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THE PROFITABILITY ANALYSIS OF FINTECH MICROLENDING: ADVANCED WHALE CURVE TOOLS APPLYING

Fintech is actively expanding its activities in various directions in the modern financial system. One of these directions is the development of consumer lending, which forms an important competitive factor for banks and other traditional lenders. Lending models implemented by fintech companies have a number of fundamental differences from classic ones. The article is devoted to the study of the fintech microcredit model and the profitability analysis of this model based on the advanced Whale curve toolkit adapted to lending.

In the article, the microcredit model is structured into three blocks, which include income generation, credit risk management systems, and borrower lead generation. Income generation is considered within the PDL (payday lending) approach. The methodological components of the application of the Whale curve toolkit for lending are justified. The first component outlines a holistic visualization of the relationship between risk and profitability of the credit portfolio of microcredit. The second component is the use of two approaches to the application of the Whale curve toolkit. The first approach is based on the choice of the basis of analysis of income from borrowers, and the second – on the choice of the basis of analysis of income from loans issued. The third component of the methodology was the segmentation of the loan portfolio into 4 segments: A, B, C, and D. It was done for both approaches. Segment A is characterized by the generation of high profitability for the creditor, segment B is close to a neutral level of profitability, and segments C and D are defined by a negative financial result of different levels.

The analysis, based on the developed methodology, made it possible to identify a number of regularities between risk and profitability both in terms of segments A, B, C, and D and in terms of repeated loans. The analysis was conducted on the basis of data from several Ukrainian fintech companies for the 2nd and 3rd quarters of 2021.

Within the methodological components, the analysis of income sensitivity based on the scenario approach was used in the work. A number of scenarios regarding changes in credit characteristics and risk management parameters were formed. On this basis, the sensitivity of income to these changes was modeled, and a comparative analysis of the results was carried out.

The methodology proposed in the article makes it possible to implement an optimization analysis of fintech microcredit, to determine the relationship between credit risk and profitability, and to choose the optimal strategy for increasing the profitability of lending.

Keywords: fintech, consumer lending, payday loans, customer profitability analysis, Whale curve, segmentation, sensitivity analysis.

JEL classification: G23, L25

Introduction and research problem. Consumer lending markets around the world are undergoing transformations associated with the introduction of new financial and information technologies. Although banks and other traditional lenders remain the main source of household financing in most economies, in the last decade fintech companies have been actively mastering the consumer lending market. The share of loans issued by them is constantly growing. The impact of fintech companies on the market becomes very tangible from a competitive point of view, because they "bite off pieces of customers" from traditional lenders. Thus, McKinsey & Co predict that over the next 10 years, commercial banks may lose up to 60 % of profits in favor of fintech (Geniusee, 2021). Investigations of Harvard Business Review Analytic Services indicated that 65 % of the polled bank executives believe that fintech competitors will become a significant threat (Harvard Business Review Analytic Service, 2019). In our opinion, the economic reason for this threat is primarily the Sense-and-Response strategy used by fintech companies. While banks use Make-and-Sell strategies more (Haeckel, 1999). The use of the Sense-and-Response strategy is driven by a high innovation focus and a softer regulatory aspect. The last aspect is generated by the fact that fintech companies do not operate with the deposits (they do not have a deposit function, like banks).

Unsolved part of the problem. The rapid development of fintech leads to a rethinking of approaches for the provision of financial services. Areas that can be replaced by fintech startups are consumer finance, microloans, payment services and other. In particular, the digital lending models such as peer-to-peer (P2P)/market-place lending have grown in many economies over the past decade. These types of loans facilitated by online platforms have been dubbed "debt-based alternative finance" (Wardrop et al., 2015), "fintech lending" (FSB та CGFS, 2017). KPMG (2023) indicated that nearly €81 billion was pumped into fintech's of all sorts in the first quarter of 2022. This growth of fintech lending objectively leads to the need to build new business models for the credit organization. Such models should include specific features of financial technologies. In this paper, we consider the business organization of fintech companies in the microloans segment. This segment is a complex combination of such components as online technologies of interaction with the client, customer profitability management and, in fact, short-term loan granting (in many ways there is a payday lending). The combination of these components gives rise to a number of features of business models that distinguish this segment from banking. The first feature is the ratio between risk and profit. Classical business models of bank lending consider credit risk as a "pure" risk (that is, when it is realized, there will be losses. And if not, then the profit is fixed, associated with an interest rate). At the same time, when considering fintech models, credit risk is "speculative." This means that borrowers with more risk tend to generate more profit. The second feature is the factor of borrowers' repeatability of loans received. This finds to apply tools of Customer Profitability Analysis (CPA). First of all, such an indicator as Customer Life-Time Value (CLV) indicator. Therefore, one of the ideas of our research is to link the allocation of marketing resources with the issuance of loans in the context of larger increases in the CLV sense. The third feature is the alternative databases significant use. And the fourth feature is the logic of processing the information from credit bureaus, which differs from the logic used by traditional lenders. These features essentially affect the business model of fintech microloan lending. Optimization of the business model of lending is very important, because optimal solutions appear in a different form from optimal solutions in traditional lending.

