MODELLING CREDIT STRUCTURES AND SECURITISATIONS WITH DATA SCIENCE

Insurance Data Science Conference
16-18 June 2021

Fernando MIERZEJEWSKI PhD – Non-Life Risk Officer
AG Insurance

Global Financial Crisis 2008

- The 2008 financial crisis has been described as a generalised and coordinated event of credit-default, resulting from the combined effect of two separate shocks:
  - A **shock of increasing uncertainty** about the valuations and disclusers of structured products, and
  - A **shock of increasing deterioration in the credit ratings** of the tranches of funding structures and securitisations.

- During the crisis episode, credit rating agencies were compelled to make abrupt and massive downgrading.
  - Thus creating confusion among investors, who tended to assume that the credit standing of structured products was as stable as traditional fixed-income instruments.

- Criticism of structured finance has revolved around its **potential to cause massive credit delinquency**.

Global Financial Crisis 2008

- The 2008 financial crisis has been described as a generalised and coordinated event of credit-default, resulting from the combined effect of two separate shocks:
  - A **shock of increasing uncertainty** about the valuations and disclusers of structured products, and
  - A **shock of increasing deterioration in the credit ratings**

Credit rating models strongly dependent on **QUALITATIVE assessment**.

Data Science can be used to improve/correct expert qualitative assessment.

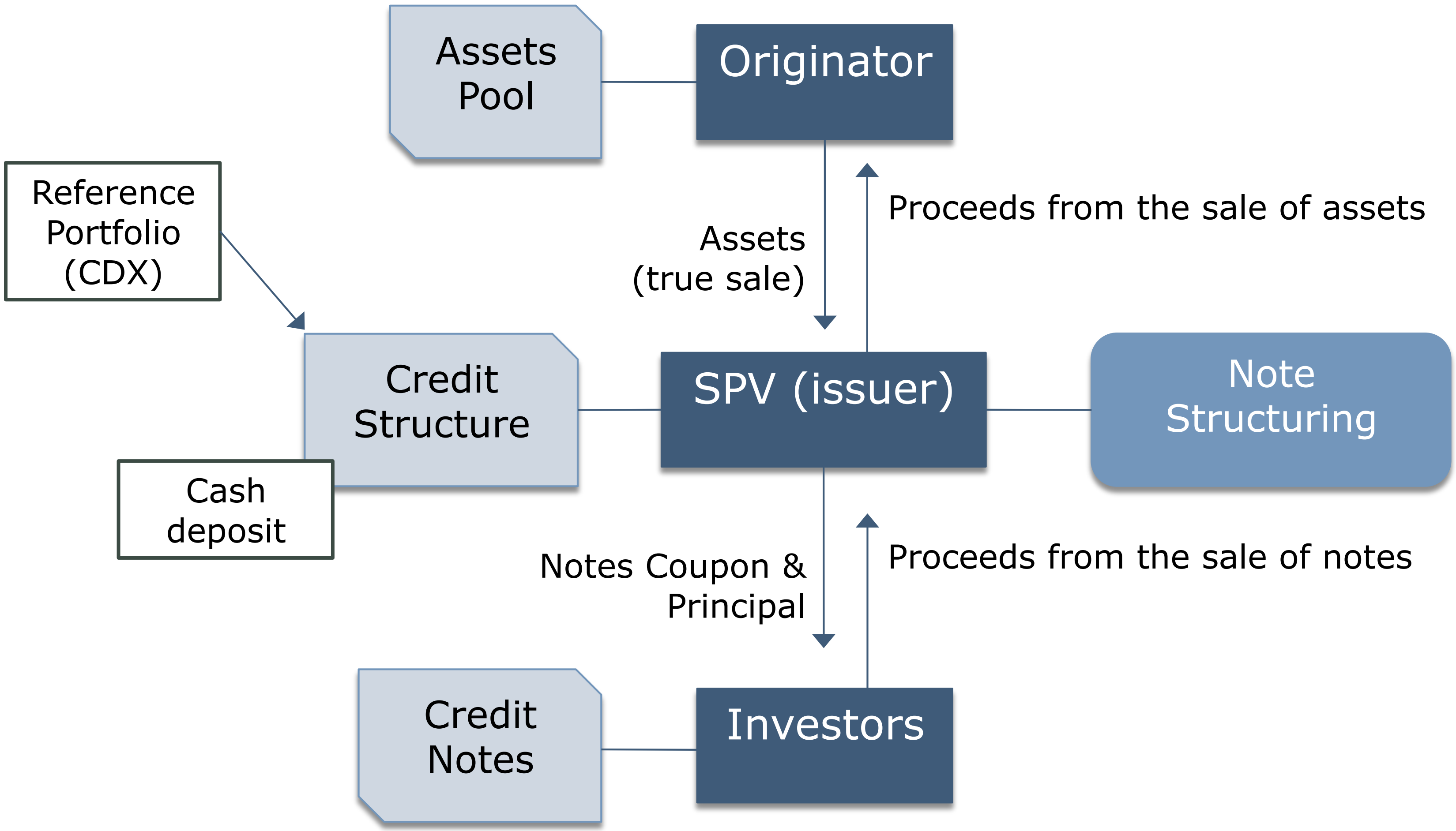
stable as traditional fixed-income instruments.

