FRACTAL
LABS

Data Science

MAY 2020

Table of contents

Data Science

FEBRUARY 2020

1. Our view of the market
2. What information lies within the client's transactional data
3. The next generation of credit scoring
4. Transforming fraud detection
5. Loan origination experience
6. Our team

Our view of the market

Digital around the world vs Africa - Jan 2020

World Africa

Total population
7.75 billion

55%
Urbanisatoin

1.32 billion

43%
Urbanisatoin

Internet users
4.54 billion

59%
Penetration

453.2 million

34%
Penetration

Social media users
3.80 billion

49%
Penetration

217.5 million

16%
Penetration

Unique mobile users
5.19 billion

67%
Penetration

Mobile connections
1,08 billion

81%
Penetration

https://datareportal.com/reports/digital-2020-global-digital-overview

Future of Fintech

Key trends

50%

Percentage of global payments predicted to flow through FinTech channels by 2022 (McKinsey)

$200m

Investments poured into RegTech companies since 2017 (FinTech Global)

80%

Percentage of large banks set to support FinTech's application development through open banking

50 B

Number of devices to be connected to the internet (IoT) by 2020 (Cisco)

> " FinTech's currently lack the ability to scale due to a lack of brand recognition. This is all set to be a thing of the past once they partner with banking leaders. "

Reference: The state of fintech and fraud in 2019: SEON

AI solutions

Sales lab

Scrutinisation of clients' personal data to optimise leads and define quality and well as which clients are more likely qualify and convert into a sale.

Score lab

Supervised machine learning to make predictions within seconds. Using financial and psychometric data allows faster more accurate decision making, greatly improving the speed of loan application processes as well as user experience.

Offer lab

Transactional behaviour modelling creates opportunity to up-sell, cross sell and identify where improvements can be made on spending habits with product expansion possibilities.

Lender lab

Reduce risk, eliminate human error, improve turnaround time and improve over all customer experience.

Fraud lab

Identify organized groups of fraudsters, synthetic identities, stolen identities, compromised networks and hijacked devices.

Risk lab

Seamless provisioning modelling allowing inputs from all other modules delivering IFRS9 compliant models with scenario analytics for macro-economic and SIC-R impact assessments and implementations

What information lies within the client’s transactional data?

Transaction Modeling Engine

Offer Lab

- This is an AI classifier that identifies different transactions based on their descriptions using advanced algorithms and feature engineering.
- Automated classification and analysis of transactions ensure consistent and fast results compared to manual processes.
- Transaction data is a rich source of information and can be utilised for further modelling problems, including credit scoring.
- Transactional behaviour modelling creates opportunity to up-sell, cross sell and identify where improvements can be made on spending habits with product expansion possibilities.

The data modelling process

DATA SOURCES

Source: Document

- OCR data extraction
- Metadata extraction

Source: API's

- Direct from bank

PROCESS

DB

↓

Classifier

Labels transactions

↓

Analysis

Report details & stats

CONSUMERS

Credit scoring

- Predicts possibility of defrauding

Affordability

Loan application processing

Fraud

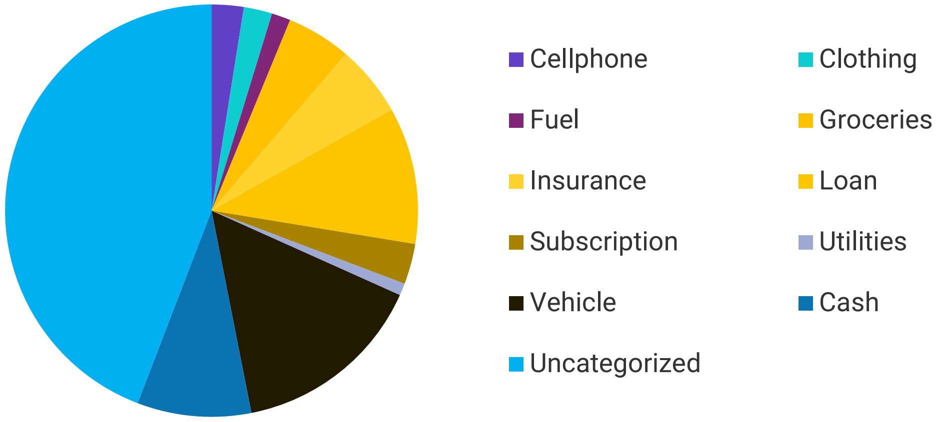
Anomaly detection

Easily plugged into any flow or process | New sources such as open banking data can be fed into the pipeline | New consumers are easily added

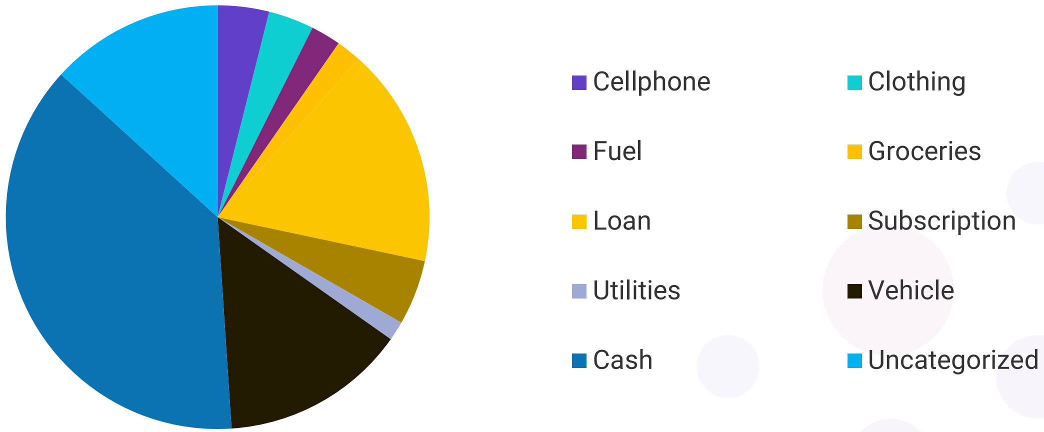
Anomaly detection as example

Knowing that the distribution of transaction categories follows a Zipfian distribution, a spending profile such as the one on the right, where cash withdrawals make up more of the total debits, may be flagged as suspicious.