The purpose of this article is to provide profit analysis of fintech microloan granting by applying advanced Whale curve tools. Storbacka (1998) described the Whale curve tool (also named "Stobahoff curve"). Then this tool has been developed by several papers, in particular, Ø. Helgesen (2006). We have elaborated an adaptation of the Whale curve tool for fintech microloan granting. The profitability analysis was developed on the basis of this adaptive tool. It is based on the application of sensitivity analysis to the credit model.

The article is organized as follows: Section 2 briefly discusses the previous literature. In Section 3 we present the adaptation model of the Whale curve tools, background for introducing segments of borrowers/loans and logic of our methodology. Section 4 contains empirical results. Finally, in Section 5, we draw conclusions, discussion and possible directions for the development of the proposed approach. Section 6 is devoted to references.

Recent publications analysis. The deep transformation is a distinctive feature of modern credit markets around the world. Fintech "broke" into the consumer lending market 10 years ago and is rapidly developing. This development and changes are investigated by Nguyen (2022) in the context of financial stability in emerging markets. The paper presents groundings about the hypothesis that fintech development negatively affected financial stability. Also, this study focuses great attention to the role of market discipline at the framework of fintech development. Cornelli et al. (2023) present results of analysis of a global database of fintech and big tech lending volumes for 79 countries over 2013–2018. It is very interesting from our research that authors of this research arguing for fintech and big tech credit seem to complement other forms of credit, rather than substitute for them. Wardrop et al. (2015) investigated another type of fintech lending, which was facilitated by online platforms.

Taking account that fintech focused on microlending there are logically to analyses publications, devoted to this problem. Hansen (2022) found that the main cause for the demand for high-cost loans is the personal traits of borrowers: they are more present-biased than other borrowers. Also, they tend to make temptation spending and spend more than they earn. Disney and Gathergood (2013) found a significant influence of borrowers' financial literacy on a choice of credit product. The borrowers with low level of financial literacy tend to have high-cost loans. Gathergood et al. (2019) discovered that the use of PDL causes borrowers to apply for the next loans within six months, which increases borrowers' consumer debt. The use of PDL also increases the likelihood of delinquency on other loans. The borrowers' decision to apply for PDL was analyzed in detail by Social System Design Lab (2010) and was represented by a causal loop diagram. A significant share of PDL borrowers is underbanked and has low income. In some cases, PDL starts to be profitable after a second or third loan (Holman et al., 2018). To decrease the share of borrowers who are likely to default, lenders use credit scorecards. Agarwal et al. (2018) suggest enhancing traditional scorecards by using phone-based social behavior data.

The behavior of PDL borrowers is different compared to traditional banks' borrowers. It is common for PDL borrowers to delay payments and pay higher penalty fees. So, it requires another approach to evaluating such borrowers. Kaminskyi et al. (2022) suggest segmenting borrowers based on their CLV instead of distinguishing them only by default, not default. In that way, lenders can build scoring models to optimize their risk–return–marketing efforts. Storbacka (1998) designed a Whale curve to represent graphically how profit is distributed by clients. Helgesen (2006) suggests segmenting clients based on their profitability to gain additional insights.

Research Methodology. The object of our research is the fintech company business process at the segment of short-term loan granting. In the overwhelming number of cases, such lending is carried out online and typically has payday lending. The subject of our study is optimization approaches based on the advanced Whale curve toolkit. In this article, we use the term "advanced" for the Whale curve toolkit, which is specially adapted to the features of the consumer lending processes.

The peculiarities of the credit process in the segment of short-term loans granting essentially affect its business model. Moreover, such a business model differs significantly from the models of classical (banking) consumer lending. Generalizing in some way, it is possible to indicate three building blocks of the model.

The first building block is grounded on a return generating pattern. Pattern includes typically daily-based interest accrual. The daily rate is typically 0,5-2 %, which in the transfer to the annual rate can be 180-700 %. Prolongation of the loan term significantly increases the amount of payments by the borrower, and is also part of the scheme. Another element of this pattern is the recurrence loans. This conceptually leads to the applying CPA and CLV assessments. Namely, the crucial part of lender profit is formed by recurrence loans by many borrowers. The CPA indicators can be effectively used for economic analysis of return generating patterns. However, an important difference arises here. This difference comes from the possibility of default after each re-credit. This feature leads to an extension of the CPA to the probabilistic framework. Probabilistic nature converts the CLV indicator into a random variable that can take both positive and negative values. In particular, if the first-received loan was in default, then CLV equals the amount of this loan with a minus sign. This is the important difference in applying CLV indicators for lending business models.

The second building block is the credit risk management system. As part of our research, we clearly identify, including through the advanced Whale curve tool, that it should be based on the principle of risk-return correspondence, rather than the principle of risk minimizing. Because borrowers with high risk demonstrate high profitability. One of the optimization tasks is the task of finding the maximum profit depending on the scoring values of the bureaus of credit histories (BCH).

