always overestimated by the model. The mispricing is greater during 2012 and 2013, when the bank was subject to the **Spanish Government's program** called "Fund for Orderly Bank Restructuring" (FOBR). Differently from Dexia, the market tends to appreciate the government support.



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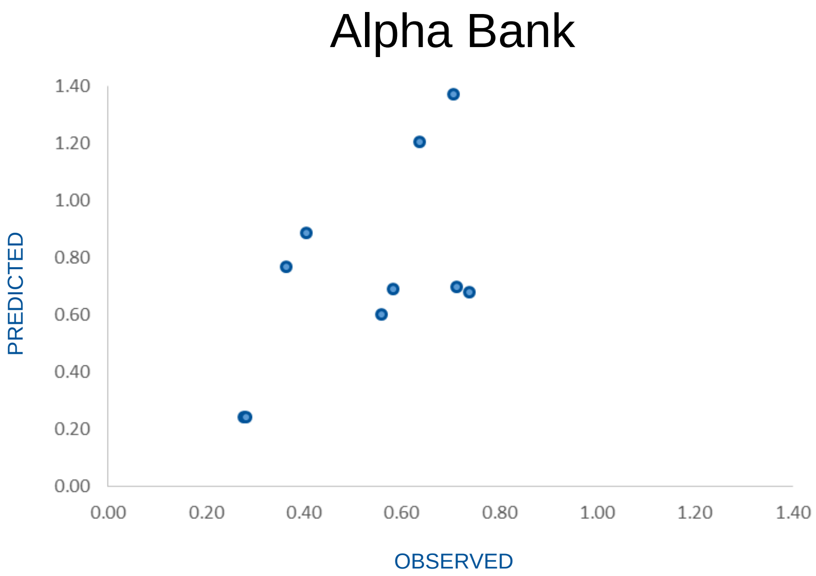
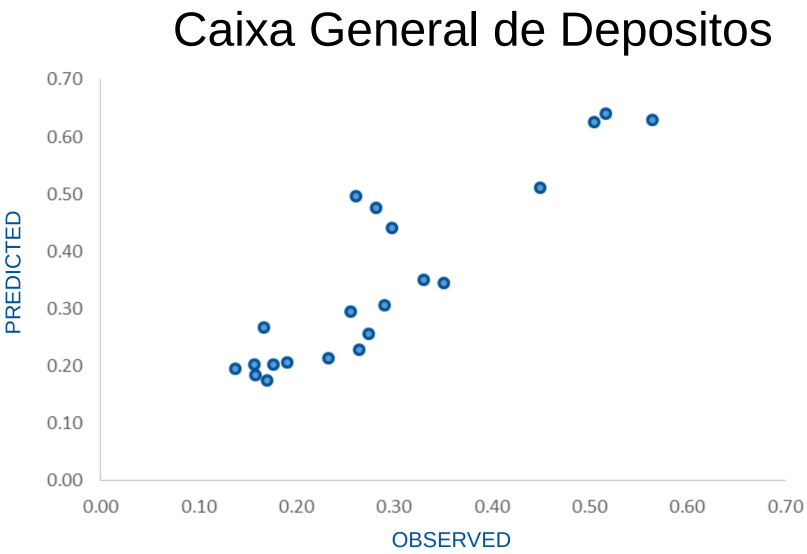
CDS prediction