Normal profile >



Anomalous profile >



Automating affordability

Calculating the remainder of a client's money after paying necessary bills and obligations.

Understanding the spending behaviours

Learning from spending behaviour to accurately predict a client's probability of defaulting on a loan.

Defining the norm and detecting fraud

Modelling normal spending patterns and flagging a client too far removed from the norm.

Transaction Modeling Engine

Offer Lab

- Models are country/context specific.
- South African model used by GetBucks SA.
- Used for automated affordability calculation and credit scoring.
- 30 categories used for identifying recurring (and non-recurring) expense and sources of income.
- South African model created with ~270 000 transactions.
- High performance model with scores up to 98%.

Model building

- Labelled real world transaction data required for training new models.
- Amount of labelled data required depends on:

  Nature of data (homogeneity, text nature, etc.)

  Amount of categories required

  Accuracy requirements. (More data, more accuracy)
- Fractal labs data science team analyses data and determines best model building strategy and data requirements
- Example: Very homogeneous data, 20 categories: 5000 labelled examples

The next generation of credit scoring

Affordability and risk forecaster

Score Lab

- A **fully autonomous AI credit scoring system** that is capable of assessing the risk of clients applying for loans with the purpose of reducing loan default rates.
- Uses a **supervised machine learning** algorithm trained on both traditional financial data as well as alternative data sources such as sms messages and social media data.
- Not only does Jessie decline or approve a loan, but also offers a client a **range of products** consisting of affordable loan amounts and terms to choose from.
- Can extract data and **make predictions within seconds**, greatly improving the speed of loan application processes as well as user experience.

The system is used in many countries for credit scoring and is designed in such a way that a new model can be easily trained and deployed in another country.

Affordability and risk forecaster

Score Lab

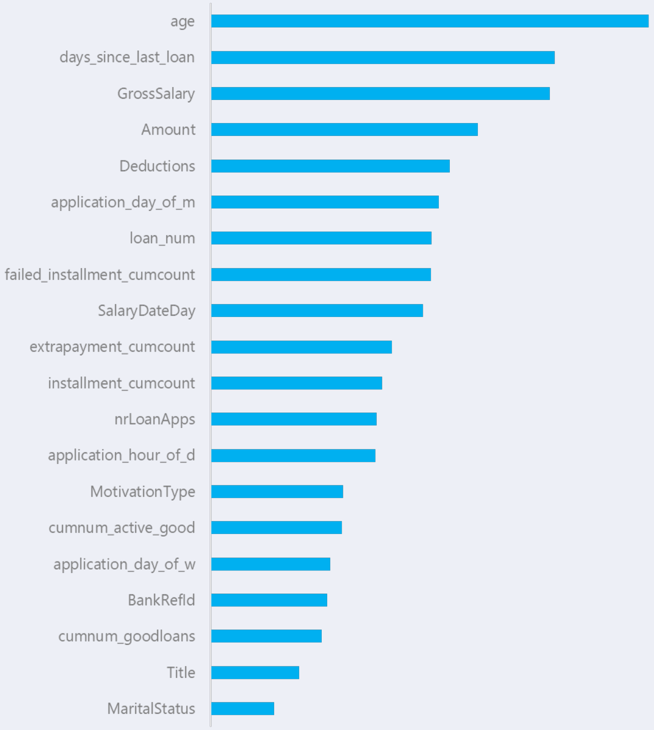
Multiple Data Input Sources

- Existing Loan
- Employer
- Social media
- Credit bureau
- Bank Statements
- Mobile device
- Psychometric

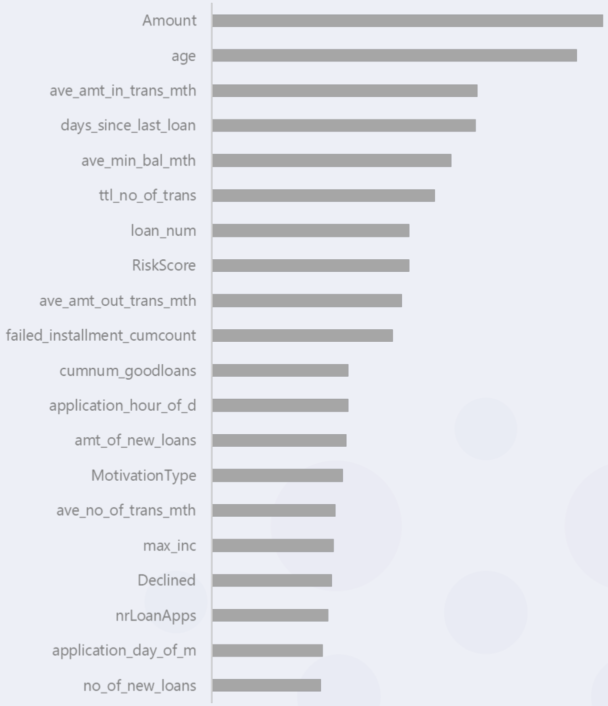
Out is a model to predict probability of default (PD)