The credit segment under study is characterized by a high level of credit risk (expressed percentage of defaulters). This fact is due to the nature of this segment. Paying capacity of borrowers in such segments is low. Moreover, in the online lending segment, a borrower can simultaneously obtain loans from several lenders, significantly exceeding their ability to repay borrowed funds. Also, in the segment of short term loans there is a relatively worse discipline of credit payments. Additionally, it is worth noting that the lender in the online short term loan segment has limited influence to motivate borrowers to pay back the loan. One of the main motivation tools is a negative record in the borrower's credit history. It should be noted that the processing of information from the BCH also has specifics. Our research shows that credit history information in this segment is significant. At the same time, information about the borrower's credit history in the banking segment is less significant. Our statistical analysis shows that borrowers treat bank loans more responsibly than short-term ones.

Building a risk assessment system in fintech lending uses alternative data to a greater extent. Since the loan processing time is a decisive element for competitive advantages. Therefore, filling out "classic" application forms with a variety of information often repels online borrowers. As alternative data, scoring of mobile operators, behavior on the company's website, reports from various registries, etc. are used.

The third block of fintech's credit business model involves lead generation procedures and more widely marketing strategy. The first disposition is the ratio between attracting new customers (borrowers) and re-lending existing ones. It was investigated by us at the CLV (customer lifetime value) aspect in Kaminskyi et al. (2022). This aspect determines the way to account-based marketing, which focuses marketing budget spending to loans with higher marginal utility. The second disposition includes increasing the loan amount and offering complementary products/services. Increasing the amount of credit directly gives rise to the task of optimal increase, which includes income growth and increased risk. An example of a complementary product is the purchase of a time interval in which you do not need to pay a loan.

The interaction between these three building blocks were investigated in Kaminskyi et al. (2022). Our optimization methodology includes the following steps. First step embraces the adaptive to lending Whale curves construction. We use two designs of such Whale curves. The first design is based on the borrowers ordering by cumulative profit over some definite time period. The logic of the curve construction consists in the allocation of borrowers into 4 segments: A, B, C, D. The economic essence of such segmentation allows a holistic consideration of the risk-profit relationship of the creditor. Segment A represents 25 % of borrowers (top profit makers), B — the remaining positive profit borrowers, C — those borrowers who have returned only part of the credit amount and D defaulters who have not paid anything. The overall view of borrowers-based Whale curve is presented in Fig. 1.

The second construction of the Whale curve is based on the order of total profit from loans, not borrowers. Each design plays a role in our approach to optimization. The borrowers-based curve underpins the lead generation analysis, the risk assessment of borrowers and the aggregate returns they generate. Loan-based Whale curve allows to do effective performance analysis characteristics (loan amounts, duration, default rates etc.) at the context issued recurrent loans.

The first advantage of using Whale curves is credit portfolio holistic visualization. Credit portfolio which is formed from lending during some time interval. We have used in our investigations 1-quarter and 1-year time intervals. The 1-quarter time interval is very useful for analyzing the dynamic of the credit portfolio through the time. At the same time, the 1-year time interval is more suitable for strategic business development.

Second step of our methodology is risk-profit analysis by borrowers-based Whale curve and loans-based Whale curve. Their specificity is described in Table 1.

Two comments on our methodology should be noted. First comment, the basis of profit in our methodology is the amount of payments that exceeds the loan amount. Such approach is not the only possible one. It does not take into company's operating expenses, the company's planned profit or coverage of attracted funds in the financial market (ex. issued bonds). Similar generalizations can be implemented in the model by involving some minimum acceptable return from loan. In this paper, we present a model with an emphasis on "net" lending. Second comment embraces differences of ordering loans and borrowers. Loans can be ordered with the classical rule "the more the better." But an analogical approach for borrowers is not only possible. As example, borrower could pay off for three recurrent loans but his/her fourth loan lead to partial default. Borrower may belong

