

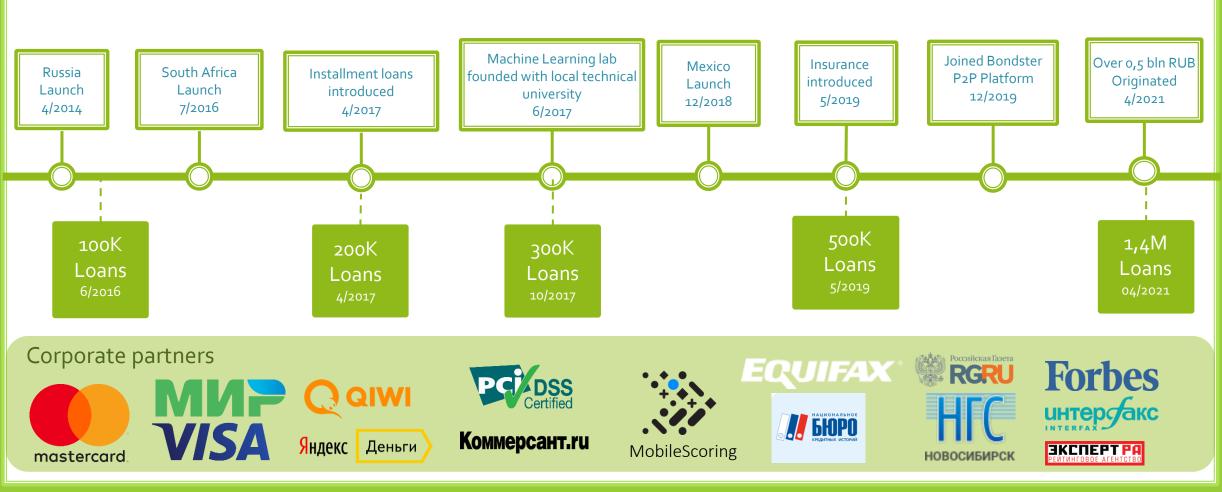
# **LIME LOANS** MULTI-MARKET ONLINE CONSUMER LENDING

MAY 2021





# **CORPORATE MILESTONES**



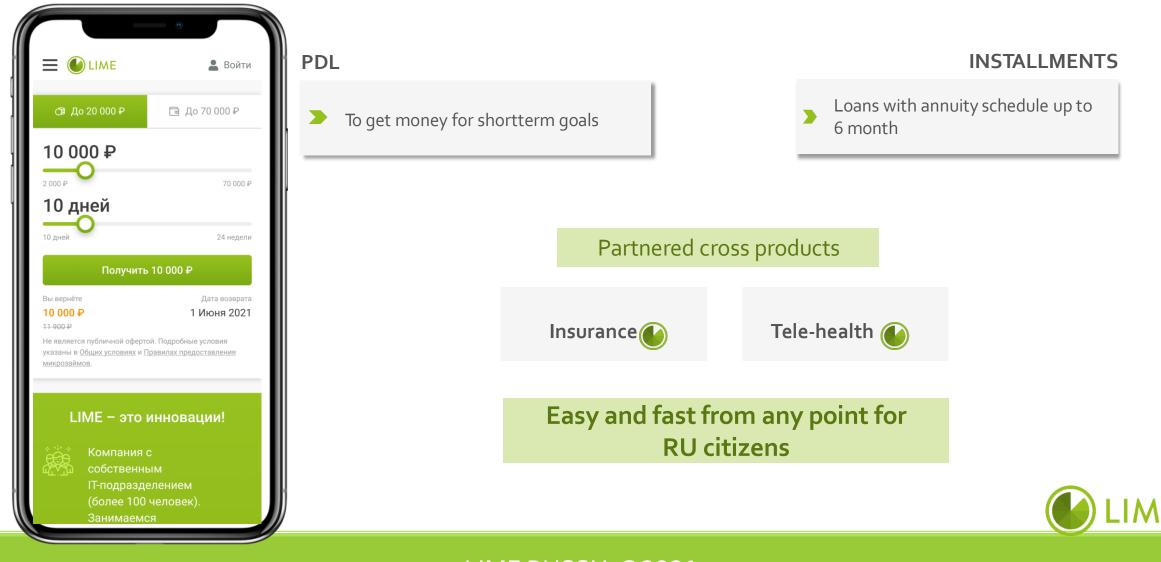


## > 9 years on market

### Internal fintech tools automating business processes



## 2 MAIN PRODUCTS: PDL AND INSTALLMENT LOANS



# **BENEFITS OF INSTALLMENT LOANS**

# Annuity predictable payment schedule:

A set term: six or twenty four weeks:



A set sum of loan: from ~ 320 to ~ 1 120 euros:

320 EUR 0 1120 EUR 22 EUR 1120 EUR

Due to predictable annuity payment schedule clients definitely know when and in what amount to make a payment Approval of higher quality clients



Only clients with a high credit score and meeting the pool of additional criteria are approved for installment loans



Significantly lower level of fraud





# 2020-2021 HIGHLIGHTS

YonY Originations up By 60%	Originated 13,4 M EUR in Q1 2021 vs 8,0 M EUR in Q1 2020				
Increased Principal Recovery	Principal Recovery 60 dpd +8 p.p. in Q1 2021 vs Q1 2020				
Increased Loan amount	Average loan amount +7% in Q1 2021 by changing the approach to limit policy				
Increased LTV	LTV +15% in Q1 2021 vs Q1 2020 due to an overall improvement in product quality				
LIME RUSSIA © <b>2021</b>					

# **LENDING KPIS - RUSSIA**

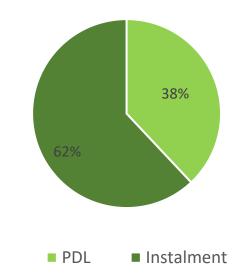
#### **Annual Quantities and Values of Loans**

	Qty of Ioans	% changes	Total originations (EUR)	% changes	
2014	7 769		450 219		
2015	50 782	554%	2 465 398	448%	
2016	88 614	74%	5 010 293	103%	
2017	163 493	85%	14 172 854	183%	
2018	295 776	81%	34 377 067	43%	
2019	340 066	15%	51 584 176	50%	
2020	306 366	-10%	33 271 418	-35%	
Q1 2021	114 756	60%	13 429 060	60%	

#### Average Loan Size (EUR)

	Blended	PDL	Instalment
2014	60	60	
2015	49	49	
2016	57	57	
2017	87	78	304
2018	122	82	332
2019	151	121	333
2020	107	85	186
Q1 2021	113	80	195

#### Current Working Capital structure





## **LENDING KPIS - RUSSIA**

#### Cumulative Recovery (as % of Originations), \*figures as of 31.12.2020 and 31.03.2021 at historical FX, \*money-weighted average