Predictive behaviors in different geographies will differ

Country A

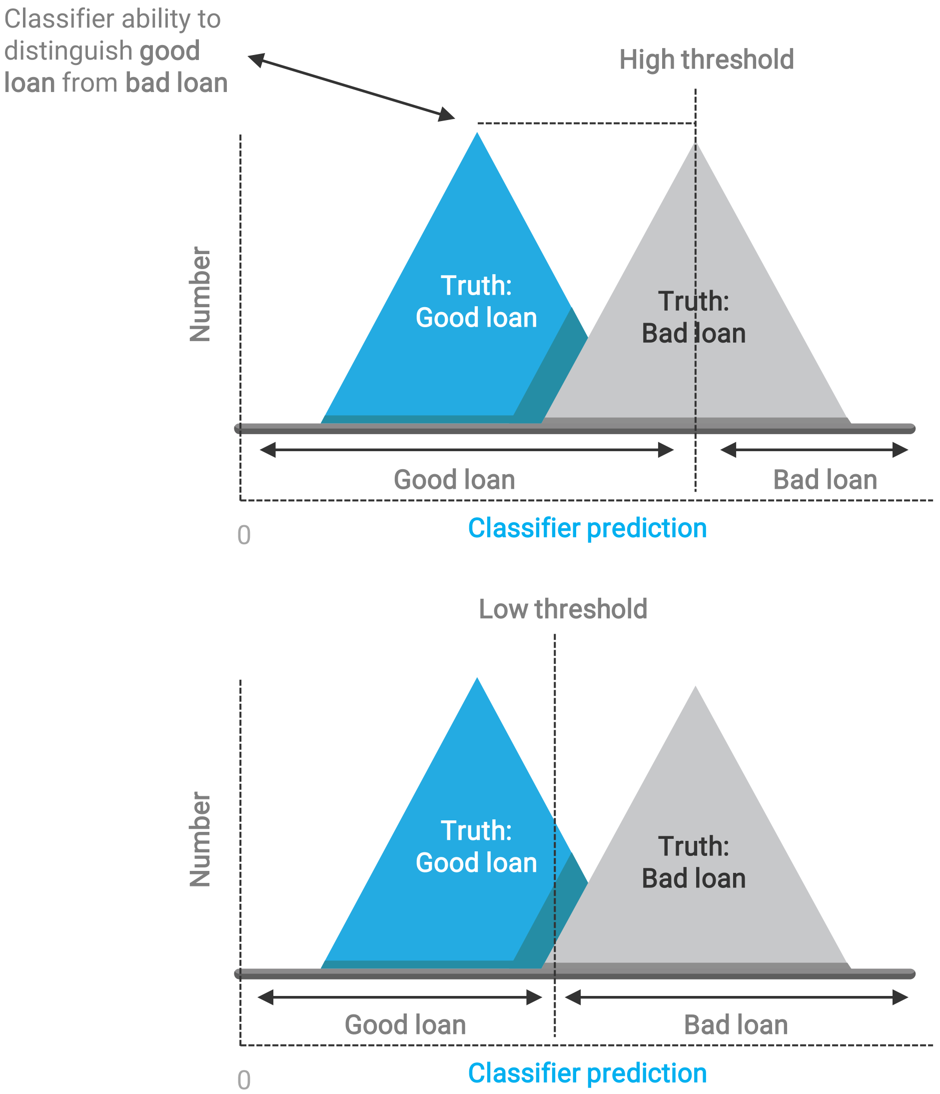


Country B



Affordability and risk forecaster

Score Lab: How do we accomplish this



- Realtime classification across all products the client can afford.
- Links to any platform via API, and directly to SQL backend returning results.
- Client is then presented with only products he/she can afford.

Affordability and risk forecaster

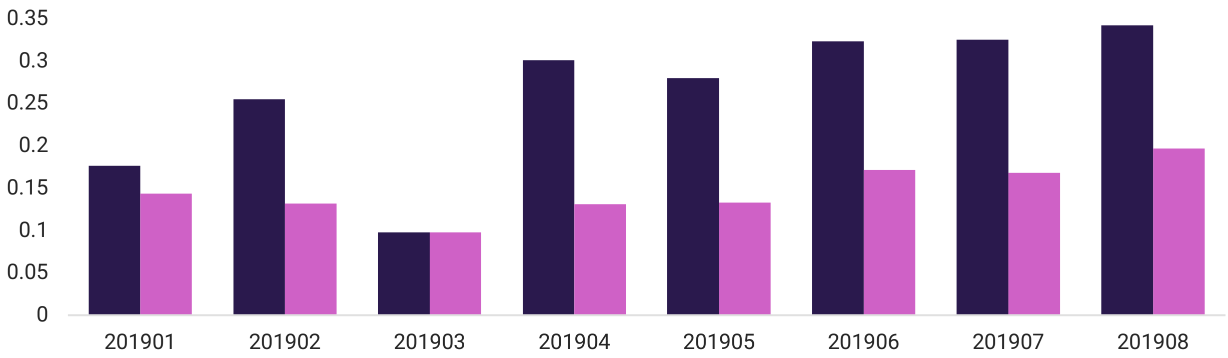
Score Lab: A real example of the default rate lift that we have experienced