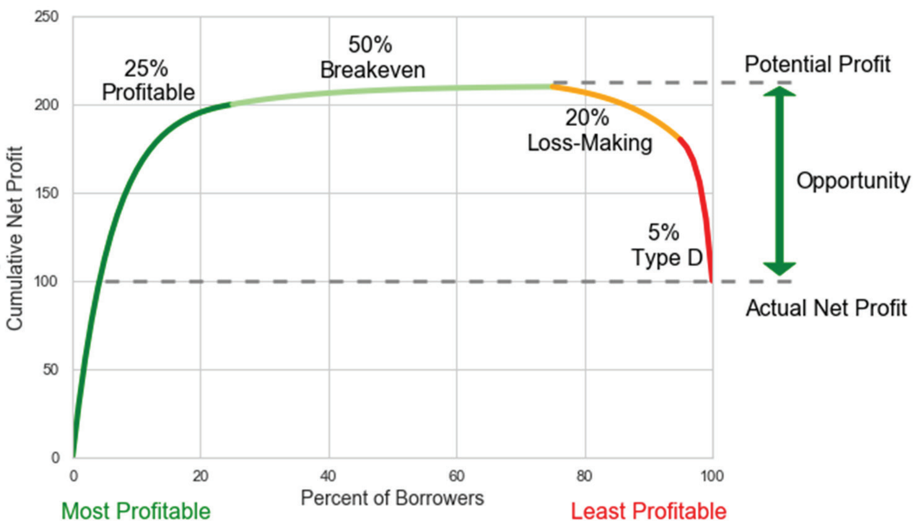

Fig. 1. Adaptive to lending Whale curve. Borrowers-based segmentation

Table 1. **Description of segments**

Segments	Borrowers-based Whale curve	Loans-based Whale curve
A	25 % borrowers with higher profit are involved here. There are 2 types of borrowers. First is those who pay day interest rates and other. Second type embrace borrowers with high recurrence rate. Borrowers from segment A raise up Whale curve. The ratio of profit from them can be up (according to the results of our research) 200 %-600 % compared to the total profit from lending.	25 % of issued loans into segment A indicated by higher profit. This ordering embraces all loans by recurrence number – first, second and so on. This is the advantage of this approach. The structure of this segment allows to indicate most profitable loans in order.
B	Segment includes borrowers which generate profit ≥ 0 and which are not in segment A. There are two types of borrowers here. First type consists from borrowers who pay off fair and square Second type indicates borrowers which previously paid off high, but now demonstrate last loan as C or D.	Segment involves loans which generate profit ≥ 0 and which are not in segment A.
C	Borrower which are in partial or complete default into the last loan in recurrence loan ordering.	Loans which are in partial default. The payments for these loans are less than the loan amount and more than 0 (payments > 0, profit < 0).
D	Borrowers with one loan which are in total default. There are no payments.	Loans in total default. There are no payments. The crucial difference of this segment concerns comparing such loans frequency by recurrence number – first, second and so on. There are no payments.

formally to B segment, but loan granting for the next loan is problematic (because borrower very risky after partial default).

The third step of our methodology is segment analysis and identification of ways to increase revenue in each segment. We consider two main approaches to increase revenues in borrower's segment A. The first is the boost of loan amounts. The analysis of such a strategy is based on the comparison revenue from boosting amount and default rate growth. Such analysis can be carried out on the basis of a credit portfolio database. The second approach is to focus on recurrent loans. It stimulates the receipt of the next loan and is associated with optimality in the context of marketing costs and marginal growth of CLV. This aspect is discussed in Kaminskyi, et al. (2022).

The consideration of loans' segment A indicates distribution of recurrence loans numbers. This is the background of development marketing strategies for next loan granting.

The optimization approach for segment B is conceptually similar to segment A. The differences are as follows. Credits in the segment do not provide a great profit. Payments of these loans are in full and on time. Without leaving payment schedules, they do not generate penalties and fines. Therefore, a more promising strategy is to increase the loan amount. The amount increment should be less than for borrowers from segment A. The advantage of this approach is also that in segment B there are significantly more borrowers than in A. So, the optimization strategy of increasing the loan amount will be competitive with a similar strategy in segment A due to the correspondence "amount increasing – number of borrowers in the segment."

The core strategy for segments C lyes in improving the debt recovery system. Optimality is achieved through the comparison of investments into such systems and growth in the percentage of repayment credit debt. In addition to this strategy, a strategy can be focused to minimize the loan amount and improve the assessment of creditworthiness on the inflow. Moreover, constructed for loans segment C grounds the understanding of what number of recurrence loans is most risky.

The optimal solution for the borrower's segment D supposes separation of the first loan and followings. Strategy for first loan granting corresponds to improvement of the identification system for such borrowers. Often they are characterized by unwillingness to repay the loan at all. However, improving the credit management system by changing the cut-off point of credit scoring (both application scoring and BCH scoring) is not an optimal strategy. This is because changing the cut-off point also rejects borrowers who will pay for the loan. As a rule, these are class A borrowers (they are riskier than B in BCH scoring). Therefore, in this case, it is necessary to focus on the rules for rejecting loan applications that are not presented in the scoring. Strategy for second and following loan granting should be closely connected to improving scoring by adding information about payments from previous loans.

The logical follow-up is scenario and sensitivity analysis. It covers the fourth stage of our optimization methodology. Sensitivity analysis consists in consideration of changing due to some scenario. We are talking about different loan's parameters: the amount of loans, the number of recurrent loans, etc. Scenario analysis is implemented in each segment and results focus on profit sensitivity studies. A scenario that generates a larger profit gain indicates an optimal strategy of credit business development.

Results. The methodology we developed was used to analyze and optimize the credit business of three fintech companies. These companies carried out online lending in the Ukrainian market in 2021 in the payday loan segment. 2Q and 3Q 2021 loan portfolio data were used for analysis. The portfolio for analysis included 57,997 borrowers (information on borrowers was not personified) and 103,196 loans.