PDL

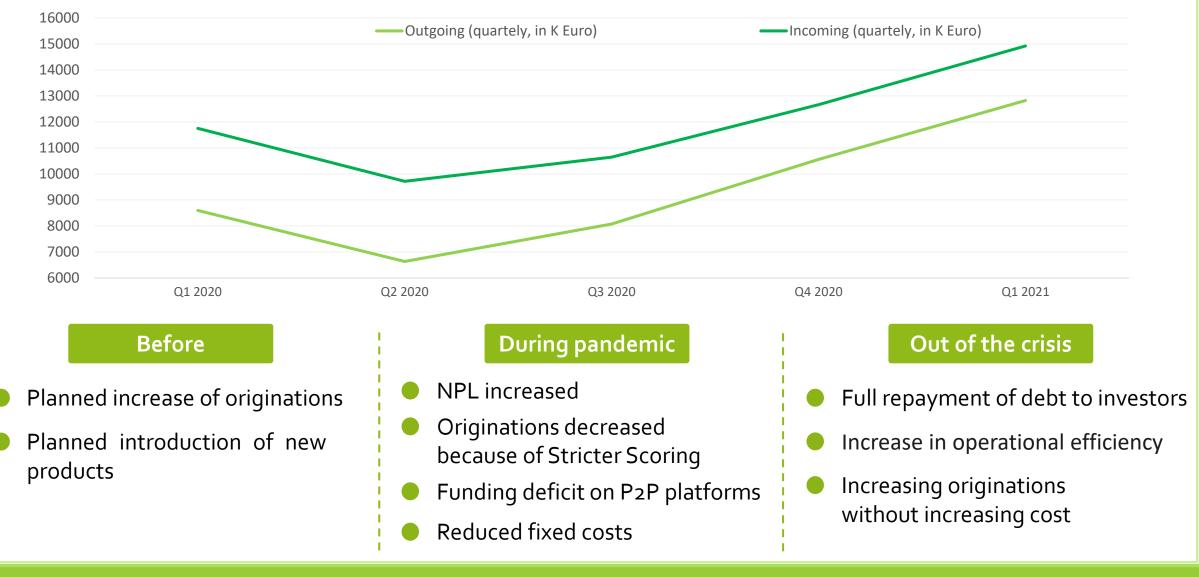
IL

2020	Originations (EUR)	Мı	M2	M <sub>3</sub>	M4	M5	М6	M12
Qı	5 07 <sup>8</sup> 755	118	122	123	124	124	125	125
Q2	4 132 212	131	135	136	137	138	138	
Q3	4 418 397	125	128	129	130	130		
Q4	5 802 093	117	119	120	121			
2021	Originations (EUR)	Мı	M2	M <sub>3</sub>	M4	M5	M6	M12
FY expectations	34 625 000	123	126	127	128	129	130	136

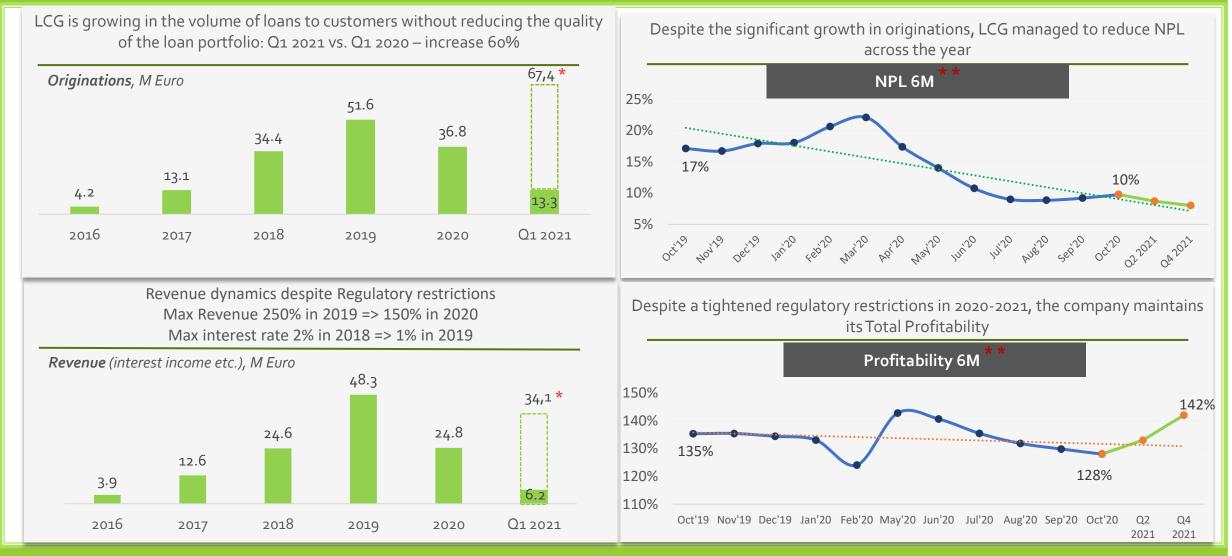
2020	Originations (EUR)	Мı	M2	M <sub>3</sub>	M4	M5	M6	M12
Qı	2 506 683	127	129	130	130	131	131	132
Q2	2 069 649	141	143	145	145	145	146	
Q <sub>3</sub>	3 878 743	132	134	134	135	135		
Q4	5 384 886	128	129	130	130			
2021	Originations (EUR)	Мı	M2	M <sub>3</sub>	M4	M5	М6	M12
FY expectations	32 727 000	131	134	135	135	136	137	141

\* Implies vintage analysis by loan generations: the financial results of clients (took a loan, for example, in Feb'20 then M3 is May'20). Thus Q1 2021 will appear at the end of Q2 2021.