Default Rate by Loan Count

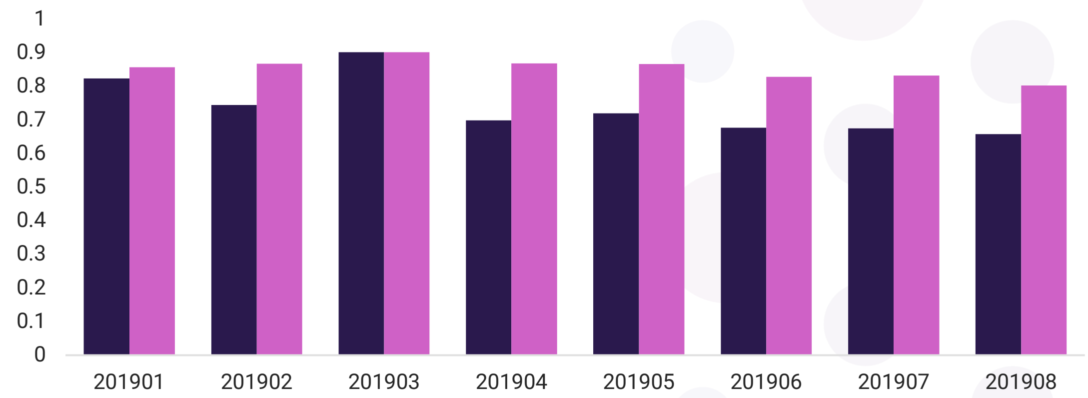
Impact: 10.38%

Default Rate by Amount

Impact: 11.58%

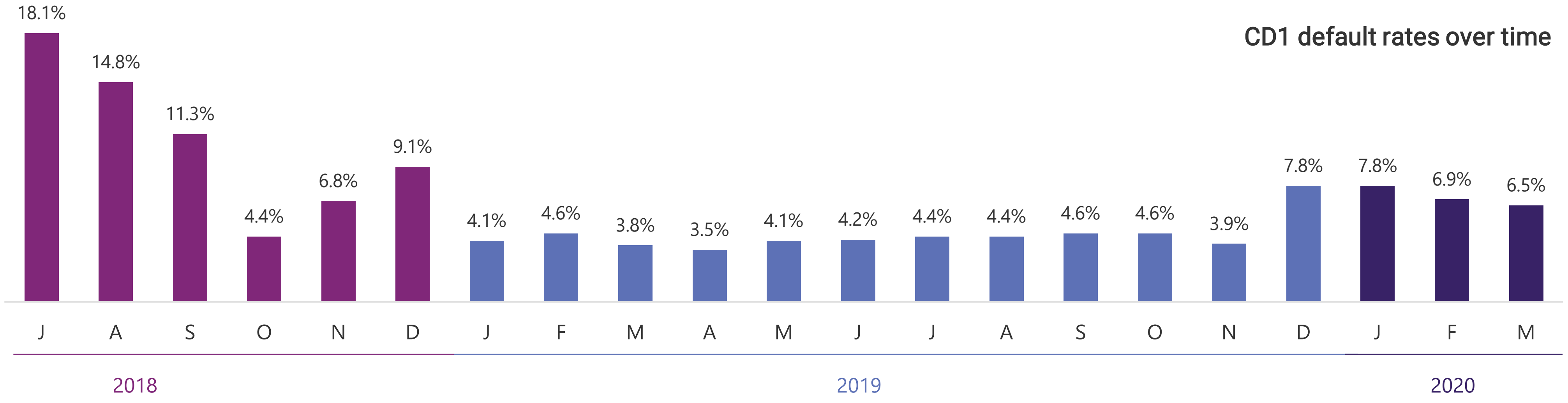


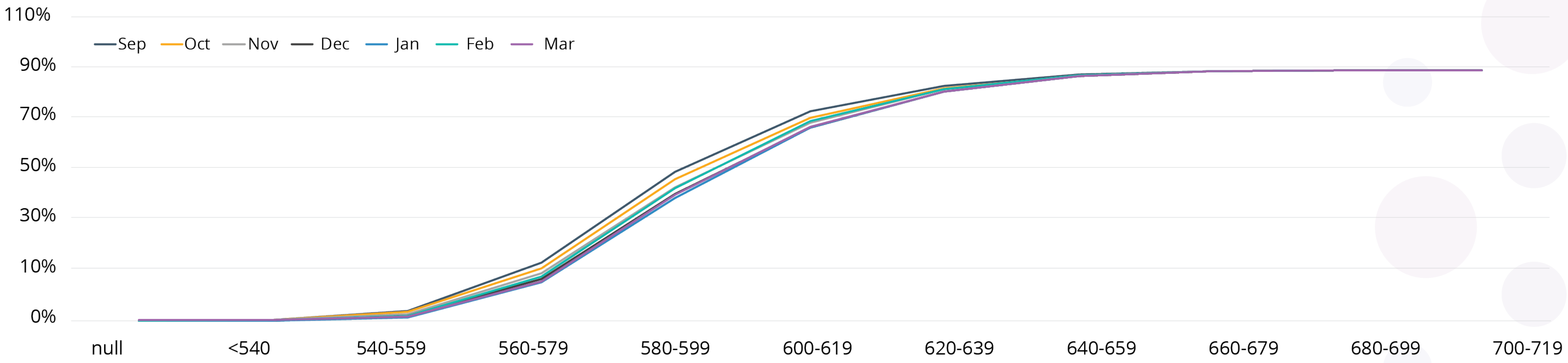
Collection Rate 6 Month Vintage



Affordability and risk forecaster

Score Lab: And how it's allowed us to reposition ourselves against the industry

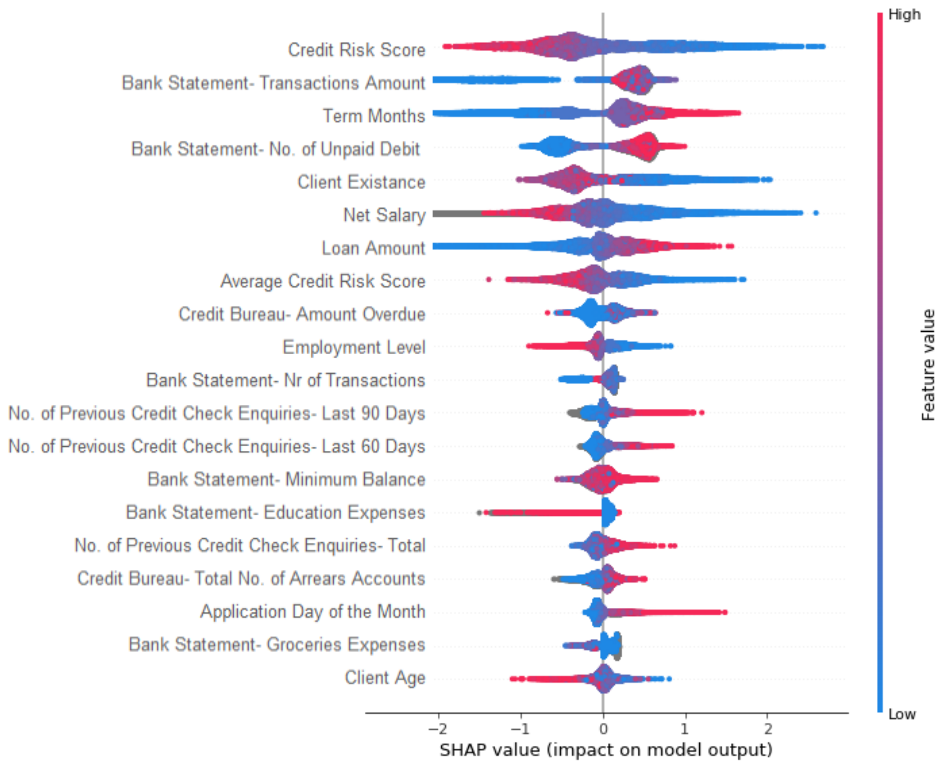




*Source: Xpert Decisions Systems

Affordability and risk forecaster

Score Lab: The models continue to evolve on a quarterly basis



Transforming fraud detection

Fraud Lab

Fraud prevention

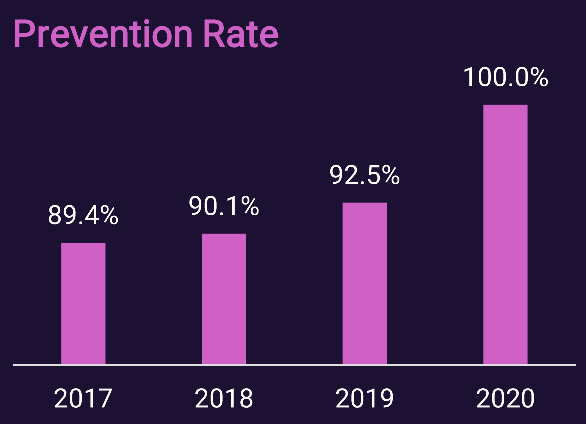
To combat fraud, Fractal Labs has developed an AI fraud detection system that characterizes client actions and detects anomalous behavior.

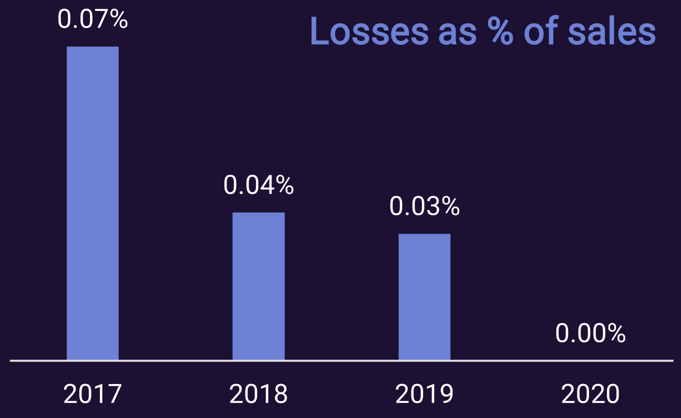
Detect fraudulent actions between FinCloud and all its interfacing systems.