The initial step we carried out was the construction of Whale curves and formed segments A, B, C, and D. Fig. 2–3 demonstrate received results. Unbroken lines are Whale curves (the dotted lines are explained below).

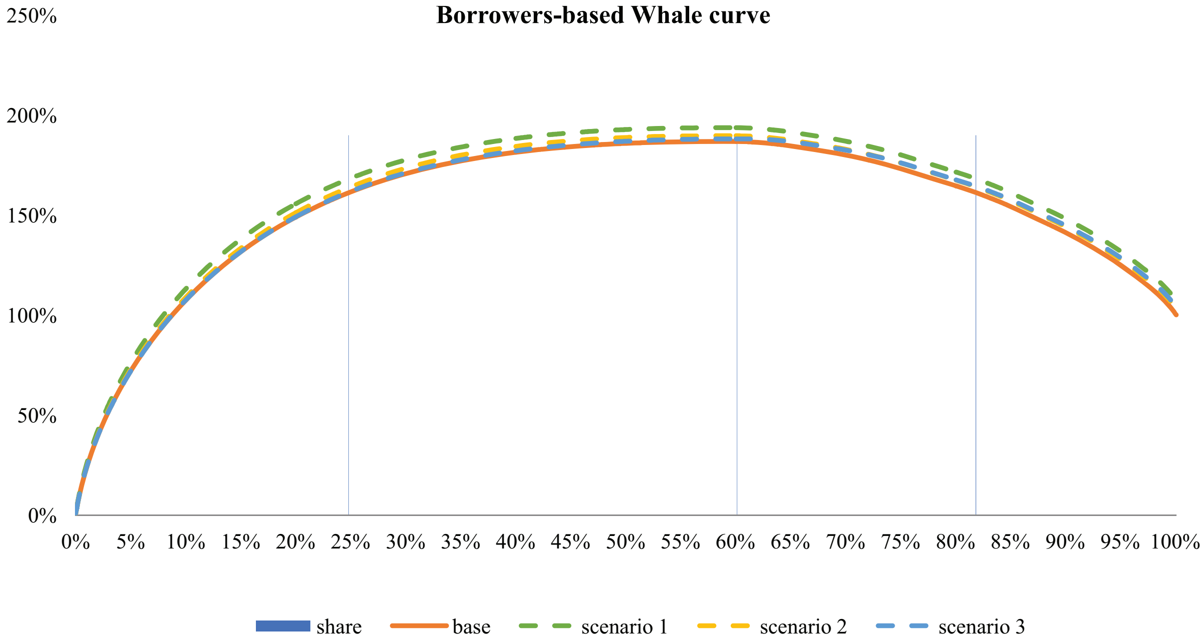

Fig. 2. Whale curves for investigated credit portfolio

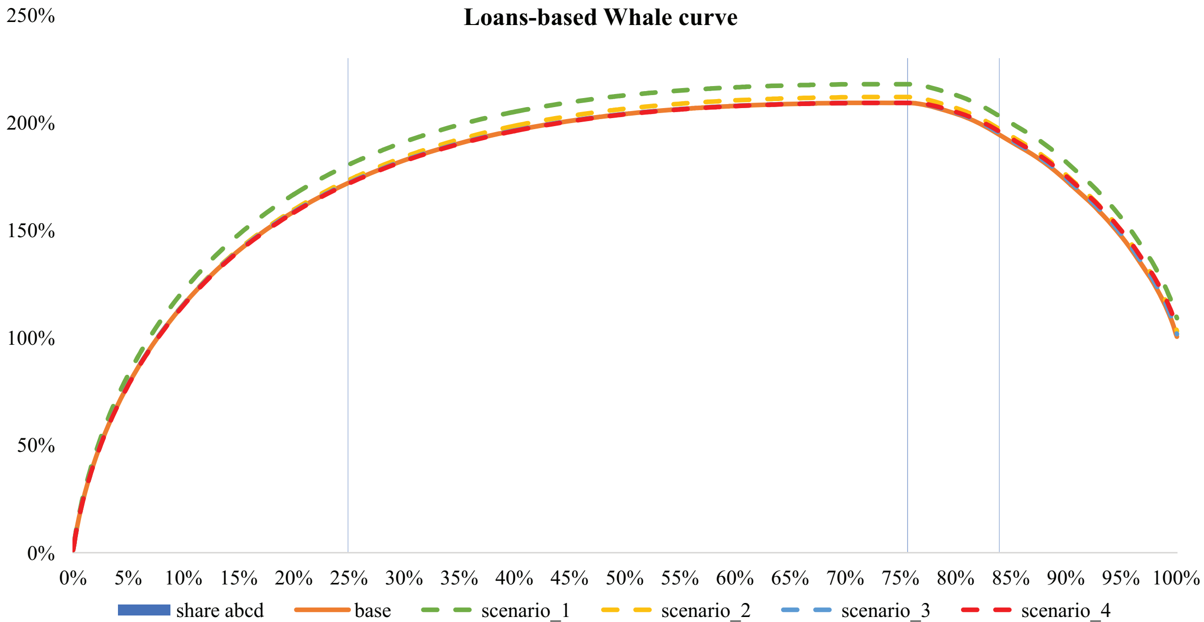

Fig. 3. Whale curves for investigated credit portfolio

Table 2. **Structural data of investigated credit portfolio**

Segments	Indicators	Recurrence loans number						
		1	2	3	4	5	6	7
A	count (% to first loans)	100 %	53 %	21 %	9 %	5 %	2 %	1 %
	share of all	23 %	31 %	27 %	22 %	20 %	17 %	14 %
	avg amount	3 396	4 203	4 940	5 664	6 279	6 304	6 698
	avg profit	113 %	105 %	99 %	97 %	94 %	91 %	80 %
B	count (% to first loans)	100 %	36 %	19 %	11 %	7 %	4 %	3 %
	share of all	50 %	45 %	53 %	59 %	65 %	69 %	72 %
	avg amount	2 967	3 888	4 456	4 906	5 159	5 415	5 538
	avg profit	16 %	18 %	17 %	17 %	17 %	16 %	15 %
C	count (% to first loans)	100 %	39 %	16 %	7 %	3 %	2 %	1 %
	share of all	9 %	9 %	8 %	7 %	5 %	5 %	5 %
	avg amount	3 266	4 167	5 274	5 986	6 447	6 420	7 253
	avg profit	-51 %	-50 %	-50 %	-50 %	-54 %	-56 %	-49 %
D	count (% to first loans)	100 %	33 %	13 %	6 %	3 %	2 %	1 %
	share of all	18 %	15 %	13 %	12 %	10 %	9 %	9 %
	avg amount	2 880	3 818	4 565	5 490	5 683	6 433	6 561