# **PAYMENT FLOW**



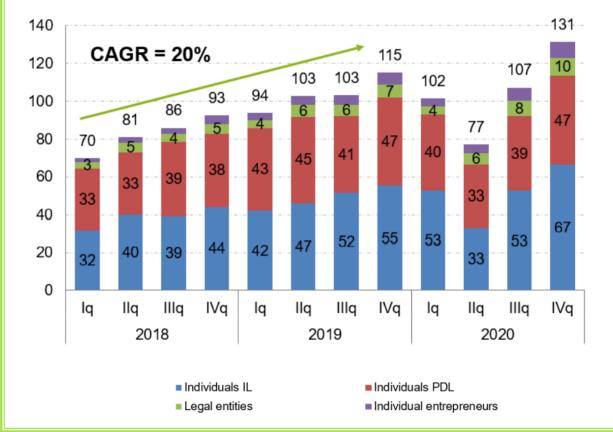
## LIME CREDIT GROUP DEMONSTRATES STABLE GROWTH ON THE RUSSIAN MARKET



#### \* 2021 Budget Forecast

**\*\*** Implies vintage analysis by loan generations: NPL and Profit in 6 months

# **MFI MARKET DYNAMICS IN RUSSIA**



#### Microloans Originations, billions rubles

- MFI market has been booming in Russia in recent years;
- For the first time, fall of volumes occurred in H1 2020, but already in H2 2020 all indicators recovered, and in 2021 there is already a widespread growth;
- Next year, market growth will be around 15%. Volume of loans will come close to 0.5 trillion, that is, more than 1.3 billion rubles in loans per day. 85% of this volume - individuals;

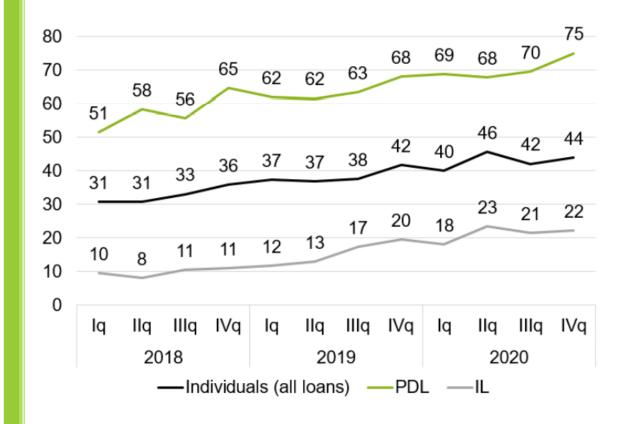


• Despite the slowdown in growth rates, the MFI market in Russia will only grow

Source: CBR industry reviews; Expert RA MFI-industry analytics

# **MFI MARKET DYNAMICS IN RUSSIA. ONLINE DOMINATION**

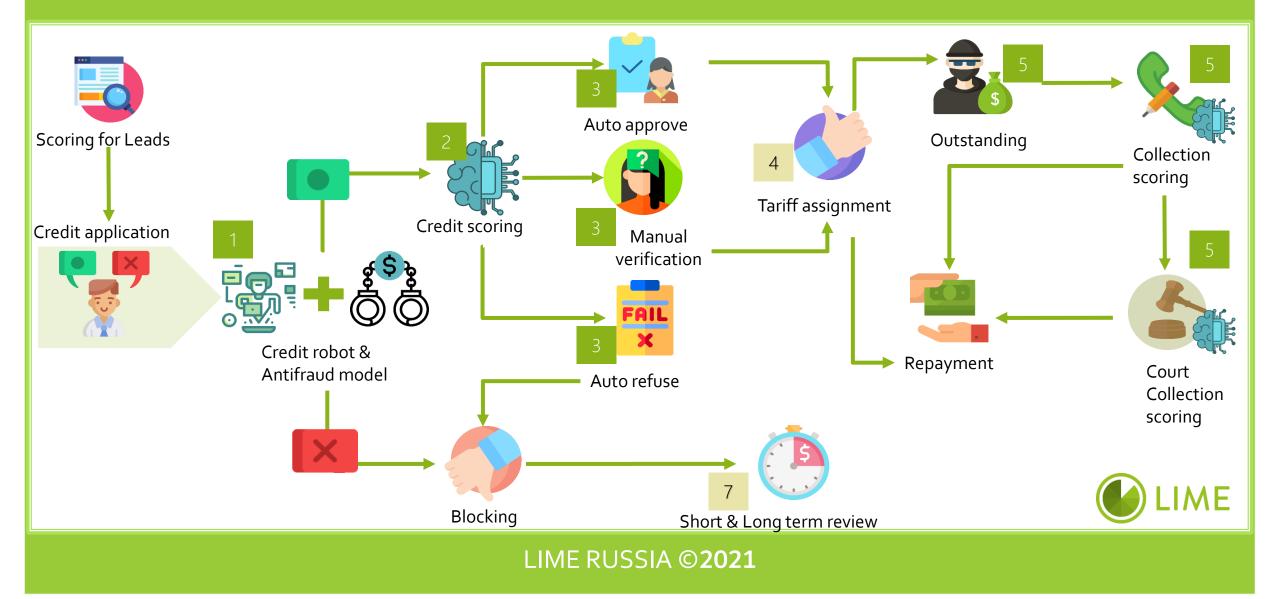
## Share of online originations,% in money