In-house developed software system monitors e-wallet activity, associations between customers and other alternative data.

Identify organized groups of fraudsters, synthetic identities, stolen identities, compromised networks and hijacked devices.

Identify rogue agents within the Fractal network, employees modifying data for their own gain, criminals trying to game financial processes, and individuals using stolen identities.





- Local credit bureau information
- Our closed-loop fraud bureau (all participating organisations in a jurisdiction)
- Supplemented by online data (IP address, IMEI, phone type)
- And enhanced by digital behaviour (speed of capture; number of typing errors, is data input captured or copied)

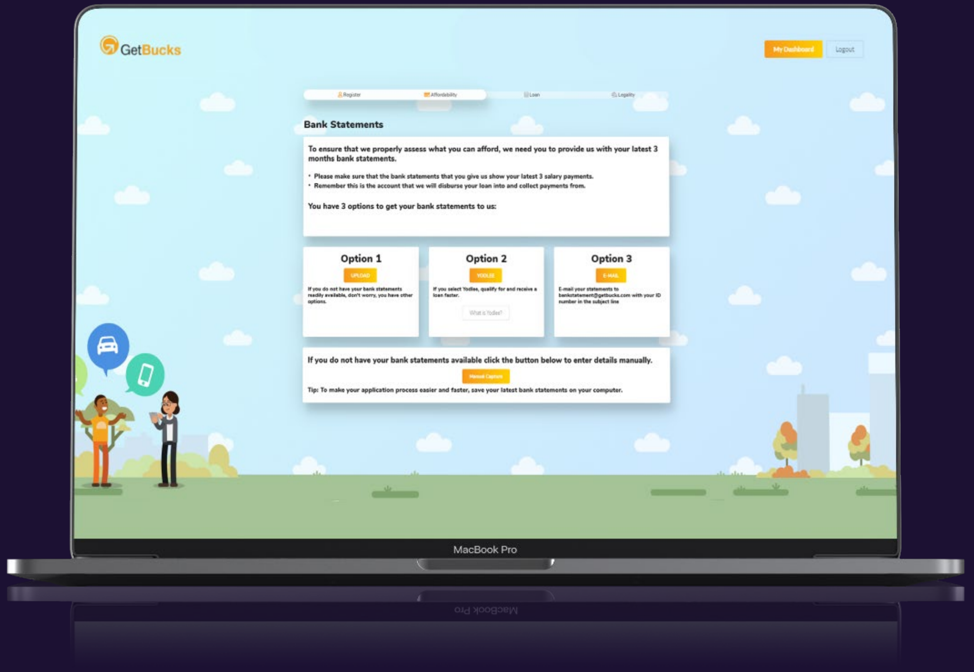
Loan origination experience

Technology driven customer experience

Using a stack of cloud-based and web technologies, loan applications are simplified and take substantially less time to complete.