- Criticism of structured finance has revolved around its **potential to cause massive credit delinquency**.

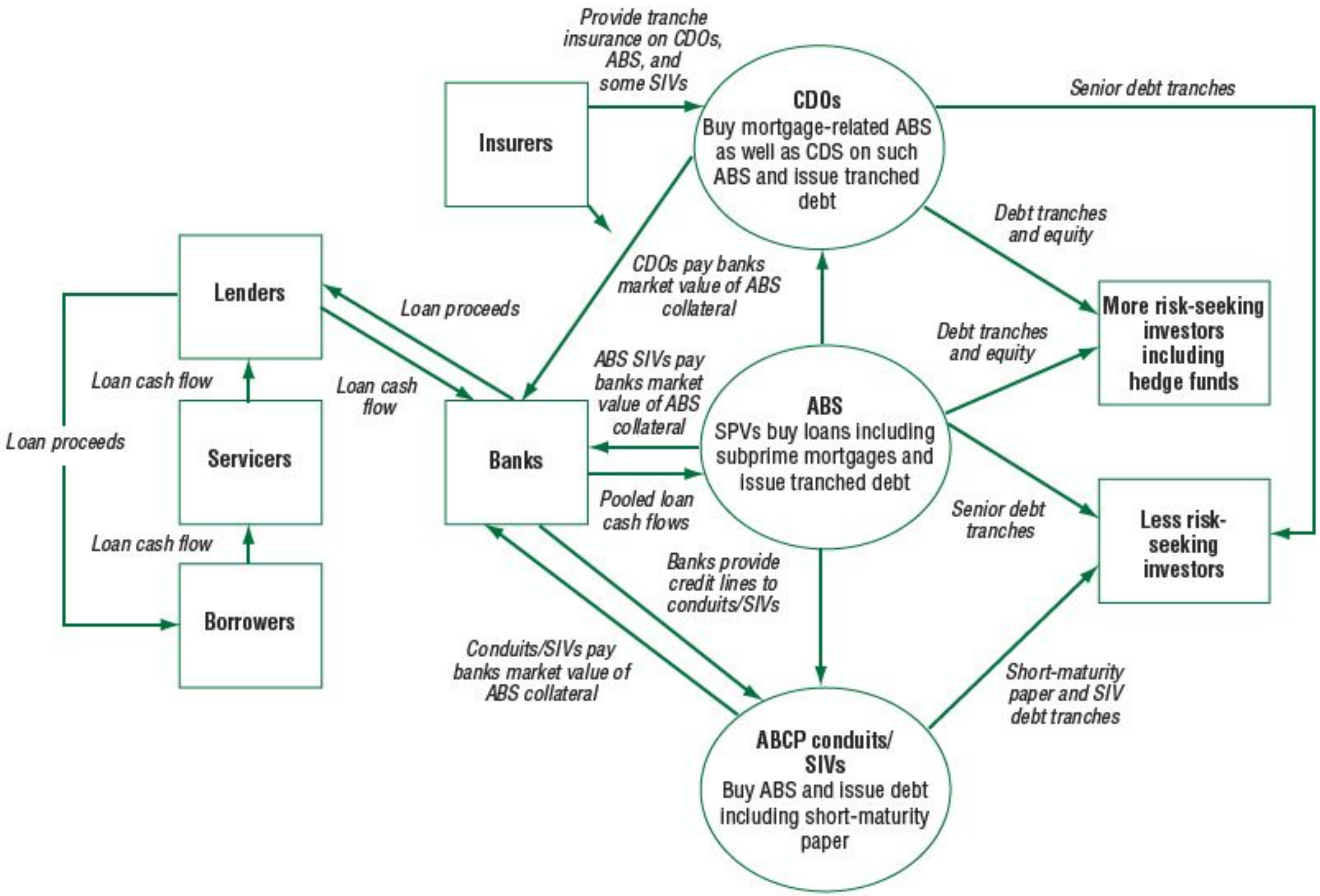
Credit-Default Obligations

- **Constant proportion debt obligations** (**CPDO**) and **collateralised default obligations** (**CDO**) are credit structures guaranteeing a (relatively high) level of portfolio returns at the end of a given investment horizon.
  - Payments are expressed as cash flows referring to some portfolio of relatively highly profitable/risky assets (typically, a credit default swaps index, CDX).
  - Proceeds are maintained in a cash deposit, as collateral for the long assets position.
- Leverage is dynamically adjusted in order to ensure that the value of assets minus liabilities is always positive.
  - Leverage is increased in the event of incurring in portfolio losses.
- **Default occurs when leverage reaches the maximum level determined at inception**.

Debt structuring process



Mortgage Market Flows



Source: IMF Global Financial Stability Report, Oct. 2007.

Data requirements

- **Data required by credit rating agencies before inception**:

  - **Loan-level data requirements**:
    - Credit standing of borrowers and originators.
    - Type and level of currency.
    - Original and current outstanding balances.
    - Loan-to-value ratios.
    - Appraisal value of collateral (properties).
    - Type (fixed/floating) and level of interest rates.
    - Original and remaining term to maturity.

  - **Historical data – portfolio evolution by cohorts**:
    - Historical yields & balances.
    - Historical prepayment rates.
    - Portfolio delinquencies.
    - Portfolio defaults.
    - Portfolio recoveries.

Data requirements

- **Data required by credit rating agencies before inception**:

- **Loan-le requirer** **portfolio orts**:
  - Credit and or
  - Type a
  - Origina outsta
  - Loan-t
  - Apprai (prope
  - Type (of inte
  - Origina maturi

balances.

ment rates.

ncies.

es.

- The provision of data is one of the most challenging aspects of debt structuring.
  - It brings on the need of developing & maintaining a complex IT platform.