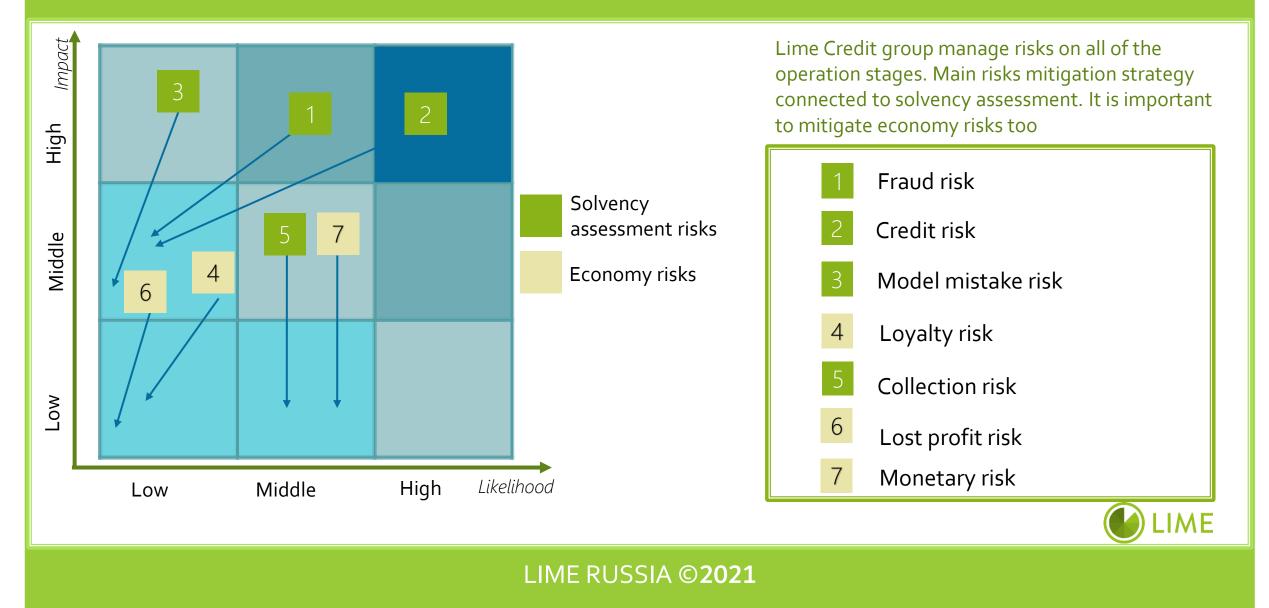
- First online MFOs began to appear in Russia in 2015, then no one believed in this segment - risks were too high. But over time, share of such companies only grew
- Now 44% of microloans are issued online. If we estimate in pieces, more than 70% of loans are originated in online
- Growth stimulus of online segment is high operational efficiency, customer friendliness, easy scaling and of course COVID
- Current challenge for online is to learn how to originate not only small PDLs, but also to cope with risks in IL segment

Source: CBR industry reviews; Expert RA MFI-industry analytics

# **AUTOMATED SCORING**



# **RISK MATRIX**



# CREDIT ROBOT & ANTIFRAUD MODEL

Firstly, applications are processed by the Credit Robot's checkpoints to block the criminal and clients with false data



**Credit robot** based on integrations and static risk rules verifies the authenticity of client information in loan applications



Antifraud system is based on ML algorithms model that performs dynamic verification based on open sources data and borrower's device data (blacklist and etc.)