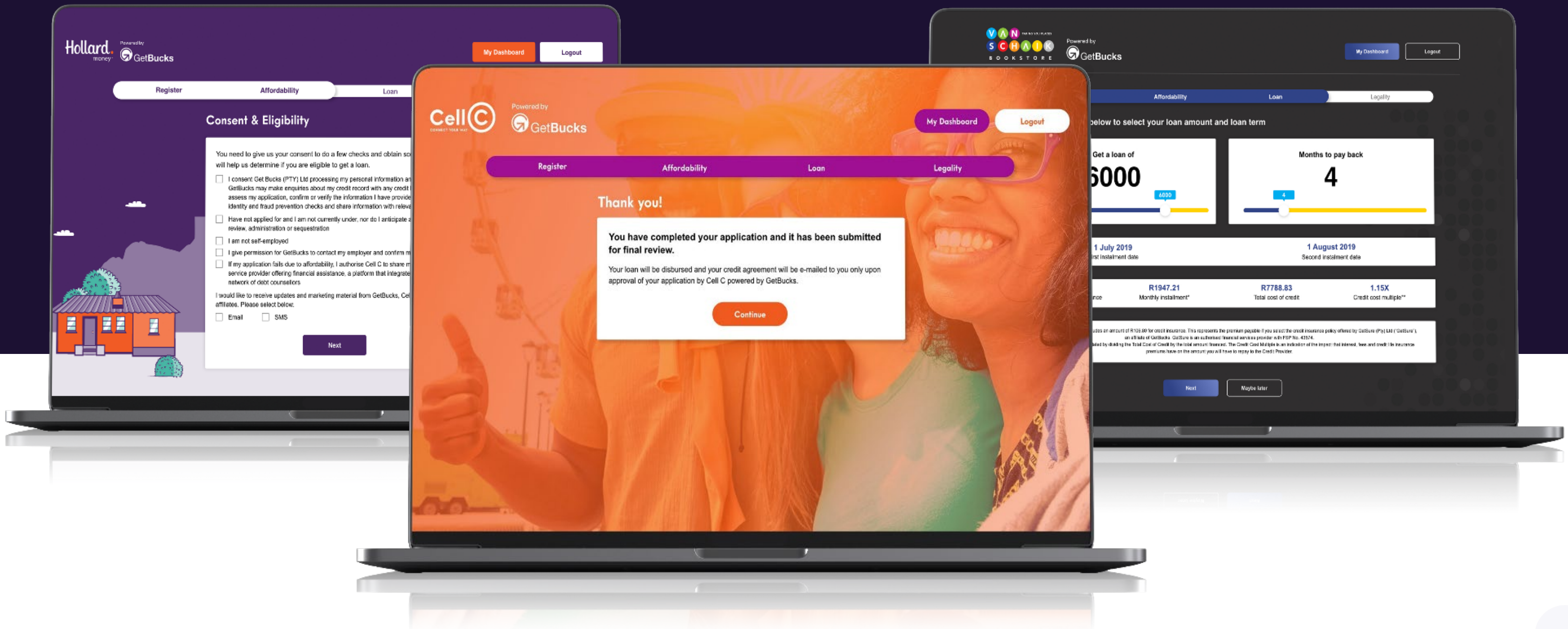
Benefits also include:

- Reduced risk for client as well as lender
- Improved level of compliance
- Elimination of human error probability
- Quicker turnaround time and ultimately Resulting in improved customer experience
- Platform agnostic. Can be deployed with the data science modules or on a standalone basis