	avg profit	-100 %	-100 %	-100 %	-100 %	-100 %	-100 %	-100 %

The next step of our research was data analysis and their structuring. Structuring was carried out in the context of segments A, B, C, D of the corresponding Whale curves and sequence numbers of credits. The result of structuring the loans-based Whale curve data is presented in Table 2.

One of the patterns obtained was the change in the percentage of segments with an increase in the sequence number of loans, which is reflected by us in Fig. 4. With the growth of the serial number of loans, the percentage of loans from the B segment increases.

Another regularity corresponds to patterns profitability and churn rate for different classes of sequence number of loans. The diagrams in Fig. 5 demonstrate that class of credit number two is different from others. It is characterized by highest profitability and, simultaneously, highest churn rates. Further, these indicators decrease with the growth of the ordinal number of loans.

The next stage of the study was a scenario analysis to optimize the credit business. Scenario analysis consisted in the introduction of changes in a certain indicator and the study of profit sensitivity

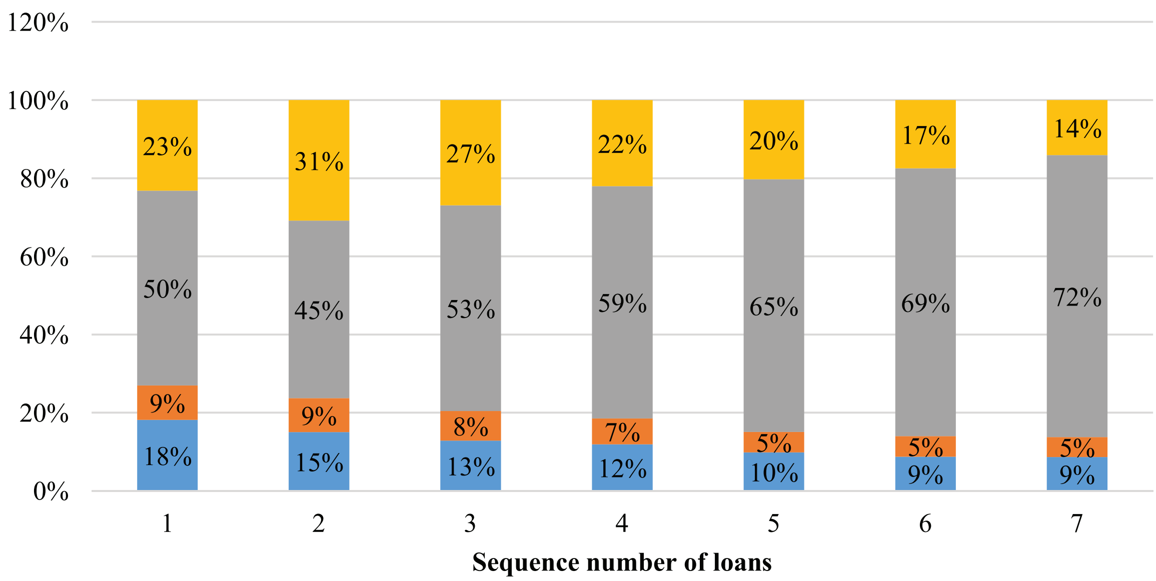

Fig. 4. Allocation loans through segments (A, B, C, D top-down)