Extracting single issuers – some evidences





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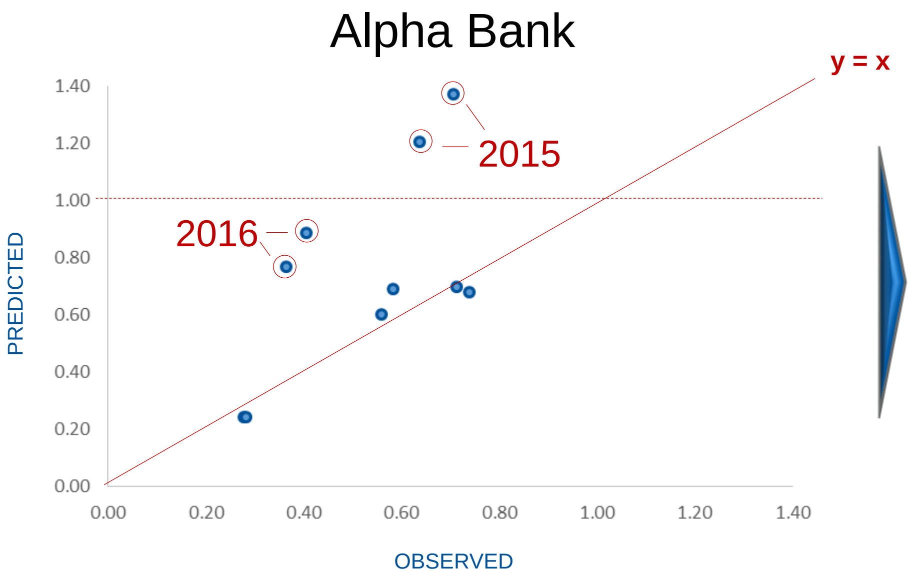
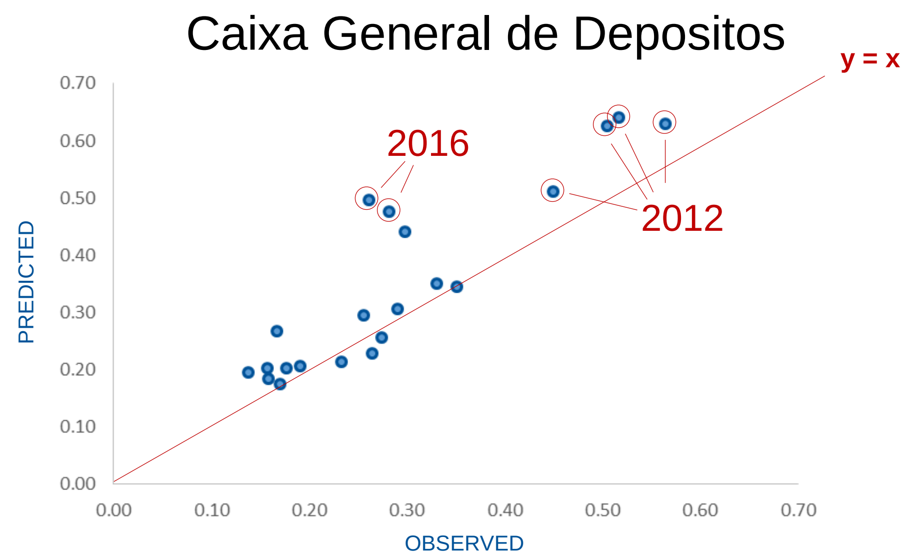
CDS prediction

Extracting single issuers – some evidences



The two default probabilities of 2015 are greater than 100% (these are the only cases seen during the analysis). During the 2015, in fact, Alpha Bank asked for a **liquidity support** (Emergency Liquidity Assistance) to National Bank of Greece. The bank was assigned a SD rating at that time. In this case, the market might have priced the government support.

The bank was already subject to a **bail-out** program during the 2012.
In the 2016 the bank received a **recapitalization** by the Portuguese Government, whose last tranches are going to be completed during the current year (2017). Also in this case, the market might have priced a government support.