Lender Lab

Ultimate loan process

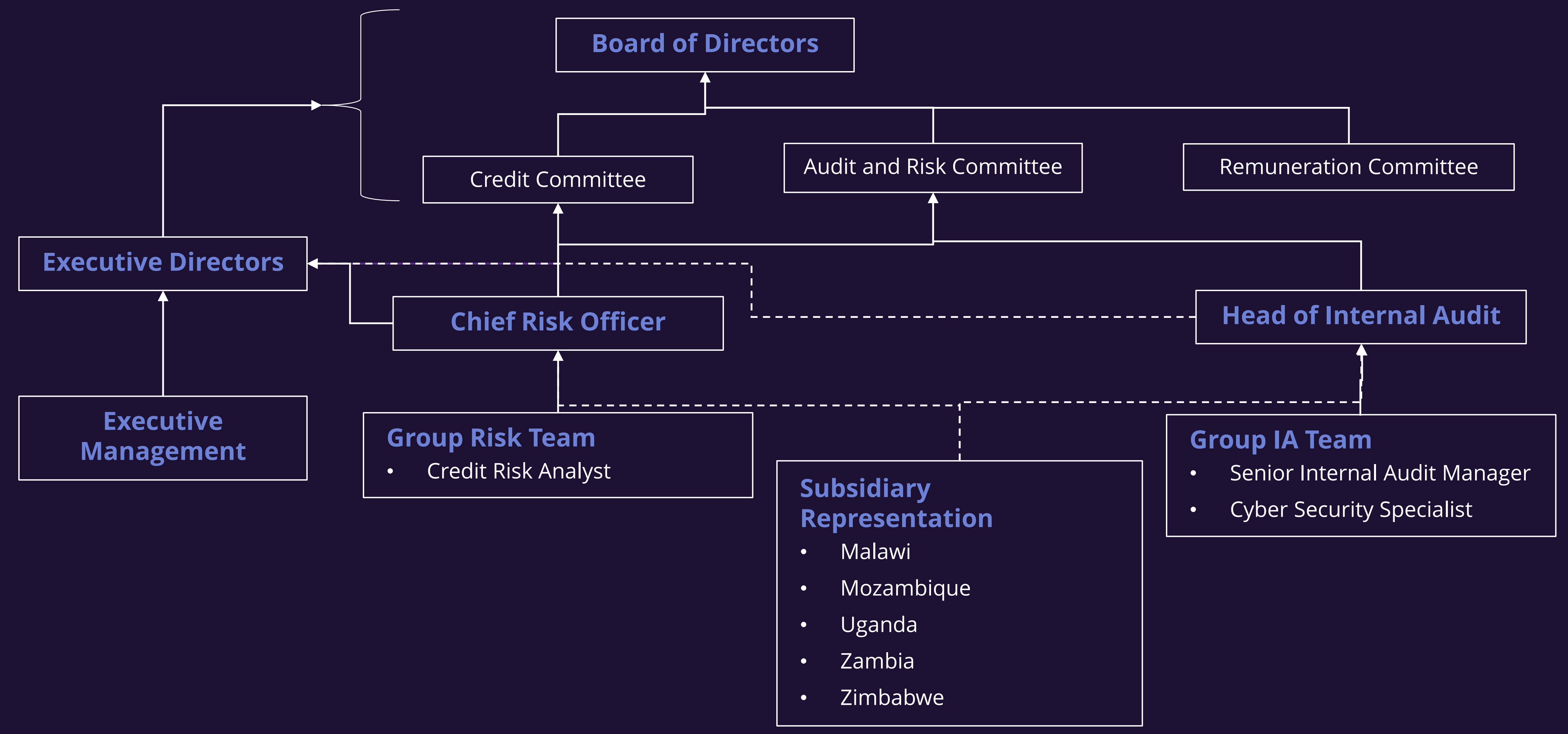


The platform has been developed in a way that can be easily adapted to different business requirements.

Design, flow and functionality can be tailored to market and customer experience

Risk

Corporate governance



Risk reporting

COUNTRY	2018/07/31	2018/08/31	2018/09/30	2018/10/31	2018/11/30	2018/12/31	2019/01/31	2019/02/28	2019/03/31	2019/04/30	2019/05/31	2019/06/30	2019/07/31	NPV rank in last month
Botswana_CC	23.3%	36.7%	40.0%	36.7%	33.3%	36.7%	36.7%	33.3%	30.0%	43.3%	36.7%	43.3%	43.3%	15
Botswana_GB	76.7%	73.3%	76.7%	66.7%	83.3%	90.0%	90.0%	83.3%	83.3%	86.7%	83.3%	83.3%	86.7%	9
Botswana_TU	93.3%	86.7%	96.7%	90.0%	96.7%	83.3%	90.0%	96.7%	90.0%	90.0%	90.0%	83.3%	83.3%	10
Br.Net_Zambia	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	53.3%	46.7%	60.0%	60.0%	56.7%	33.3%	40.0%	13
Br.Net_Zimbabwe	25.0%	45.0%	50.0%	45.0%	40.0%	45.0%	45.0%	40.0%	35.0%	50.0%	40.0%	50.0%	45.0%	17
Capfin	15.0%	35.0%	35.0%	35.0%	35.0%	15.0%	35.0%	35.0%	35.0%	25.0%	25.0%	40.0%	50.0%	12
FairGo	40.0%	70.0%	65.0%	70.0%	75.0%	45.0%	60.0%	65.0%	65.0%	60.0%	55.0%	65.0%	75.0%	3
Haraka	30.0%	30.0%	30.0%	30.0%	30.0%	30.0%	30.0%	30.0%	30.0%	30.0%	20.0%	30.0%	30.0%	20
Kenya	53.3%	73.3%	73.3%	63.3%	73.3%	46.7%	73.3%	70.0%	63.3%	66.7%	63.3%	63.3%	66.7%	8
Malawi	50.0%	13.3%	36.7%	50.0%	63.3%	76.7%	46.7%	40.0%	73.3%	83.3%	70.0%	76.7%	70.0%	4
Mozambique	60.0%	86.7%	100.0%	90.0%	100.0%	96.7%	56.7%	76.7%	86.7%	46.7%	60.0%	53.3%	36.7%	2
Namibia	30.0%	30.0%	36.7%	16.7%	36.7%	30.0%	16.7%	30.0%	16.7%	30.0%	16.7%	30.0%	33.3%	21
Ol_Kenya	33.3%	16.7%	23.3%	43.3%	26.7%	43.3%	43.3%	33.3%	40.0%	30.0%	33.3%	40.0%	36.7%	16
Ol_Kenya_GB	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	40.0%	36.7%	36.7%	36.7%	33.3%	18
Ol_Mozambique	56.7%	66.7%	63.3%	66.7%	66.7%	53.3%	60.0%	43.3%	33.3%	33.3%	30.0%	43.3%	46.7%	6
Ol_Tanzania	52.0%	60.0%	52.0%	20.0%	20.0%	52.0%	52.0%	48.0%	56.0%	36.0%	36.0%	40.0%	48.0%	22
Ol_Uganda	64.0%	68.0%	64.0%	60.0%	60.0%	64.0%	60.0%	60.0%	52.0%	60.0%	64.0%	60.0%	48.0%	1
South_Africa	33.3%	33.3%	26.7%	26.7%	43.3%	33.3%	33.3%	23.3%	36.7%	56.7%	50.0%	73.3%	63.3%	5
Swaziland	60.0%	63.3%	60.0%	60.0%	60.0%	63.3%	60.0%	40.0%	56.7%	43.3%	53.3%	56.7%	60.0%	11
Tanzania	60.0%	46.7%	46.7%	46.7%	73.3%	46.7%	83.3%	76.7%	76.7%	83.3%	60.0%	53.3%	90.0%	19
Zambia	43.3%	60.0%	43.3%	50.0%	43.3%	53.3%	70.0%	16.7%	46.7%	36.7%	43.3%	56.7%	56.7%	7
Zimbabwe	93.3%	90.0%	83.3%	90.0%	83.3%	86.7%	86.7%	73.3%	90.0%	86.7%	86.7%	70.0%	66.7%	14
Group	47.7%	57.5%	56.2%	55.6%	58.9%	55.8%	54.0%	49.3%	50.5%	47.4%	48.1%	50.2%	45.9%	

