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Artificial Intelligence & Machine Learning – Market developments and financial stability implications

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Outline

1. Who is the FSB
2. Overview of the FSB work on FinTech
3. Financial stability implications of FinTech
4. FinTech credit: some figures
5. AI/ML in Financial services
6. AI/ML in the Insurance industry

Who is the FSB?

- The Financial Stability Board (FSB) brings together senior officials of:
  - national financial authorities
    - ministries of finance
    - central banks
    - supervisory and regulatory authorities
  - international financial institutions
  - international regulatory and supervisory groups
  - committees of central bank experts

What is the FSB for?

- To address financial system vulnerabilities
- To drive and coordinate the development of strong regulatory and supervisory policies
- To assess implementation of agreed policies
- Goal: to strengthen financial stability

- Broad-based agenda for strengthening <u>national</u> financial systems and the stability of <u>international</u> financial system
  - Joint diagnosis of problems
  - Policy development and coordination
  - Monitoring and follow up on implementation

Overview of FSB work on FinTech

FSB FinTech Work Plan

"Actively monitor fintech to assess developments and to help policymakers articulate a consistent and well thought out posture towards FinTech" (November 2016)

Stocktaking

Member Activities

Innovation Facilitators

Industry Outreach

Continuous Activity

In-depth Analysis

FinTech Credit Study

AI / ML Case Study

Broad Analysis

Key Elements of FinTech

FinTech issues

Financial stability implications of FinTech

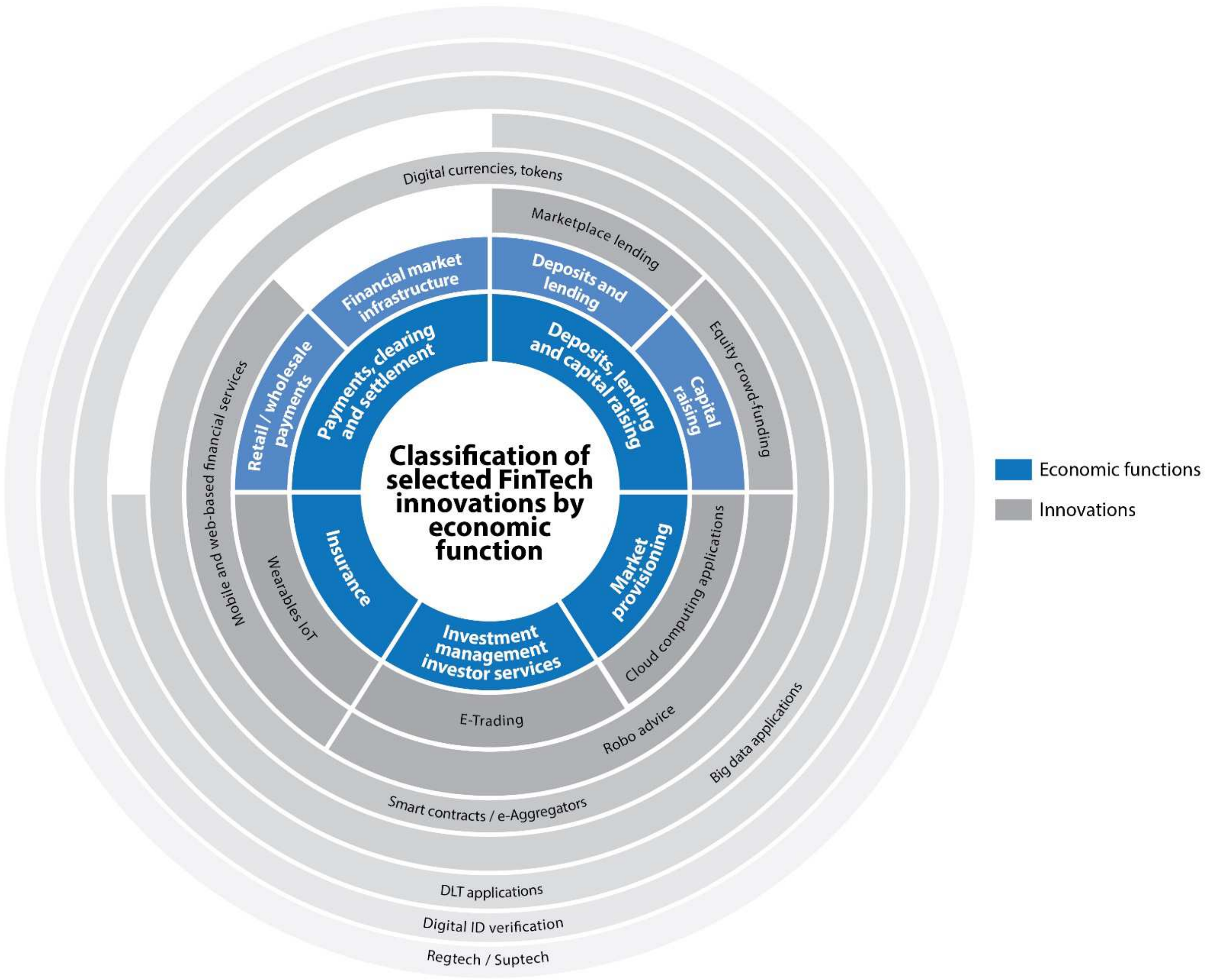
The Framework

I. Scope: classification of FinTech by primary economic functions
   – Focus on activities, not underlying technologies

II. Drivers of innovation and considerations for market structure

III. Potential benefits and risks of FinTech innovations
   – "Two-sided approach" to financial stability implications