#### Checkpoints examples

- terrorists
- risk PANs / bill numbers
- loosed document

- match table
- age limits
- data from credit bureaus

#### What we do for improvement

- Develop potential checkpoints
- Retro-testing checkpoints for target results to confirm efficiency
- Periodically re-analysis the checkpoints.

 name from filled bank account owner differs from name filled in application form



# **CREDIT SCORING ML SERVICE**

#### Automatic estimation for the probability of loan repayment by this client based on ML algorithms



Services performs step-by-step estimation result of these model is the clients score that normalized from o to 1. Client's score is a probability of repayment

#### 1 On the first step model:

- Use only free data sources
- Rating clients on these data
- Passes on the next stage only clients with good rating



At each iteration model use new NON FREE data source and:

- Rating clients on these data
- Passes on the next stage only clients with good rating

... then additional, more expensive data are requested, and the check is carried out again

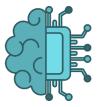
#### Step-by-step estimation advantages



Less mistakes due to fraud blocking by Credit Robot and Anti Fraud Model



Less money spend on pay data



Scoring model could be retrained on the better quality train

# **CREDIT SCORING ML SERVICE**

#### Combination of different data sources increases model's quality rapidly



#### - Black lists

- Terrorists
- Extremists
- Clients at risk of money laundering
- The Federal Tax Service reports
- Clients application
- Intersection of personal data of the application with the current database

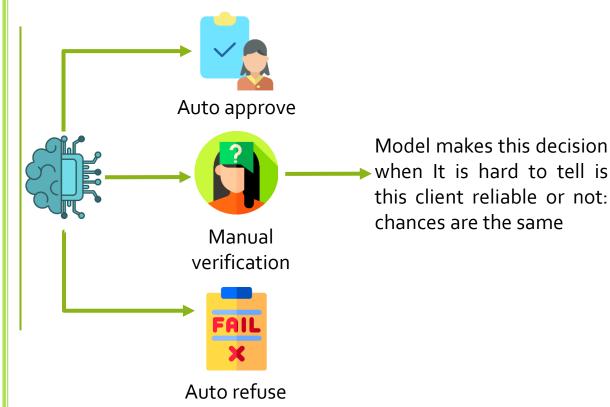


- Bank transactions' sources
- Credit history bureaus
- Anti-fraud sources
- Mobile operators
- complex to get sensitive data
- Borrower's device data
- no personal data, only technical variables
- UI-telemetry



## ADDITIONAL DATA SOURCES AND MANUAL VERIFICATION

### Verifiers complement application with manually found data so model could make a concrete decision



#### Manual verification process



Verifiers review client's applications and look through needed data, check photos of documents



Personal verification that could not be automated. Mostly calls to clients or to client's employer/ confidant



Fulfilling the or correction the application data

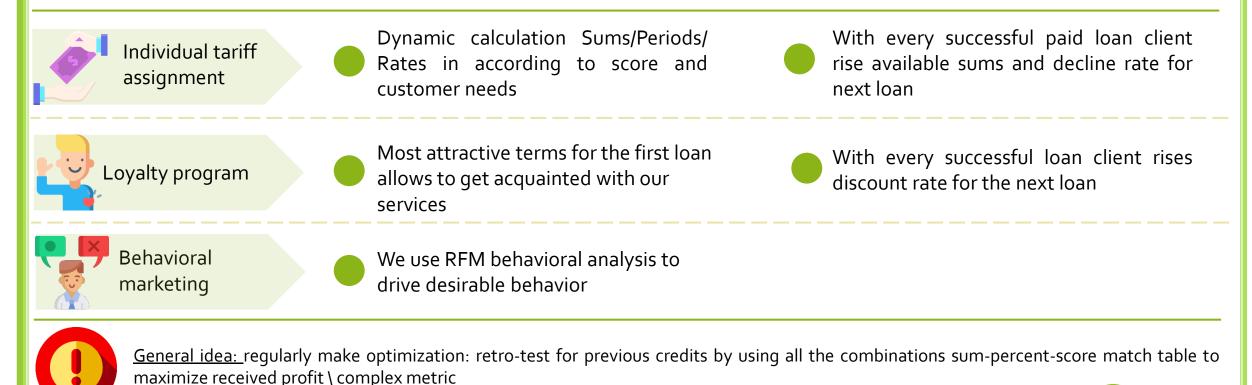


Checks on a sources that has not yet been automated -Quick Payments System, Kronos