  - Such infrastructure can be used by SPVs for the management of structured debt until maturity.
  - **It can be used, in particular, for the implementation of a neural network reviewing/improving the model estimations of PD rates & credit ratings**.

Model specification

- **Traditional statistical methodologies**:
  - Linear discriminant analysis (LDA).
  - Logistic regression (LOGIT).
  - Univariate & multivariate models.
- Other:
  - Decision trees.
  - Operational research.
  - Evolutionary approaches.
  - Fuzzy logic.

- **Option-based framework** (geometric Brownian motion).

$$\frac{dS_t}{S_t} = \left(r_t + \rho_t\right) \cdot dt + \sigma \cdot dW$$

$$\rho_t : risk \ premium$$

  - Default occurs when the level of portfolio losses surpasses a given threshold L*.

$$\frac{\partial PD}{\partial L^*} > 0, \frac{\partial PD}{\partial \sigma} > 0, \frac{\partial PD}{\partial r} > 0, \frac{\partial PD}{\partial \rho} < 0$$

  - Two main categories:
    - Exogenous default-trigger (L*).
    - Endogenous default-trigger (L*).

Neural network framework

- **Input layer**:
  - **Input neurons** receive and process the incoming stimuli as stipulated by some **transfer function**.
  - Results are thus transferred to the neurons in the **middle layers**.
- **Middle layers**:
  - Results produced in the middle layers are adjusted by **weights** representing the connections between consecutive neurons.
  - Every neuron is described by a **transition function** and a **threshold**.
    - The threshold is the minimum value that activates the receiver neuron.
- **Reinforced learning**:
  - Reinforced learning trains the network by **introducing prizes and penalties** as a function of the network response.
    - Prices and penalties are used to modify the weights.
  - Reinforced learning is applied to train adaptive systems that perform tasks composed of a **sequence of actions**.
    - The final outcome is the result of the sequence of actions.
    - The contribution of every single action is thus evaluated depending on the impact on the resulting action chain.