Scope: classification by function



Drivers of financial innovation

Shifting consumer preferences:

Higher customer expectations for convenience, speed, cost and “user-friendliness”

Evolving technology:

Advances in technology related to the internet, big data, mobile technology, and computing power

Changing financial regulation:

Changes in regulatory and supervisory requirements, and related changes in business incentives of incumbents and new players

Demand side (shifting consumer preferences)

Supply side (evolving technology; changing financial regulation)

Impact on market structure

- Financial innovation may have material implications for market structure:
  - Level of **concentration** could be reduced given greater competition
  - Lower barriers to entry drive **contestability**
  - **Composition** of service providers may be affected due to the unbundling of financial services, new entrants

Why does FinTech matter?

Potential benefits	Micro-financial risks	Macro-financial risks
Decentralisation and increased intermediation by non-financial entities	Financial sources: • Maturity mismatch • Liquidity mismatch • Leverage	Contagion
Greater efficiency	Operational sources: • Governance/processes • Cyber risks • Third-party reliance • Legal / regulatory risk • Business risk of critical financial market infrastructure	Procyclicality
Greater transparency and reduction of information asymmetries		Excess volatility
Improved access to and convenience of financial services		Systemic importance/ Too-big-to-fail

FinTech credit: some figures

FinTech credit: small but growing fast

Size of FinTech credit market by jurisdiction

In USD million

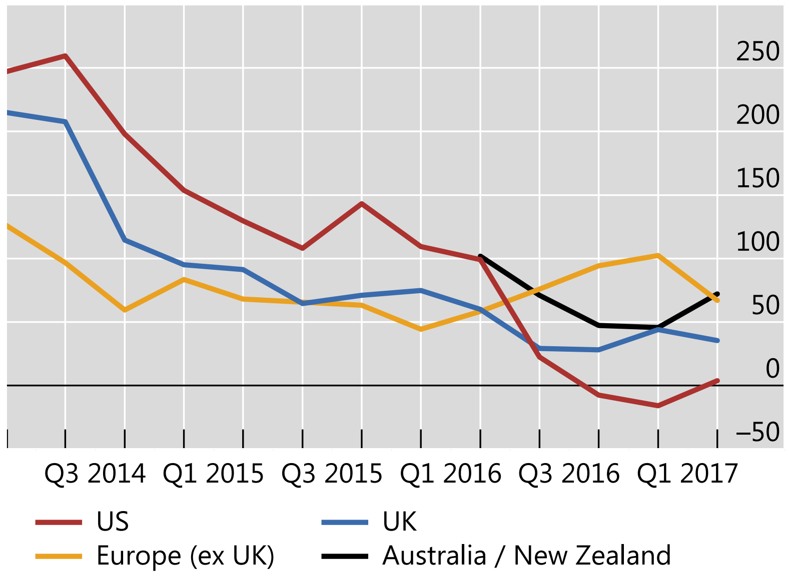
	Volume of new credit[1]			Credit outstanding[1]	
	2013	2015	*Memo: % of new credit*	2016 (latest)	*Memo: % of credit*
China	5,547	99,723			
France	59	201			
Germany	48	205			
Japan	79	326			
Netherlands	48	91		180	<0.1
New Zealand	0	245			
Nordics	112	84			
Russia[3]		140			
Singapore	0	21		7.4	
UK	906	4,126	<5.0		1.4
United States	3,757	34,324	2.0		