## Lime credit group mitigate loyalty risk by offering individual terms and discounts to clients

Important to give clients what they need so they'll stay loyal and regular. In other case clients will prefer competitors services

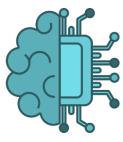




# COLLECTION SCORING AS OUTSTANDING'S MANAGEMENT

Collection scoring advantages

### Collection scoring provides most efficient strategies for non-performing clients



Collection scoring gives probability of repayment the outstanding by this concrete client. Collection score provides the communication strategy that is the most efficient for this deb loan.

#### First collection score:

Provides insides for debtor's communication strategy

- On which day to start the automatic newsletter
- On which day to start personal calls
- How much unfulfilled promises could we take before taking case to the court

#### In progress

#### Second collection score – court score:

Provides insides for taking case to court

- Trial requests additional costs
- How old should be debt to take this additional costs



personal estimates

Automation:

way

Collection scoring allows to reduce excessive funds spend on personal communication

Machine learning services is

more efficient then





## REHABILITATION PROCESS FOR REJECTED CLIENTS

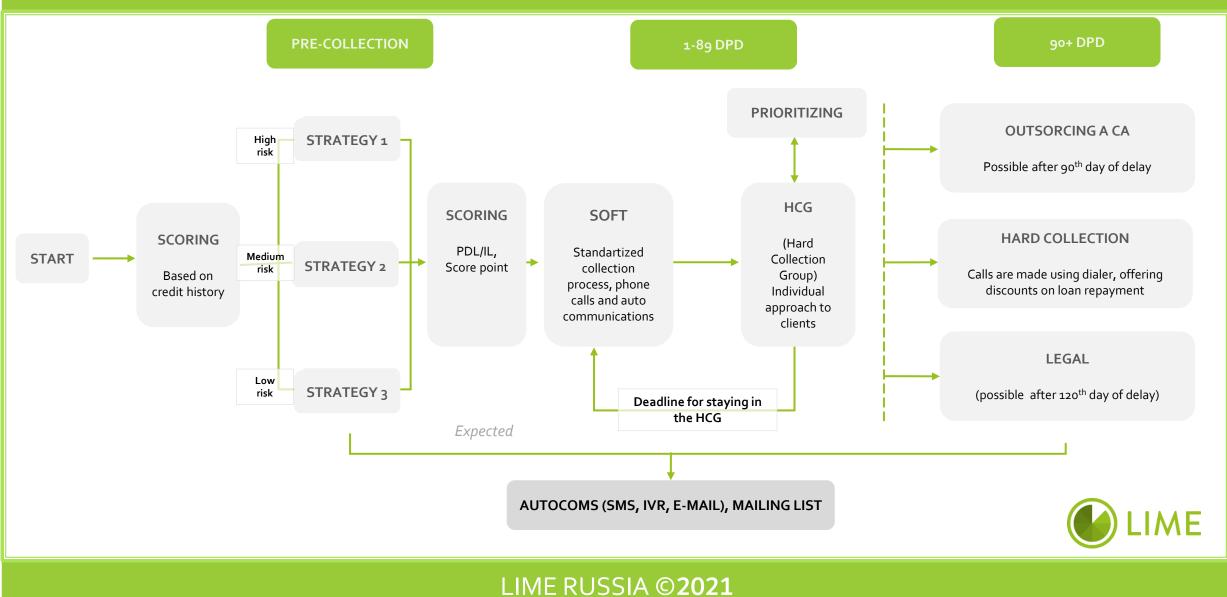
#### Review client's relatability allows to satisfy the maximum requests and get maximum profit

