Innovation in loan market: prudential concerns for the financial sector and supervision

Summary

The market for small business loans has in recent years seen several new entrants, mostly operating as online platforms and offering quick and automatic processing of loan applications. Technological innovations and the availability of more data sources offer significant opportunities for improving the quality and speed of lending services. The market for automated small business lending is currently very small, but is growing rapidly. Automated lending is relatively easy to scale up due to its digital nature. Banks and institutional investors are also increasingly becoming involved as funding providers of loans originated by online platforms. Dutch banks also participate in foreign online platforms.

Further growth in automated lending presents possible prudential concerns for the financial sector and supervision. The entry of new players with limited expertise and no track record of credit risk management, and their increasing interaction with incumbent banks may increase the complexity of the system. To ensure safe growth of automated lending, adequate assessment and pricing of credit risk is required, as well as consideration of the relatively high uncertainty surrounding the predictive power of advanced credit risk models. Also, effective protection of small and medium business borrowers is important in ensuring fair and transparent treatment. Incumbent banks must therefore have in place appropriate due diligence, internal controls and monitoring of innovative lending operations.

Given the presently limited size of the automated lending market, the existing supervisory framework provides sufficient tools to supervise banks' innovative lending activities. Nonetheless, widespread use of automated lending could change traditional market structures and business models, and shift activities outside the scope of the regulatory framework. To ensure that supervision remains effective, it may be necessary to adjust the framework and expand the set of instruments to capture new players and activities. Against this backdrop, DNB is seeking to expand and enhance its knowledge of technological innovation by continuing the dialogue with financial institutions and innovative market players on this important topic. Since innovations and new entrants are not expected to be constrained by national borders, international cooperation with other supervisory authorities is also a priority.

Automated lending: brief overview

Technological innovations are changing the practice of providing credit. Loan application procedures for small business loans are increasingly automated, making applications quicker and easier, with less human intervention required. Moreover, innovative credit providers are increasingly using larger and more diverse data-sources, such as payment data and real-time business account data, in combination with advanced methods for credit risk assessment, such as machine learning algorithms. In this paper, the term automated lending refers to this development.

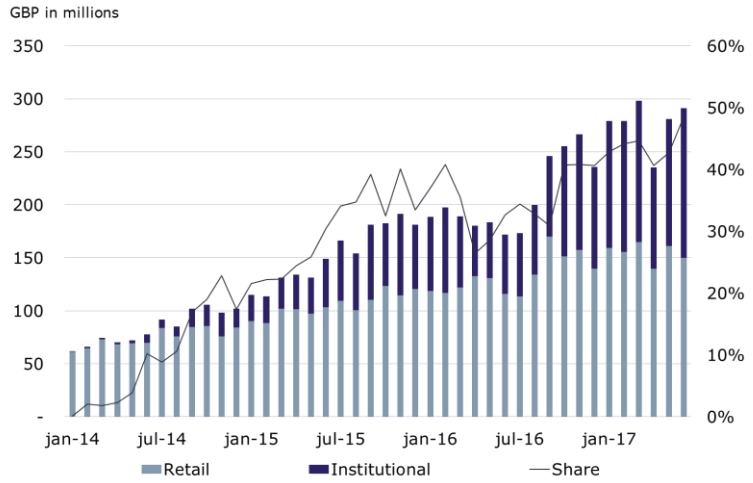
To date, innovative credit providers have been mainly new entrants operating as online platforms focusing on small loans to consumers and entrepreneurs. The benefit of automation yields relatively more cost advantages in these segments of the loan market.[1] Between 2013 and 2015 the volume of

[1] Online platforms have diverse business models. Generally, three types are identified: traditional peer-to-peer model (platform performs matching services); notary models (the loan is originated by a partnering bank); guaranteed return models (platform

loans provided by online platforms in Europe increased fivefold to reach over EUR 5 billion.[2] Although automated lending still represents a small fraction of overall credit lending, it may have larger shares in specific market segments. For example, in the United Kingdom, automated lending was estimated to represent around 14% of equivalent gross bank lending flows to small businesses in 2015.[3]