[1] Data on lending volumes are sourced from academic surveys of market participants (with the exception of the official data from Russia) and cover the range of platforms shown in Graph 1. Data are adjusted to USD using average daily exchange rates for 2013 and 2015 where necessary. Credit outstanding data are from national responses to the CGFS-FSB survey on FinTech credit. [2] Credit outstanding data are adjusted to USD using average daily exchange rates for 2016. The denominator for the percentage of credit is loans by depository institutions. [3] 2015 data are for first half of 2016. [4] Only data for consumer lending are available.

Sources: BIS; Cambridge Centre for Alternative Finance and research partners; national responses to CGFS-FSB survey on FinTech credit.

Growth in FinTech credit volumes[1]

%, annual change

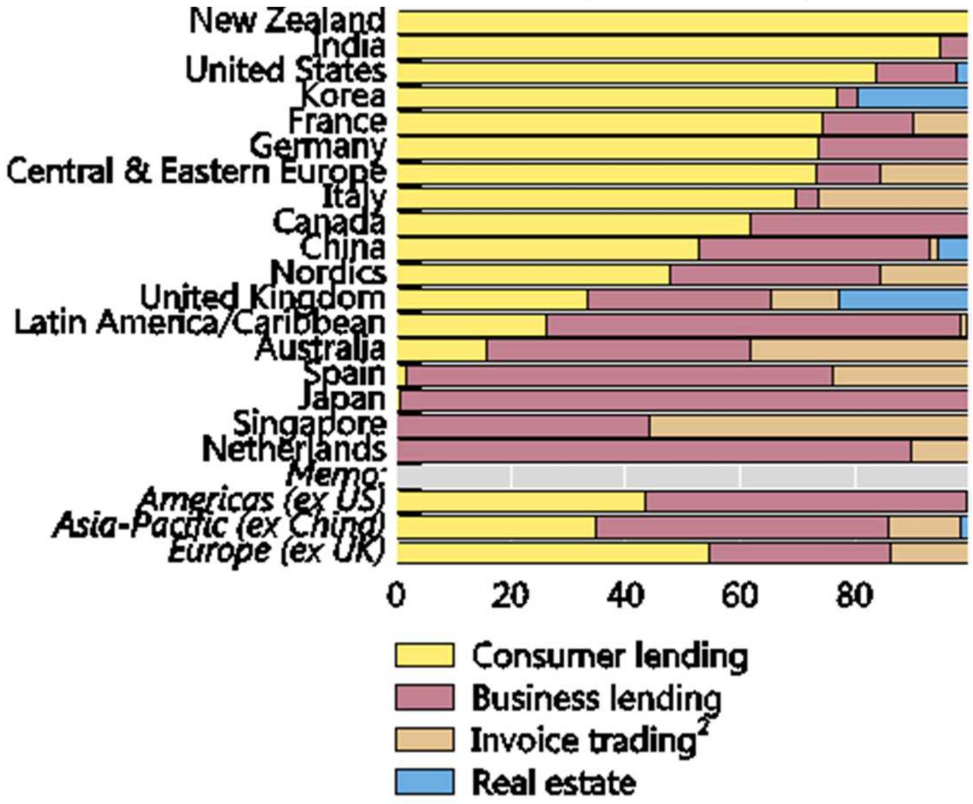


[1] Data are based on four large platforms for the US (SoFi, Lending Club, Prosper, and OnDeck), 29 platforms for the UK, 31 platforms for Europe and three platforms for Australia and New Zealand (SocietyOne, RateSetter in Australia, and Harmony). US data for Q1 2017 are projections. Australia and New Zealand data start in Q4 2015 based on data availability for all three platforms.

Source: AltFi Data

Lending to both consumers and firms

Lending volumes in 2015 by sector[1]
% of total, ranked by consumer lending



[1] Includes a very small amount of debt-based securities for France, the Netherlands and the United Kingdom.

Source: Cambridge Centre for Alternative Finance and research partners.