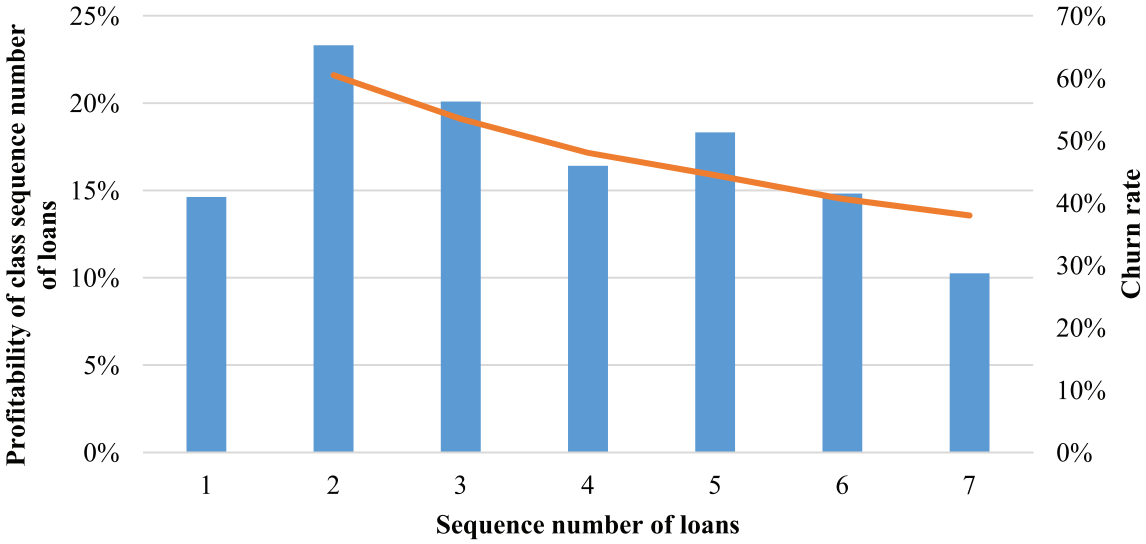

Fig. 5. Profitability and churn rate of the classes of sequence number of loans

to these changes. We considered changes in the second and subsequent loans. Because, the lender, having information about the borrower's servicing of the first loan, can make a better assessment of the characteristics of the borrower in relation to subsequent loans.

We studied the following 4 scenarios:

Scenario 1. Increase in segment A by 10 % in the amount of loans subsequent to the first issued and returned loan;

Scenario 2. Increase in segment B by 10 % in the amount of loans subsequent to the first issued and returned loan;

Scenario 3. Increase in segment B by 10 % the size of the amount Decrease in segment C by 10 % the number of loans subsequent to the first issued and returned loan. By transferring such clients to segment B with 0 profit.

Scenario 4. Decrease in segment D by 10 % in the number of loans subsequent to the first issued and returned loan.

It is not possible to realise Scenario 4 for borrowers-based Whale curve because if borrower had first credit D they will not receive next loans. The results are presented in Fig. 6. The presentations of Whale curves corresponding to these scenarios are figured by dotted lines in Fig. 2–3.

As the sensitivity results show, Scenario 1 gives the greatest effect of increasing profit.

Conclusions and further research discussion. Fintech is actively expanding its activity in various segments of the modern financial system. One of these segments is consumer lending, where its development forms an important competitive factor for banks. To date, this factor is realized through the ribbed development of fintech microcredits.