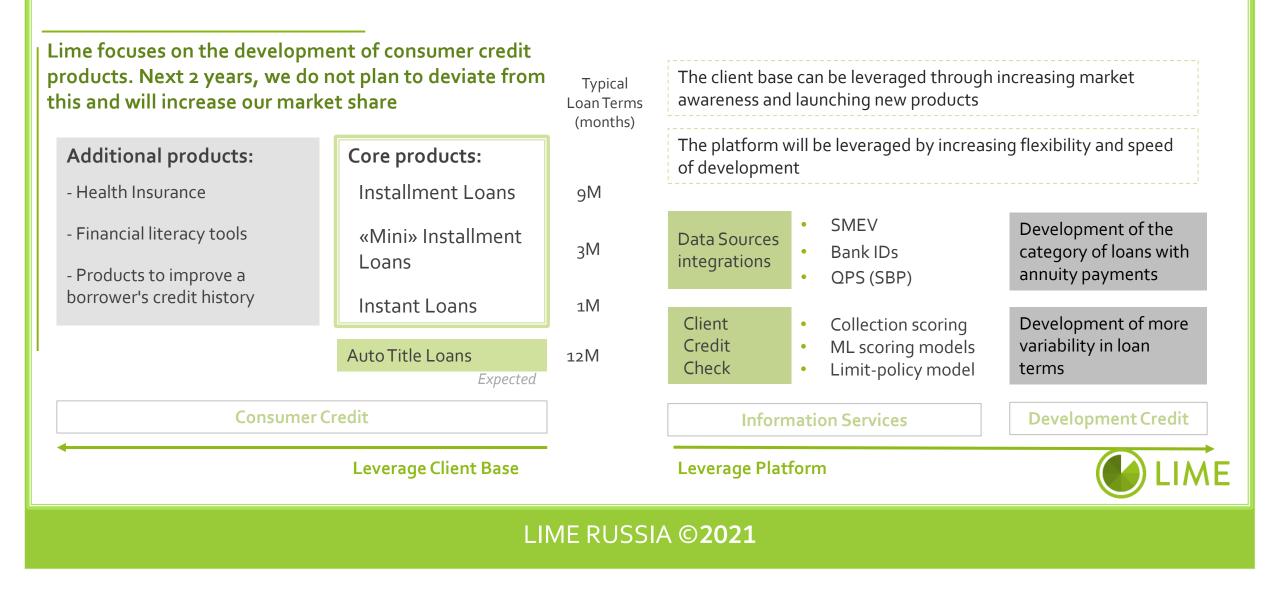


Client could be blocked on different stages. It is important to monitor client's reliability over time. If, for example, a client will fill an application with correct data, relatability will grow and the model will be able to give more positive decisions. Not tracking such changes could lead to losses.



## **COLLECTION PROCESS**





## FOUNDERS



#### Alexey Nefedov CEO / Co-founder

Before co-founding Lime, Alexey spent a few years working as an implementation consultant for an enterprise applications developer and as a credit card underwriter at a major Russian bank. In his day-to-day role as CEO of Lime, Alexey sets strategic priorities, is the chief system architect, makes most HR decisions, and oversees legal and regulatory compliance. In the three years since its establishment, Alexey has spent time in pretty much every role in the company from collector to underwriter to programmer.

#### Stanislav Sergushkin COO / Co-founder

Stanislav and Alexey met at university in the UK, and since both of them had prior experience as underwriters, their ideas about a better on-line lending platform quickly came together. As Lime's COO, Stanislav handles day-to-day operations in addition to leading product development and territorial expansion. The business process flows, risk management procedures, and scoring models in use at Lime are all products of Stanislav's guidance.





## FOUNDERS



#### Olesya Kiseleva Managing Director, Russia

Olesya graduated in Applied Informatics from the Siberian State Industrial University. At the beginning of her career in the Lime Credit Group, she held the position of Head of the Project Department and led a team of 40 employees in Moscow and Novosibirsk. Then she moved to the position of Deputy Development Director.

At the moment, Olesya is the Managing Director of Lime in Russia and is responsible for business performance, the development of the company, and maintaining a competitive position in the market.

#### Kevin Hurley CFO

Previous to joining Lime Credit Group in 2015, Kevin served for 10 years as the COO of a private equity fund and for 15 years in various roles in management and consulting in IT. Kevin has spent his entire professional career living and working in emerging markets around the world. He is a graduate of the Johns Hopkins University.



# **LIME LOANS** MULTI-MARKET ONLINE CONSUMER LENDING

Contact: Kevin Hurley CFO k.hurley@limecreditgroup.com



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