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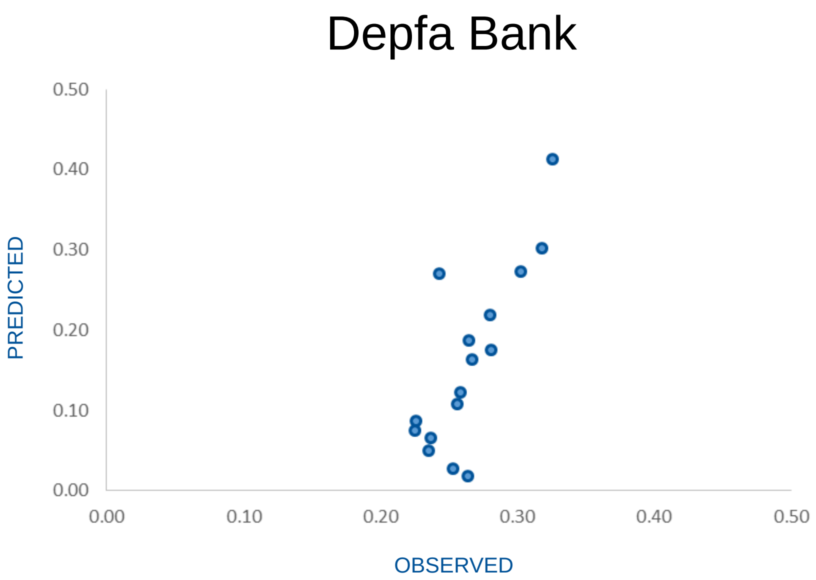
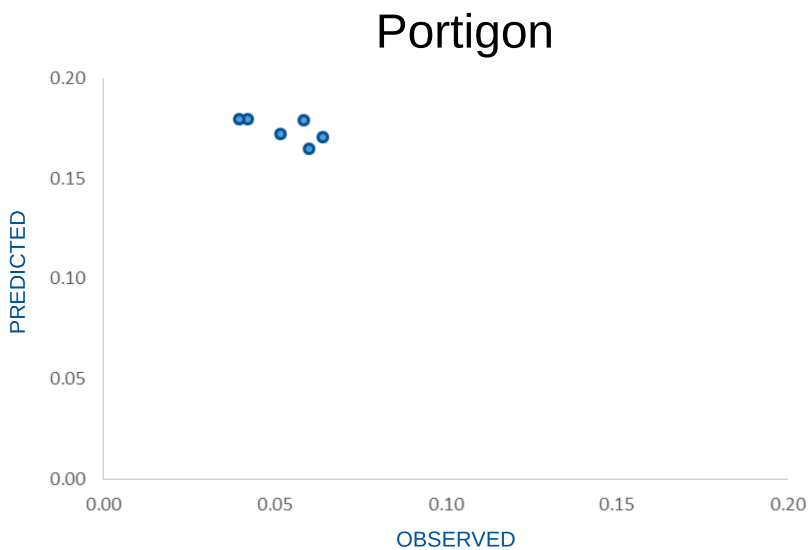
CDS prediction

Extracting single issuers – some evidences

CDS





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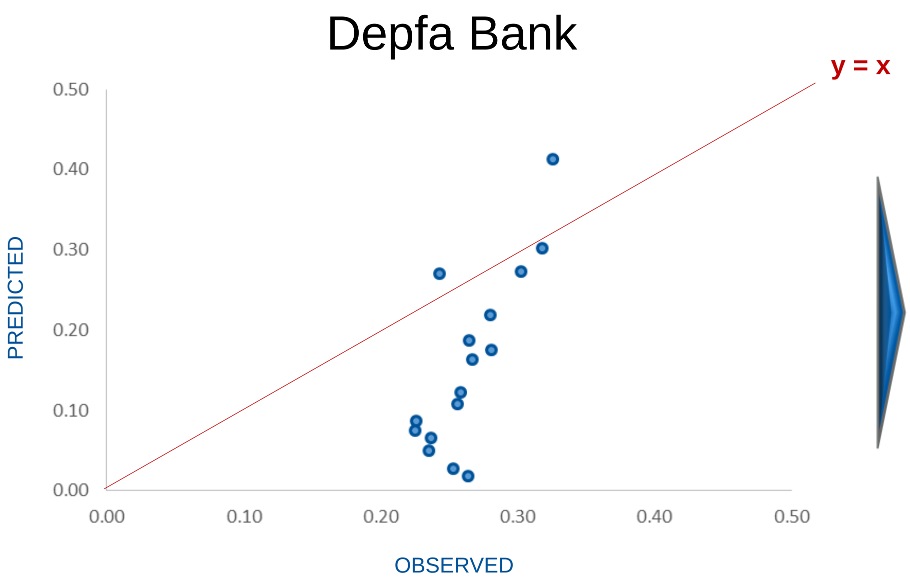
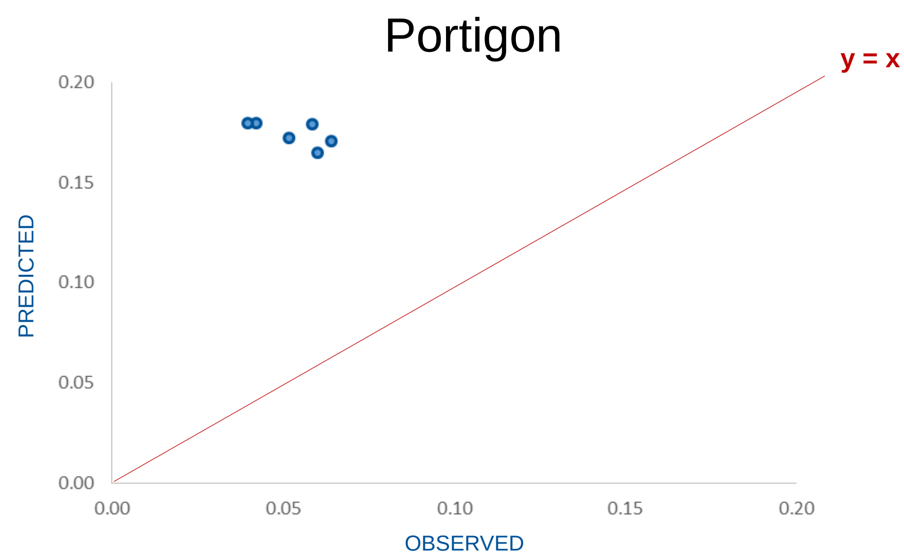
CDS prediction