Multi-layer perceptron network

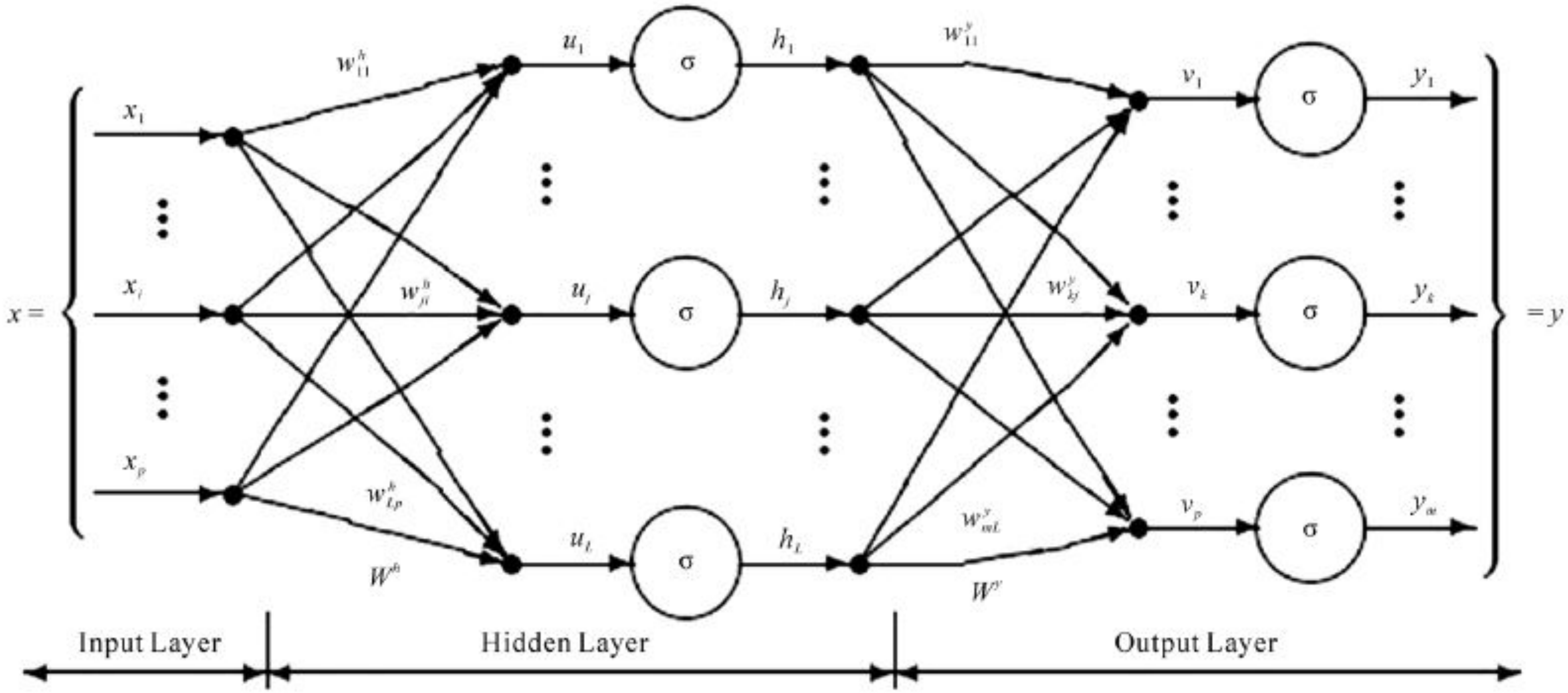


Figure 3. Perceptron network.

Source: Pacelli, V. & Azzollini, M. (2011).

Multi-layer perceptron network

- **Back Propagation learning algorithm**.
  - The network learns by means of a series of attempts to estimate the weights linking the input to the output results – through a series of hidden layers of neurons.
    - Starts with random weights affecting the neurons in the input layer.
    - Weights in the intermediate and output layers are progressively adjusted.
    - At every iterative step, the error between the network result and the desired/ observed output is minimised.

- **Output**.
  - Internal credit score categories.
    - SAFE;
    - VULNERABLE;
    - RISK.
  - Credit score categories as defined by the different credit rating agencies,
    - Standard & Poor’s (S&P);
    - MOODY’s;
    - FITCH Group.