As automated lending has developed further, banks and institutional investors are increasingly collaborating with new, innovative entrants. Within just half a decade, this type of lending went from being entirely funded by retail investing, to institutional investors and banks buying substantial portfolios of whole loans. In the United Kingdom, around half of the newly originated loans by the four biggest online platforms are funded by institutional investors (figure 1). However, only a few established online platforms are considered to be suitable partners or investment options based on their scale, organisation and risk models, transparency, financial base and effective rate of return.[4]
Investments by institutional investors have increased the capital available to platforms to continue the rapid growth of automated lending. At the same time, investing in whole loans proves attractive to institutional investors searching for diversification and high yield. Banks are collaborating to learn more about improving borrower experience and satisfaction, increasing speed of underwriting against lower operating costs and analysis of alternative data sources. New entrants benefit from banks' compliance expertise as well as large numbers of savings account holders with proprietary data.

Figure 1: Estimated aggregated institutional participation in loans originated by four UK online platforms[1]



[1] Four online platforms include Funding Circle, Zopa, Ratesetter and Market Invoice. Most of the loans granted are to small businesses. The graph also includes consumer loans.
Source: AltFi (2017)

Automated lending may present opportunities…

There is expected to be ample room for continued growth in the automated lending market over the coming years.[5] In the first place, this market services a more or less neglected segment of borrowers. Research shows that high-risk borrowers with small credit lines substitute traditional bank loans for non-traditional financing, as banks are unwilling or unable to service this market segment.[6] For example, new and small companies do not have financial statements, which are often required for traditional credit risk

guarantees the creditors' principal and/or interest on loans) and balance sheet model (platform originates and retains loans on its balance sheet). See e.g. BIS and FSB (2017)
[2] See Cambridge Centre for Alternative Finance (2016) for a full overview.
[3] See, e.g., Bank of England (2016)
[4] See, e.g., HJCO Capital Partners (2016)
[5] Idem footnote 1
[6] See, e.g., De Roure et al. (2016)

assessment. This can be solved by using rich and real-time data, such as payment transactions, which provide insight into the financial position of new and small businesses.

Second, automated lending can lead to a more accurate assessment of a borrower's financial situation and improve forecast of defaults (see box).[7] For banks, a better forecast of defaults will become more important with the introduction of new accounting standards under IFRS 9. These new accounting standards will require banks to apply a forward-looking approach to determine provisions taking into account expected losses. It can contribute to a more accurate risk analysis, leading to differentiation in the interest rates charged to borrowers. Many banks do not apply risk-based pricing, or only to a limited extent, because they often still lack sophisticated algorithms to facilitate risk-based pricing. They also choose to focus on the highest quality customers, with prime credit scores and debt service capacity.[8]

Finally, innovation by new and existing players may bolster diversity and competition in the lending market, resulting in lower transaction costs and more convenient and faster service to borrowers.[9] The stability and efficiency of banking services are best guaranteed in a sector characterized by less concentration and more diversity.[10] Credit expansion through financial intermediation from entities other than regulated banks may lead to more fragmentation of the financial system, making it more resilient. The premise here is that if financial institutions are allowed to develop their own models internally and are not subjected to the same regulation, this is more likely to prevent them from reacting in the same way.[11]

Box: Methods and data used in credit risk assessment

Traditionally, banks use scorecard methods when providing credit. Scorecards use a limited number of criteria to determine whether to provide a loan to an applicant. The criteria in credit scoring are typically based on historic observations or data from clients who defaulted on their loans plus observations on a large number of clients who have not defaulted. Most empirically derived credit scoring systems have between ten and twenty variables, such as income, credit rating, homeownership and accounting ratios. A drawback of simple methods is the limited room for making trade-offs between weak and strong features of a potential borrower. After all, in reality, the unsatisfactory level of one ratio is frequently mitigated by the strength of some other area. More rigorous econometric and statistical techniques are able to overcome such shortcomings. More recently, we have seen applications of machine learning in the field of credit risk assessment. These modelling techniques are able to analyze more complex and unstructured datasets such as payment data, real-time business accounting data and social media data. Machine learning is generally used to identify correlated patterns, rather than determining causality. Therefore, the outcomes can be opaque, and more research is needed to improve the explainability of these advanced modelling techniques.[12] Machine learning tools are currently only applied on a small scale.

