ACADEMIA | Letters

Financial Technology Risk Management

Paolo Giudici, Department of Economics and Management, University of Pavia
giudici@unipv.it

Abstract

Financial technologies that derive from the application of Artificial Intelligence to financial services are complementing bank lending with platform-based lending. While financial technologies may improve financial inclusion and sustainability for both borrowers and lenders, they may also increase risks.

The European FIN-TECH research project has developed fintech risk measurement models, to make fintech innovations more secure and sustainable.
Keywords: Explainable artificial intelligence; peer to peer lending; robot advisory; cryptocurrencies.

The FIN-TECH project

Modern data-driven artificial intelligence (AI), made possible by powerful machine learning models and advances in computing power, is rapidly changing financial services in all areas of modern finance - from banking to asset management, to payments - giving rise to the widespread diffusion of fintech (financial technologies) both in new technological companies and in traditional banking intermediaries.

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While financial technologies offer important new opportunities, such as greater financial inclusion, better transparency, lower transaction costs and a better user experience thanks to the personalization of services, they can also bring new risks, of a different nature (Tanda and Schena, 2019). For example, peer-to-peer (P2P) lending, which replaces banking intermediation with a technological platform, can add a systemic risk component to the classic credit risk, which arises from the interdependence between borrowers generated by the platform. At the same time, robo-advisory, which replaces or supplements human consultants with automatic or semi-automatic portfolio allocations, can add to the classic market risk a systemic risk component that derives from the multiple correlations generated by the algorithmic portfolio allocation on a large collection of assets. On the payments side, digital payment means can introduce, in addition to increased volatility, a greater probability of cyber attacks.

The activities of the FIN-TECH project, supported by the HORIZON 2020 funds of the European Commission (Contract number 825515), took place in the three-year period 2019-2021 with the aim of measuring the aforementioned platform risks and including them in management models of the risk for fintech activities. In this way, the project has contributed to improving the offer of financial services, enhancing the advantages brought by financial technologies, but also proposing possible standards for measuring the risks associated with them, thus improving financial inclusion and safeguarding at the same time consumers and their data.

Main results of the FIN-TECH project

In credit markets, the recent literature on financial networks exploits topological measures to quantify connectivity between companies and to include centrality scores, which summarize the position of companies in their network, in credit scoring models. In this context, networks allow to improve the predictive accuracy of the individual probability of default (PD), considering similarities or links between borrowers. This becomes even more crucial with the advent of new P2P lending platforms, where individuals are able to directly provide small, in most cases unsecured, loans to small and medium-sized businesses. (SMEs), without the availability of financial and behavioral information typically exploited by banks. In the FIN-TECH project, Avdjiev, Giudici and Spelta (2019) and Giudici, Hadji-Misheva and Spelta (2020) showed how network analyzes can be incorporated into credit scoring models; Bussman, Giudici, Marinelli and Papenbrock (2021) extended this approach

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with an explainable machine learning model; Ahelegbey, Giudici and Hadji-Misheva (2019) have shown how the grouping of SMEs based on latent risk factors, inferred from financial networks, can improve P2P credit scoring models.

In financial markets, the interconnectedness between economic sectors and institutions is known as an additional source of financial risk, often referred to as systemic risk or contagion risk. In this context, the network models were applied as part of the FIN-TECH project to analyze and represent the channels of contagion originating from the interconnections between markets, sectors and countries, using financial market data such as equity returns (Ahelegbey and Giudici , 2022), CDS spreads (August, Ahelegbey and Giudici, 2020), capital flows (Giudici and Spelta, 2016; Giudici, Sarlin and Spelta, 2020) and data relating to the counting of defaults (August and Ahelegbey, 2020).

In payment markets, both traditional and with virtual currencies, such as Forex and Crypto, market prices form complex interaction patterns that may also reflect speculative behavior, rather than the fundamentals they refer to. Also in this context, the network models have proved to be very useful for measuring the correlations and spillovers between the different markets. The FIN-TECH project mainly focused on digital asset markets, characterized by high volatility (Giudici and Abu-Hashish, 2019; Giudici and Pagnottoni, 2020; Ahelegbey, Giudici and Mojtahedi, 2021), also in order to develop stable coin (Giudici, Leach and Pagnottoni, 2021) and optimal portfolio models (Giudici and Polinesi, 2021; Giudici, Polinesi and Spelta, 2021).

Finally, the FIN-TECH project found that, in addition to greater credit and market risks, the development of financial technologies involves a significant increase in operational risks and, in particular, IT risks (Aldasoro, Gambacorta, Giudici and Leach, 2021; Giudici and Raffinetti, 2021b). Given the limited availability of data regarding these risks, it may be appropriate to enrich traditional market information with data from alternative sources, in order to improve estimates (Cerchiello, Giudici and Nicola, 2017).