Network output

Table 1. Neural network's results.

Rating	Safe	Vulnerable	Risk
Safe	84.2%	15.8%	0%
Vulnerable	23.1%	73.9%	3.0%
Risk	15.2%	50.0%	34.8%

Source: Pacelli, V. & Azzollini, M. (2011).

Network output

EXHIBIT 3.3 Portfolio defaults, historic basis

Percentage Defaulted	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
2006/Q4	0.00%	0.00%	0.00%	0.10%	0.25%	0.68%	1.61%	3.06%	4.98%	5.48%	6.46%	7.94%	8.94%	9.20%	9.50%	9.80%	10.00%	10.10%
2007/Q1	0.00%	0.00%	0.00%	0.06%	0.24%	0.83%	1.83%	3.25%	3.87%	4.97%	6.50%	8.57%	8.85%	9.40%	9.70%	10.20%	10.40%	
2007/Q2	0.00%	0.00%	0.00%	0.04%	0.32%	0.90%	2.00%	2.45%	3.32%	4.60%	5.30%	6.69%	7.70%	8.60%	9.38%	9.70%		
2007/Q3	0.00%	0.00%	0.00%	0.07%	0.46%	1.25%	1.73%	2.66%	4.09%	5.99%	6.49%	7.34%	8.51%	10.01%	10.26%			
2007/Q4	0.00%	0.00%	0.00%	0.11%	0.51%	0.99%	2.00%	3.62%	5.79%	6.31%	7.18%	8.45%	10.04%	10.38%				
2008/Q1	0.00%	0.00%	0.00%	0.09%	0.51%	1.44%	2.93%	4.00%	5.62%	6.66%	8.16%	9.10%	9.70%					
2008/Q2	0.00%	0.00%	0.00%	0.06%	0.53%	1.58%	3.27%	3.98%	5.25%	7.01%	8.30%	9.00%						
2008/Q3	0.00%	0.00%	0.00%	0.14%	1.00%	3.70%	5.50%	7.00%	8.70%	9.70%	10.50%							
2008/Q4	0.00%	0.00%	0.00%	0.10%	1.20%	3.50%	5.00%	7.30%	8.40%	9.20%								
2009/Q1	0.00%	0.00%	0.00%	0.13%	0.90%	1.76%	3.00%	5.20%	6.40%									
2009/Q2	0.00%	0.00%	0.00%	0.11%	0.67%	1.86%	3.20%	4.69%										
2009/Q3	0.00%	0.00%	0.01%	0.12%	0.83%	1.50%	3.25%											
2009/Q4	0.00%	0.00%	0.00%	0.14%	0.75%	1.63%												
2010/Q1	0.00%	0.00%	0.00%	0.06%	0.58%													
2010/Q2	0.00%	0.00%	0.00%	0.08%														
2010/Q3	0.00%	0.00%	0.00%															
2010/Q4	0.00%	0.00%																
2011/Q1	0.00%																	

Source:Baig & Choudhry (2013).

Conclusions

- Data science provides a theoretical framework for the **management of credit-default structures**.

- Estimations of the **default probabilities** of the underlying loans can be periodically reassessed – thus reflecting changes in:

  - Portfolio management decisions – buying and selling orders of loans;
  - Model & parameter misspecification;
  - Market conditions.

- Eventually, the implementation of neural networks leads to the automation and progressive improvement of **expert knowledge** – **qualitative assessment**.

References

- **Addo, Guegan & Hassani (2018)**. Credit Risk Analysis Using Machine and Deep Learning Models. *Risks* 2018, 6, 38.
- **Baig & Choudhry (2013)**. *The Mechanics of Securitization*. Wiley.
- **International Monetary Fund (2007)**. Financial Market Turbulence – Causes, Consequences, and Policies. *Global Financial Stability Report*. Oct. 2007.
- **Lancaster, Schultz & Fabozzi (2008)**. *Structured Products and Related Credit Derivatives*. Wiley.
- **Pacelli, V. & Azzollini, M. (2011)**. An Artificial Neural Network Approach for Credit Risk Management. *Journal of Intelligent Learning Systems and Applications* 2011(3), pp. 103-112.
- **Tarashev (2005)**. An Empirical Evaluation of Structural Credit Risk Models. *BIS Working Paper* No. 179.