…as well as potential risks

At the same time, further growth in automated lending leads to a number of potential risks.[13] First, banks need to have sufficient insight in credit risk when financing loans originated by online platforms. After all, banks bear credit risk related to these loans, while online platforms often only generate fees on loans granted. This may lead to weak quality of the credit risk assessment due to moral hazard. In addition, online platforms have hardly any experience with managing defaulted loans. The likelihood of recovering the principal of a defaulted loan is therefore very low.[14] In addition, through collaboration, banks rely on credit risk models of new entrants risking financial losses and reputational damage due to

[7] See, e.g., McKinsey (2015) and Khadani et al. (2010)
[8] See, e.g., Mills and McCarthy (2016)
[9] See, e.g., McKinsey (2015)
[10] See, e.g., DNB (2015)
[11] See, e.g., LSE (2015)
[12] See, e.g., Bank of England (2017)
[13] Integrity and privacy aspects fall outside of the scope of this analysis.
[14] Idem footnote 4

misaligned interests and information asymmetry. Credit risk models and algorithms are often considered to be "intellectual property", meaning it is uncertain as to whether all new entrants use advanced techniques. Because of this and due to limited availability of historical performance data, it can be potentially difficult for banks to assess the performance of a loan portfolio.

Second, ability to assess credit risk adequately is uncertain since the advanced models have not yet been tested through a full credit cycle. To accurately calculate expected losses on defaulted loans, a large number of defaults is required, covering one or more complete business cycle. The calculation is even more complicated because expected losses show large fluctuations over time, depending on the type of borrower, sector and type of collateral.

Finally, it may be unclear to borrowers who is responsible for the decision of machine learning algorithms, and to whom they can direct questions to better understand the outcome of the model. Modelling techniques can be opaque as well, creating a risk of inaccurate credit decisions and unfair treatment of particular borrowers. For example, machine learning algorithms only show the correlation between a number of variables, but do not explain causality, and the results may well feed on each other, magnifying existing biases. These risks could in turn impact credit providers because they would be more exposed to litigation and subsequent reputational risk due to faulty automation.

Addressing risks in supervision

The challenge for supervisors and the financial sector is to facilitate the safe growth of innovative lending by mitigating risks innovation may pose to financial institutions and the system as a whole. Given the limited size of the automated lending market, the existing supervisory framework provides sufficient tools to supervise banks' innovative lending activities.[15]

In the first place, when applying advanced techniques to credit risk assessment and underwriting, supervisors expect a bank's credit risk management and valuation policies and practices to be consistent with applicable prudential principles.[16] These principles require banks to substantiate and document (changes in) the design of the model, key assumptions, the choice of variables and parameters values. Other essential elements includes ongoing model validation and assessing model robustness and accuracy, in addition to evaluating model performance under current and changing market conditions. Banks need to understand and account for model uncertainties and limitations in order to effectively implement and use the model. The prudential principles are relevant to all banks regardless of the approach they use in calculating regulatory capital requirements. The implementation may, however, vary according to the scope and complexity of each bank's operations.

Second, banks are ultimately responsible for the performance of risk models, regardless of whether they were built internally by the institution or obtained from a third-party vendor.[17] Therefore, sufficient in-house understanding and full documentation on the risk models used are necessary to ensure that the model is appropriate for the intended use and is performing as expected. Existing Basel principles require banks to have appropriate processes for due diligence, risk assessment and ongoing monitoring of any operation outsourced to a third party to ensure its continuity.[18] Banks investing in loan portfolios originated by an online platform are expected to reflect this in their Risk Appetite Statements and their Internal Capital Adequacy Assessment Process, e.g. under risk concentrations, concentration limits, and outsourcing risk. This is especially important where banks do not have adequate information about and in-house understanding of the credit risk model used by this online platform in its proprietary underwriting. Where needed, the supervisor may decide to impose additional (capital) measures on a bank during the Supervisory Review and Evaluation Process (SREP). This SREP decision is tailored to each bank's individual risk profile making it possible to address bank-specific risk exposure, such as investments in loan portfolios originated by online platforms.