Below are some illustrative figures of the main results obtained with the FIN-TECH H2020 project.

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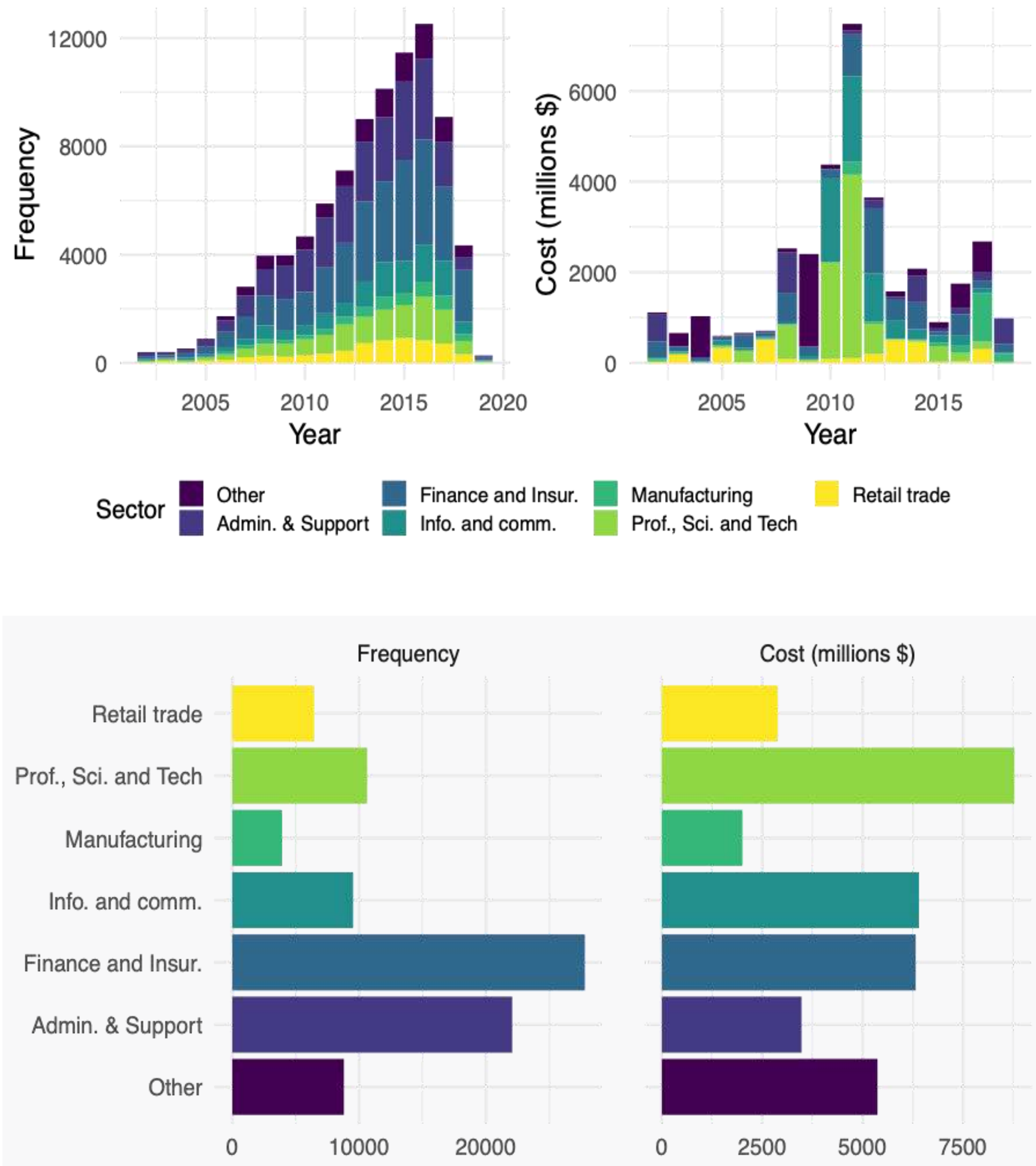

Figures 1 and 2: Evolution of cyber risks, in terms of frequency and impact. Taken from the work Aldasoro, Gambacorta, Giudici, Leach (2022): The drivers of cyber risk, Journal of Financial Stability.

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In particular, Figures 1 and 2 show the growing importance of cyber risks, but also their different impact, both in frequency and severity, on the various economic sectors.