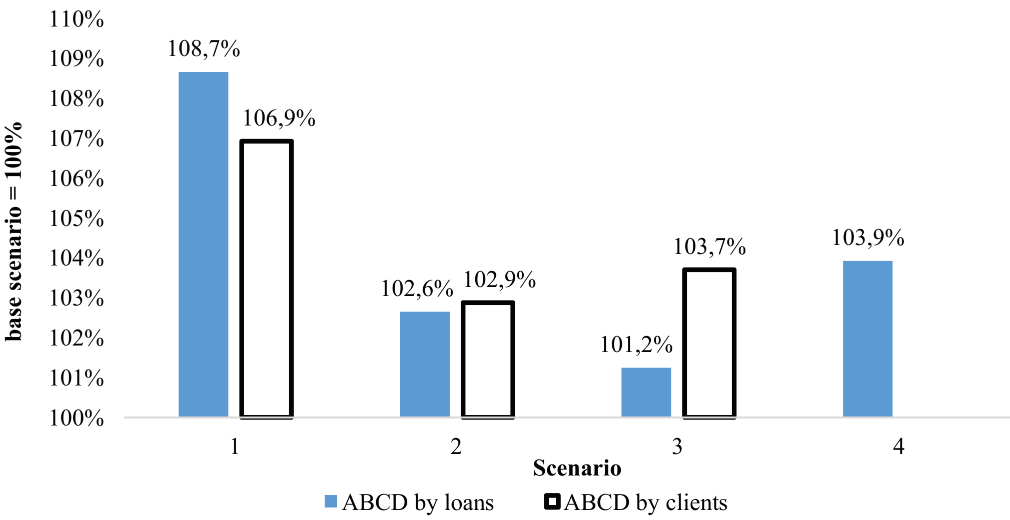

Fig. 6. Comparison profit effect of different scenarios

Analysis of fintech microcredits business models shows significant differences from business models of fintech and traditional (banks) lending. These differences relate to the generation of income, the level of risk and its relationship between risk and profitability, customer profitability management and other.

We elaborated a toolkit for comprehensive analysis of fintech microcredit and identified a number of distinctive features. The core of our toolkit is an adaptation of the Whale curve approach. Adaptation of this approach to lending allows a better insight of both profitability and credit risk. In particular, the division of borrowers into 4 segments A, B, C, D allows a much more accurate display of return generating and risk-return correspondence. This approach more accurately reflects the risk-return correspondence than is generated by the traditional division of borrowers into two groups "Good" and "Bad."

The fintech microcredit development has several debatable points. The first subject of discussion is the payday loan revenue generation scheme, which is actively used. Payday loan schemes often generate discussions with the market regulators, due to the high level of the annual rate. So, in the USA in some states such a model is allowed, and in other states it is prohibited. The limitation of the daily interest rate to 1 % per day is also considered at the regulatory level in Ukraine.

The second discussion point is the development of business models in the way of increasing loan amounts. This will affect all components of the models, such the repeatability of loans, the risk of default and the annual interest rate. Such an interest rate cannot be maintained economically with an increasing loan amount increasing.

Also, one of the key aspects of fintech loan granting further development is the strategy of banks in this competitive environment. In particular, one of the strategies may include direct competition, the second strategy may be to focus on other segments of the consumer lending market. Also, one can observe a strategic approach, which consists in the purchase by banks of fintech startups or their combination in a certain form (for example, in the form of neobanks). In our opinion, today banks have not yet formed a clear competitive strategy in this aspect.

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АНАЛІЗ ПРИБУТКОВОСТІ ФІНТЕХ-МІКРОКРЕДИТУВАННЯ: ЗАСТОСУВАННЯ РОЗШИРЕНОГО ІНСТРУМЕНТАРІЮ WHALE CURVE

Фінтех активно розширює свою діяльність за різними напрямами в сучасній фінансовій системі. Одним із таких напрямів є розвиток споживчого кредитування, що формує важливий конкурентний чинник для банків та інших традиційних кредиторів. Моделі кредитування, які реалізуються фінтех-компаніями, мають низку принципових відмінностей від класичних. Статтю присвячено дослідженню моделі мікрокредитування фінтехом та аналізу прибутковості цієї моделі на основі розширеного інструментарію Whale curve, адаптованого до кредитування.

У статті модель мікрокредитування структуровано в три блоки: генерація доходів, система кредитного ризик-менеджменту та лідогенерація позичальників. Генерацію доходів розглянуто в межах підходу PDL (payday lending). Обґрунтовано методологічні складники застосування інструментарію Whale curve для кредитування. Першим складником є цілісна візуалізація співвідношення між ризиком і дохідністю кредитного портфеля мікрокредитування. Другим складником є використання двох підходів до застосування інструментарію Whale curve. Перший підхід ґрунтується на виборі як бази аналізу доходів від позичальників, а другий – на виборі як бази аналізу доходів від виданих кредитів. Третім складником методології є поділ кредитного портфеля на 4 сегменти: A, B, C, D. Це здійснено для обох підходів. Сегмент A характеризується для кредитора генерацією високої дохідності, сегмент B близький до нейтрального рівня дохідності, а сегментам C та D властивий негативний фінансовий результат різного рівня.

Аналіз, заснований на розробленій методології, дав змогу виявити низку закономірностей між ризиком і дохідністю як у розрізі сегментів A, B, C, D, так і в розрізі повторних кредитів. Аналіз проводився на основі даних декількох українських фінтех-компаній за 2 і 3 квартали 2021 року.

У межах методологічних складників у роботі було використано аналіз чутливості доходу на основі сценарного підходу. Було сформовано низку сценаріїв щодо змін характеристик кредитів і параметрів ризик-менеджменту. На цій основі змодельовано чутливість доходу до цих змін і проведено компаративний аналіз результатів.

Пропонована в статті методологія дає змогу запроваджувати оптимізаційний аналіз фінтех-мікрокредитування, визначати співвідношення між кредитним ризиком і дохідністю та обирати оптимальну стратегію підвищення дохідності кредитування.

Ключові слова: фінтех, споживче кредитування, payday кредити, аналіз дохідності споживачів, Whale curve, сегментація, аналіз чутливості.

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