Extracting single issuers – some evidences



Depfa is a bank focused on public sector financing. After the sub-prime crisis, it was subject to a **bail-out program** conducted by the Dutch Government through its subsidiary Hypo Real Estate

The Dutch bank Portigon Financial Services is characterized by a permanently low level of credit risk observed on the market, while overestimated by the model.
In this context the mispricing is probably an effect of the **scarce liquidity** of its **CDS** that reflects on their values.



Rating prediction

In sample

RATING

On a sample of about 1.450 observations, the accuracy ratio for the prediction of the <u>exact rating notch</u> is 54.5%

		TARGET																					
		AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	SD
PREDICT	AAA	19	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AA+	9	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AA	1	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AA-	0	0	0	88	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	A+	0	0	0	34	68	37	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	1	40	99	35	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	A-	0	0	0	0	5	47	70	37	10	0	0	0	0	0	0	0	0	0	0	0	0	0
	BBB+	0	0	0	0	0	0	44	45	32	2	0	0	0	0	0	0	0	0	0	0	0	0
	BBB	0	0	0	0	0	1	4	12	66	13	1	0	2	0	0	0	0	0	0	0	0	0
	BBB-	0	0	0	0	0	0	0	4	26	52	12	1	0	0	0	0	0	0	0	0	0	0
	BB+	0	0	0	0	0	0	0	0	1	30	81	36	9	0	0	0	0	0	0	0	0	0
	BB	0	0	0	0	0	0	0	0	0	0	16	18	11	9	0	0	0	0	0	0	0	0
	BB-	0	0	0	0	0	0	0	0	0	0	2	13	36	7	2	3	0	0	0	0	0	0
	B+	0	0	0	0	0	0	0	0	0	0	0	3	6	29	5	0	0	0	0	0	0	0
	B	0	0	0	0	0	0	0	0	0	0	0	0	3	0	2	0	0	0	0	0	0	0
	B-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	1
	CCC-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	2	0	0	0	3
	CC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	SD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Rating prediction

In sample

If we allow for an error of ±1 notch, the accuracy ratio increases in a very significant way (95.1%).