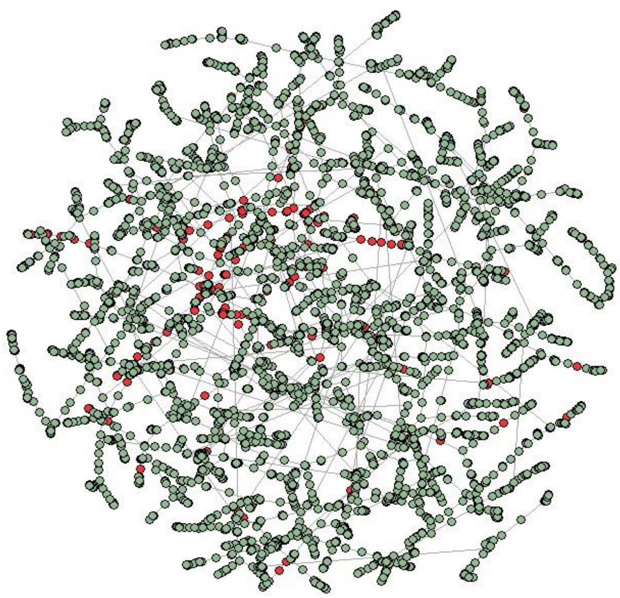

Figure 3: Network representation of correlation of (approximately) 15,000 small and medium-sized enterprises, obtained on the basis of the “similarities” in the financial statements of one year. The companies in the red defaulted the following year. Taken from Giudici, Hadji-Misheva and Spelta (2020): Network-based credit risk models, Quality Engineering.

Figure 3, on the other hand, shows how the credit risk of “healthy” firms (green nodes) can increase due to their “proximity” to defaulting firms (red nodes). This can be a “supply chain risk” or a “platform risk”, depending on whether the proximity relationships derive from a common territorial or technological belonging.

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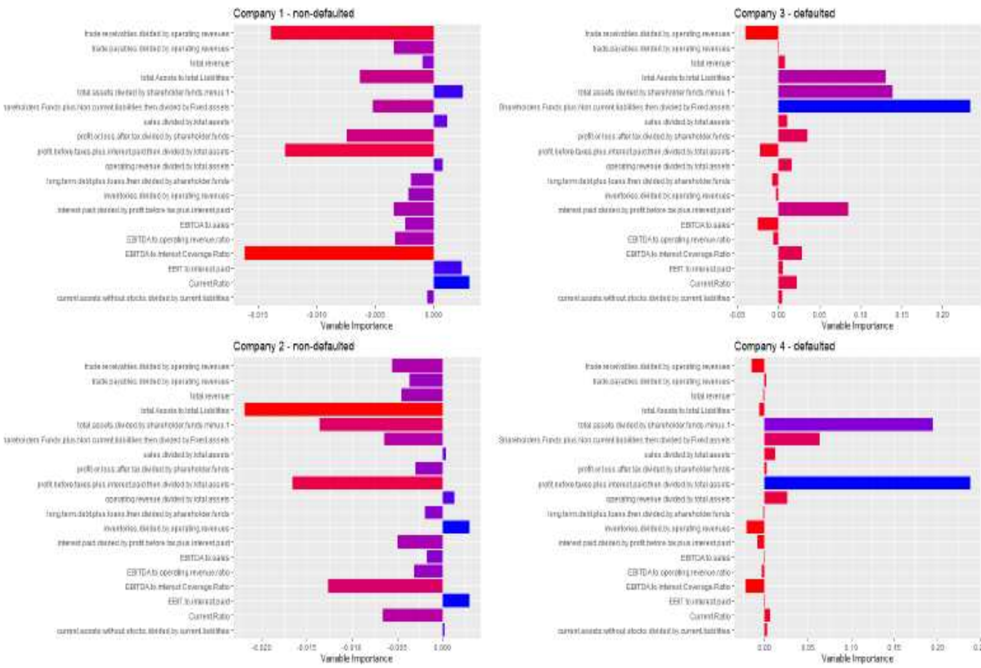

Figure 4: Representation of the share of forecast value (Shapley values) attributed to different variables, by a credit scoring model based on machine learning methods, in correspondence with four different companies. Taken from Bussmann et al. (2021): Explainable machine learning for credit risk management, Computational Economics.

Figure 4 instead shows how the forecasts (credit scores) assigned to different companies by the machine learning model considered depend on different variables. For example, a low PD value is estimated for the company in the upper left, mainly thanks to an excellent EBITDA / Interest Coverage ratio; the company in the lower left, on the other hand, has a low PD estimated following an excellent value of Total Assets / Total liabilities; the model estimates a high PD for the company in the upper right corner due to a bad value of Shareholder funds plus non current liabilities divided by fixed assets; the company in the lower right has a high PD estimated as a result of a bad value of Profit before taxes plus interest paid. In this way, each prediction (estimated PD) is "explained" in its local determinants.

i)

ii)

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