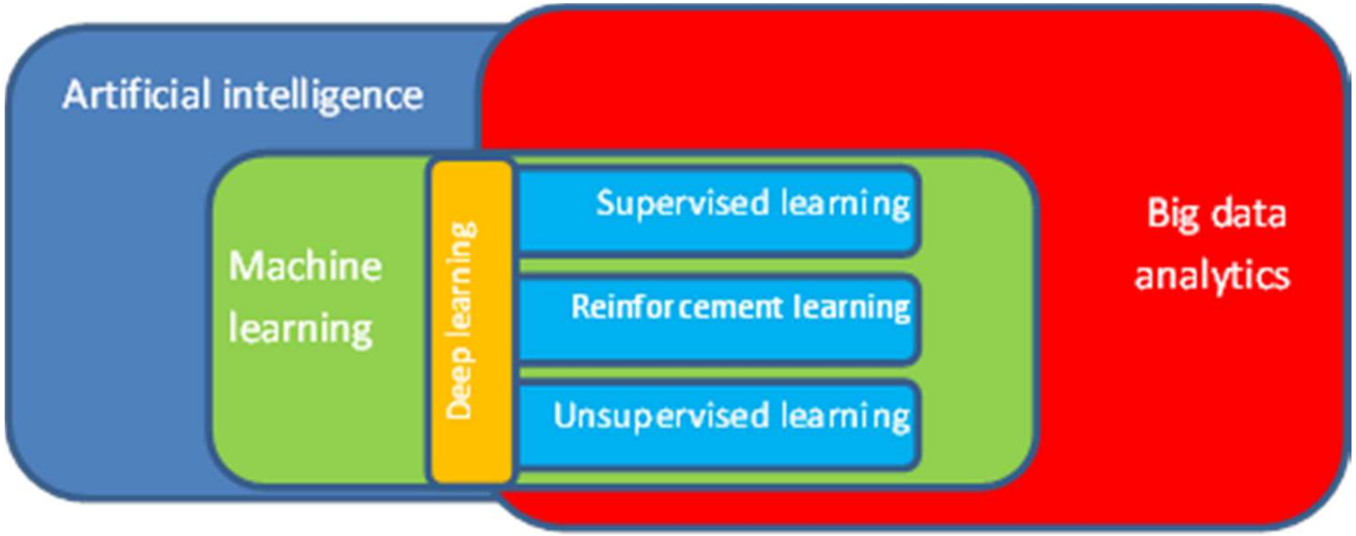
- China: consumer and business lending
- US: primarily consumer lending
- UK: businesses, consumers and real estate

FSB FINANCIAL STABILITY BOARD BANCA D'ITALIA EUROSISTEMA

AI/ML in Financial Services

Artificial Intelligence & Machine Learning

- Relationships among AI, Machine Learning and Big Data.



Selected Use cases

- *Sentiment indicators*: Social media data analytics companies use AI and machine learning techniques to provide ‘sentiment indicators’ to a number of financial services players
- *Trading Signals*: Machine Learning can help firms to increase productivity and to reduce costs by quickly scanning and making decisions based on more sources of information than a human can.
- *AML-CFT fraud detection*: Seeking to increase productivity and simultaneously reduce costs and risks, while complying with regulations, some firms use AI for AML-CFT and fraud detection at financial institutions.

Potential Applications in AI/ML

- *Credit scoring and client facing chat-bots*
- *Pricing*, *marketing* and *managing* insurance policies;
- *Model risk management*: backtesting and model validation;
- *Market impact analysis*: modelling of trading out of big position;
- AI/ML in trading execution (algorithmic trading);
- *Portfolio Management*.

AI/ML in the Insurance Industry

Insurance: what’s ahead of us?

1. Fraud detection and risk prevention;
2. Claims prevention and management;
3. Internet of Things (IoT) and product development;
4. Distribution and Payment models;
5. Reinsurance;

Examples of ML in Insurance Industry

- **Progressive Insurance** uses machine learning to predict claims from telematics and geospatial data.
- **Zurich Insurance** uses machine learning to support marketing, fraud detection, and claims management.
- **Transamerica** uses machine learning to recommend products to customers.