[15] ECB (2017) recently published guide to assessment of fintech banks licence applications to ensure that these new entities are properly authorized and have in place adequate risk control frameworks.
[16] See, e.g., BCBS (2012)
[17] See, e.g., EBA (2016)
[18] See, e.g., BCBS (2012), BCBS (2011) and BCBS (2017)

Finally, effective protection of small and medium business borrowers is important. In this context, the Dutch Authority for the Financial Markets (AFM) is committed to promoting clear information and timely communication by banks about their credit products and services, as well as providing appropriate solutions for small and medium business borrowers with payment issues.[19] The Dutch banking sector has developed a code of conduct for SME financing, which is expected to be introduced in January 2018.

Although the technology factor in lending is becoming more important, there is still a need for human intervention, particularly in terms of the advisory role in providing business loans. Human intervention also remains essential to correct potential errors in programmed algorithms. However, international research is necessary to determine if the existing supervisory approach is sufficient for a wider application of advanced analysis techniques by both new entrants and incumbent banks. A greater share of automated lending may lead to accumulation of credit risk in the financial system with parties who are less regulated and may not be equipped to manage or fully understand the risks they are exposed to. Therefore, it may be necessary to expand the set of supervisory instruments in order to cover new players and activities. International cooperation among supervisory authorities is important as innovations and new entrants operate across borders.

Literature

AFM (2016), *Toezicht in tijden van verandering*. *Agenda 2016-2018*, January.
Bank of England (2016), *Financial Stability Report*, November.
Bank of England (2017), Machine learning at central banks, Staff Working Paper No. 674.
BCBS (2017), *Implications of fintech developments for banks and bank supervisors - consultative document,* August.
BCBS (2012), *Core Principles for Effective Banking Supervision*, September.
BCBS (2011), *Principles for the Sound Management of Operational Risk*, June.
BIS and FSB (2017), *FinTech Credit: market structure, business models and financial stability implications*, Report prepared by a Working Group established by the Committee on the Global Financial System and the Financial Stability Board.
Cambridge Centre for Alternative Finance (2016), *Sustaining momentum*: *The 2nd European Alternative Finance Industry Report*, September.
DNB (2015), *Visie op de structuur van de Nederlandse bankensector - Stabiliteit en efficiëntie door diversiteit en concurrentie*.
De Roure, C., L. Pelizzon en P. Tasca (2016), How does P2P lending fit into the consumer credit market?, *Deutsche Bundesbank Discussion Paper*, No 30/2016.
EBA (2016), Final Draft Regulatory Technical Standards on the specification of the assessment methodology for competent authorities regarding compliance of an institution with the requirements to use the IRB approach in accordance with Articles 144(2), 173(3) and 180(3)(b) of Regulation (EU) No 575/2013, July.
ECB (2017), *Guide to assessments of fintech credit institution licence applications*, Banking Supervision, September.
HJCO Capital Partners (2016), *When finance meets internet*: *The Marketplace Lending Industry*, Alternative Investment Research.
Khadani, A., A. Kim and A. Wo (2010), Consumer credit-risk models via machine-learning algorithms, *Journal of Banking Finance*, Vol 34, Issue 11, pages 2767-2787.
London School of Economics and Political Science (2015), Systemic risk: what research tells us and what we need to find out, Systemic Risk Centre.
McKinsey & Co (2015), *The future of bank risk management*, McKinsey Working Papers on Risk.
Mills, K. and B. McCarthy (2014), *The state of small business lending: Credit access during the recovery and how technology may change the game*, Harvard Business School Working Paper 15-004.

[19] See, AFM (2016)