PREDICT \ TARGET	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	SD
AAA	19	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AA+	9	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AA	1	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AA-	0	0	0	88	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A+	0	0	0	34	68	37	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	0	0	0	1	40	99	35	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A-	0	0	0	0	5	47	70	37	10	0	0	0	0	0	0	0	0	0	0	0	0	0
BBB+	0	0	0	0	0	0	44	45	32	2	0	0	0	0	0	0	0	0	0	0	0	0
BBB	0	0	0	0	0	1	4	12	66	13	1	0	2	0	0	0	0	0	0	0	0	0
BBB-	0	0	0	0	0	0	0	4	26	52	12	1	0	0	0	0	0	0	0	0	0	0
BB+	0	0	0	0	0	0	0	0	1	30	81	36	9	0	0	0	0	0	0	0	0	0
BB	0	0	0	0	0	0	0	0	0	0	16	18	11	9	0	0	0	0	0	0	0	0
BB-	0	0	0	0	0	0	0	0	0	0	2	13	36	7	2	3	0	0	0	0	0	0
B+	0	0	0	0	0	0	0	0	0	0	0	3	6	29	5	0	0	0	0	0	0	0
B	0	0	0	0	0	0	0	0	0	0	0	0	3	0	2	0	0	0	0	0	0	0
B-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	1
CCC-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	2	0	0	0	3
CC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Rating prediction

Out of sample – 90% vs 10%

RATING

On an out of sample analysis consisting of about 150 observations, the accuracy ratio is 42.6% without error margin, 94.5% considering a ±1 notch tolerance level

		TARGET																					
		AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	SD
PREDICT	AAA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AA+	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AA	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AA-	0	0	2	9	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	A+	0	0	0	5	3	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	5	12	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	A-	0	0	0	0	1	4	7	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	BBB+	0	0	0	0	0	0	11	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0
	BBB	0	0	0	0	0	0	0	2	9	1	0	0	0	0	0	0	0	0	0	0	0	0
	BBB-	0	0	0	0	0	0	0	2	4	5	0	0	0	0	0	0	0	0	0	0	0	0
	BB+	0	0	0	0	0	0	0	0	0	7	3	2	0	0	0	0	0	0	0	0	0	0
	BB	0	0	0	0	0	0	0	0	0	0	4	3	2	1	0	0	0	0	0	0	0	0
	BB-	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	1	0	0	0	0	0	0
	B+	0	0	0	0	0	0	0	0	0	0	0	1	1	5	1	0	0	0	0	0	0	0
	B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	CCC-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1
	CC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	SD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

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Rating prediction

Extracting single issuers – out of sample

Extracted the observations for a single issuer, the network is trained on the remaining sample and used to predict the issuer. The exercise is done in a recursive way on all the issuers: the accuracy ratio is 59.5% with a ± 1 notch tolerance level

	TARGET																					
PREDICT	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	SD
AAA	6	16	0	1	3	0	9	1	18	0	0	0	0	0	0	0	0	0	0	0	0	0
AA+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AA	0	0	0	0	0	6	2	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0
AA-	0	0	1	66	17	7	5	3	4	3	0	0	0	0	0	0	0	0	0	0	0	0
A+	3	3	1	50	13	12	33	16	13	10	0	0	0	0	0	0	0	0	0	0	0	0
A	3	5	0	2	29	99	25	10	13	0	2	0	0	0	0	0	0	0	0	0	0	0
A-	2	0	0	22	26	29	41	27	16	2	0	0	0	3	1	0	0	0	0	0	0	0
BBB+	2	0	0	0	17	26	25	28	19	6	4	1	5	0	2	0	0	0	0	0	0	0
BBB	0	0	0	0	3	24	18	22	24	33	3	0	8	0	0	0	0	0	0	0	0	0
BBB-	8	0	0	0	6	3	8	10	19	24	13	10	4	3	0	0	0	0	0	0	0	0
BB+	0	0	0	0	0	0	9	4	16	8	30	16	9	18	0	0	0	0	0	0	0	0
BB	0	0	0	0	1	0	0	1	4	9	44	26	4	9	2	0	0	0	0	0	0	0
BB-	0	0	0	0	0	0	0	0	0	9	11	16	4	14	2	2	0	1	0	0	0	0
B+	2	0	0	0	0	0	0	0	2	3	10	8	22	2	0	0	0	0	0	0	0	0
B	0	4	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
B-	4	0	0	0	2	0	0	0	0	2	0	0	8	3	3	2	0	0	0	0	0	2
CCC+	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CCC	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0
CCC-	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	4	1	0	0	0	3
CC	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
C	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SD	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0