Source: 2 december 2017; https://vision.cloudera.com/the-power-of-machine-learning-in-insurance/

Example of ML in Insurance

Open source software framework for ML: Python, R (Julia less popular)

```
data=read.csv('file:///D:/Dati/studi/Ricerca2017/FinTech/INsurance/data.csv')
#Question 1: make all variables factors
str(data)data$previous_claim = as.factor(data$previous_claim)
#Question 2: what is the proportion of claims?
data %>%  group_by(claim) %>%   summarise(number = n())
#Quesiton 3: split the data into training and testing sets
split = sample.split(data$claim, SplitRatio = 0.8)
training_data = data[split,]testing_data = data[!split,]
#Question 4: build classifier using the training data
setclassifier = randomForest(claim ~ bmi + gender + age_bracket +
previous_claim, data = training_data, ntree = 100)
#Question 5: predict the results for the training data set
training_predict = predict(classifier, newdata = training_data)
```

Example of ML in Insurance

The dataset considered (1000 obs):

Gender	BMI	Age_bracket	Previous_claim	Claim
female	obese	31-50	0	no_claim
female	under weight	50+	0	Claim
Female	under Weight	50+	1	no_claim
male	under weight	31-50	0	no_claim
....	....	....	....	....

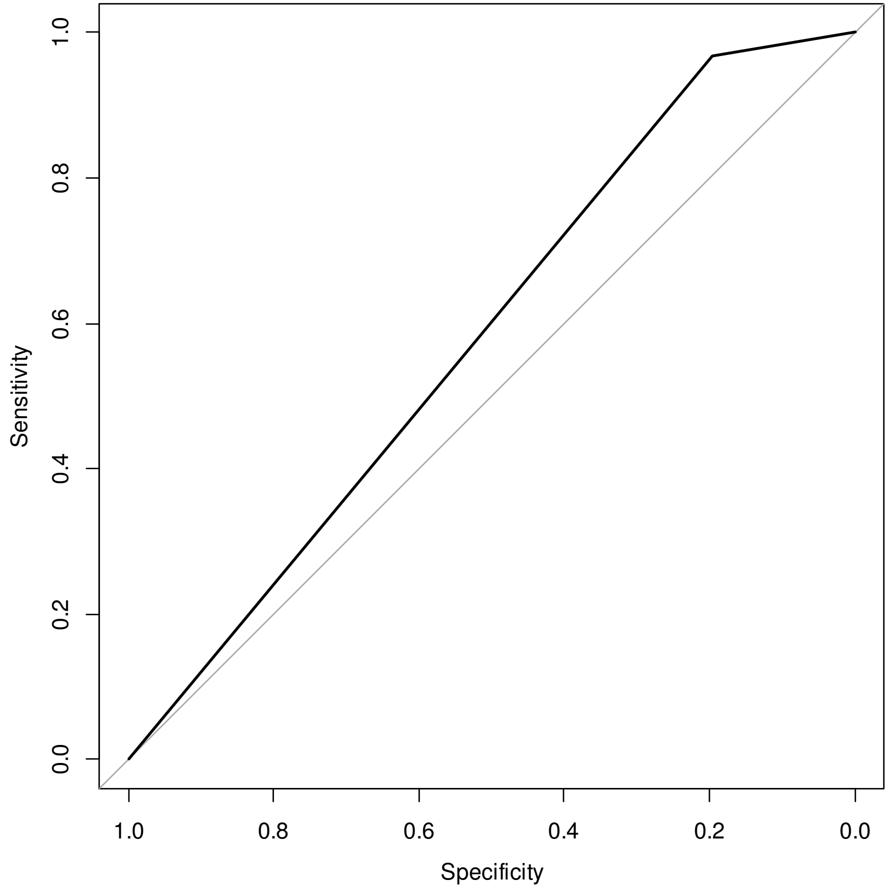
Example of ML in Insurance

Plotting the Receiver Operating Characteristic

```
claim1  <- data$claim[split]
claim1  <- ifelse(claim1=='no_claim',1,0)training_predict <-
ifelse(training_predict=='no_claim',1,0)
roc_trai  <- roc(claim1,training_predict,algorithm=0)
plot.roc(roc_trai,print.AUC=T)
```

Example of ML in Insurance

Receiver Operating Characteristic



Concluding remarks

- **Machine Learning offers big promises for data analytics;**
- **Insurance industry seems starting to uptake;**
- **How to evaluate the regulatory perimeter?** (international coordination)
- **Further analysis and experimentation is necessary to avoid risks of obsolescence.**

Supply and demand factors of financial adoption of AI & machine learning

Technology

Improvements in computing power, data availability, algorithms, costs etc.

Financial Sector Factors

Availability of infrastructure and data to apply new techniques.

Profitability

Potential for cost reduction, revenue gains, improved risk management

Competition

“Arms race” with other financial institutions and firms.

Regulation

Prudential regulations, data reporting, best execution, AML, etc.

Supply Factors

Demand Factors