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Rating prediction

Extracting single issuers – out of sample - focus

Extracted the observations for a single issuer, the network is trained on the remaining sample and used to predict the issuer. The exercise is done in a recursive way on all the issuers: the accuracy ratio is 59.5% with a ± 1 notch tolerance level

PREDICT \ TARGET	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	SD
AAA	6	16	0	1	3	0	9	1	18	0	0	0	0	0	0	0	0	0	0	0	0	0
AA+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AA	0	0	0	0	0	6	2	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0
AA-	0	0	1	66	17	7	5	3	4	3	0	0	0	0	0	0	0	0	0	0	0	0
A+	3	3	1	50	13	12	33	16	13	10	0	0	0	0	0	0	0	0	0	0	0	0
A	3	5	0	2	29	99	25	10	13	0	2	0	0	0	0	0	0	0	0	0	0	0
A-	2	0	0	22	26	29	41	27	16	2	0	0	0	3	1	0	0	0	0	0	0	0
BBB+	2	0	0	0	17	26	25	28	19	6	4	1	5	0	2	0	0	0	0	0	0	0
BBB	0	0	0	0	3	24	18	22	24	33	3	0	8	0	0	0	0	0	0	0	0	0
BBB-	8	0	0	0	6	3	8	10	19	24	13	10	4	3	0	0	0	0	0	0	0	0
BB+	0	0	0	0	0	0	9	4	16	8	30	16	9	18	0	0	0	0	0	0	0	0
BB	0	0	0	0	1	0	0	1	4	9	44	26	4	9	2	0	0	0	0	0	0	0
BB-	[illegible]	0	0	0	0	0	0	0	0	9	11	16	4	14	2	2	0	1	0	0	0	0
B+	2	0	0	0	0	0	0	0	2	3	10	8	22	2	0	0	0	0	0	0	0	0
B	0	4	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
B-	4	0	0	0	2	0	0	0	0	2	0	0	8	3	3	2	0	0	0	0	0	2
CCC+	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CCC	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0
CCC-	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	4	1	0	0	0	3
CC	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
C	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SD	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0

Rating prediction

RATING

Extracting single issuers – some evidences

names	Target	Model	Description
Deutsche Pfandbriefbank	BBB	AAA	German bank leader in the field of real estate financing. It was nationalized in 2008 and privatized in 2015
Netherlands Development Fin. Company	AAA	B+/B-	Dutch bank that primarily operates in financing investments in the private sector of the emerging markets. 51% of its equity is detained by the Dutch Government
Landesbank Baden-Württemberg	AAA	BBB-	German commercial bank which operates primarily in local activities. It is fully owned by the State of Baden-Württemberg
DVB Bank	A+	C/SD	German commercial bank that provides services of financing and advisory in the world of international transports. Very unusual business model

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Final thoughts

Neural networks and financial data

- Neural networks show a high capability to understand stochastic variables dynamics (**in sample**)
- The high level of efficiency is still shown in out-of-sample prediction when the networks have way of evaluating the dynamics of “known” processes.
- Neural networks, while maintaining high accuracy in the prediction and high levels of correlation, have great difficulties in predicting dynamics of issuers they were not trained for.
- Some cases of greater mispricing are often the results of situations particularly difficult to reproduce by pricing models (see next slide)

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Final thoughts

Rating criteria

- Rating agencies form their assessments by considering information of various kind, not only quantitative.
- Generally speaking, a rating agency takes in consideration the following criteria:

Quantitative factors

Macroeconomic
- Economic strength (GDP, Interest rates, etc.)
- Institutional strength

Financial profile
- Evaluation of the current financial ratios/measures
- Projections about firm fundamentals

Qualitative factors

Quality factors
- Factors that cannot be represented by quantitative measures, such as kind of business, reputation, ...

External support
- Probability of other companies support
- Probability of government support

Additional factors
- Other variables not directly included in the other macro areas but can influence the creditworthiness of the specific firm

- Neural networks, while not taking into account the same factors used by rating agencies, is able to detect the criteria underlying their assessments by only taking in consideration quantitative measures relative to firms fundamentals and macroeconomic risks.

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