Risk reporting

COUNTRY	2018/06/30	2018/12/31	2019/06/30	2019/07/31	NPV rank in last month
Botswana_CC	40.0%	36.7%	43.3%	43.3%	15
Botswana_GB	93.3%	90.0%	83.3%	86.7%	9
Botswana_TU	83.3%	83.3%	83.3%	83.3%	10
Br.Net_Zambia	0.0%	0.0%	33.3%	40.0%	13
Br.Net_Zimbabwe	50.0%	45.0%	50.0%	45.0%	17
Capfin	25.0%	15.0%	40.0%	50.0%	12
FairGo	60.0%	45.0%	65.0%	75.0%	3
Haraka	16.7%	30.0%	30.0%	30.0%	20
Kenya	70.0%	46.7%	63.3%	66.7%	8
Malawi	40.0%	76.7%	76.7%	70.0%	4
Mozambique	66.7%	96.7%	53.3%	36.7%	2
Namibia	33.3%	30.0%	30.0%	33.3%	21
OI_Kenya	20.0%	43.3%	40.0%	36.7%	16
OI_Kenya_GB	0.0%	0.0%	36.7%	33.3%	18
OI_Mozambique	63.3%	53.3%	43.3%	46.7%	6
OI_Tanzania	52.0%	52.0%	40.0%	48.0%	22
OI_Uganda	68.0%	64.0%	60.0%	48.0%	1
South_Africa	50.0%	33.3%	73.3%	63.3%	5
Swaziland	50.0%	63.3%	56.7%	60.0%	11
Tanzania	26.7%	46.7%	53.3%	90.0%	19
Zambia	33.3%	53.3%	56.7%	56.7%	7
Zimbabwe	90.0%	86.7%	70.0%	66.7%	14

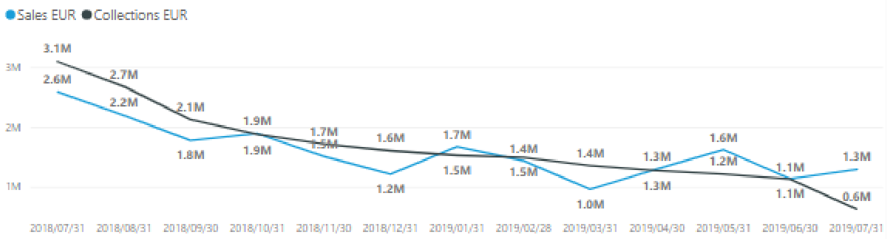
Legend

Indicator	Weight	0-20%	20-40%	40-60%	60-80%	80-100%
Stage 1 - 2 default rate (CD0 -> CD1)	16.7%	>2%	1.5 - 2%	1 - 1.5%	0.5 - 1%	<0.5%
Stage 2 - 3 default rate (CD3 -> CD4)	16.7%	>2%	1.5 - 2%	1 - 1.5%	0.5 - 1%	<0.5%
Impairments / Revenue	16.7%	>30%	25% - 30%	20 - 25%	15-20%	<15%
Collections efficiency rate	16.7%	<80	80-85	85-90	90-95	>95%
NPL	16.7%	>8%	6-8%	4-6%	2-4%	<2
Expected IRR	16.7%	<3%	3-6%	6-9%	9-12%	>12%

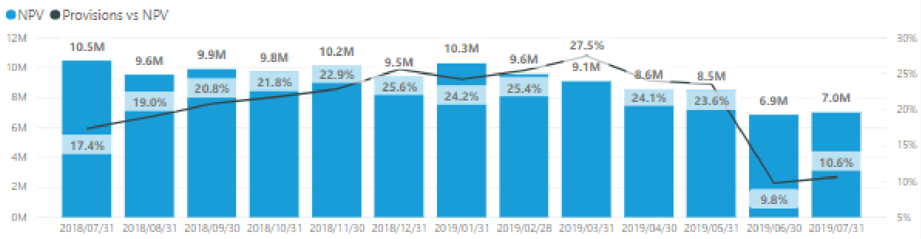
Risk - Credit

Namibia | NFB_Malawi | OI_Kenya | OI_Kenya_GB | OI_Mozambique | OI_Tanzania | OI_Uganda | Poland | South_Africa | Surechoice_FC | Swaziland | Tanzania | Zambia

SALES & COLLECTIONS



NPV AND PROVISIONS



KEY MEASURABLES

Date	Sales (€)	Sales Count	Active loans	Collections (€)	1st strike	In-contract	Out-of-contract	TOTAL	NPV	Lending Revenue (€)	Revenue vs NPV	Revenue vs Sales	Revenue per active loan	Provisions (€)	Provisions vs NPV	Provision movement (€)	Write-offs (€)	Stage 1 to 2	Stage 2 to 3	IRR Expected	IRR Actual	PAR30	PAR90	Tenure (Months)	Ave monthly install
2018/07/31	2.60M	7.70K	56.74K	3.10M	99.4%	88.0%	81.0%	93.4%	10.49M	0.60M	5.8%	23.3%	10.7	1.82M	17.4%	318.2K	97.5K	4.2%	0.9%	158.1%	123....	12.3%	8.4%	8.2	100
2018/08/31	2.20M	5.41K	54.53K	2.69M	97.1%	89.3%	38.9%	89.6%	9.56M	0.55M	5.7%	24.8%	10.0	1.81M	19.0%	181.6K	64.0K	4.4%	0.9%	121.8%	74.7%	15.0%	8.8%	10.0	84
2018/09/30	1.79M	4.70K	52.50K	2.13M	103....	85.1%	25.2%	85.5%	9.90M	0.51M	5.1%	28.3%	9.6	2.06M	20.8%	178.1K	53.0K	3.7%	1.6%	120.1%	72.0%	18.0%	10.0%	10.0	88
2018/10/31	1.90M	4.43K	51.25K	1.89M	105....	86.9%	17.6%	83.3%	9.76M	0.47M	4.8%	24.5%	9.1	2.12M	21.8%	94.4K	107.3K	2.7%	3.0%	106.9%	65.5%	19.7%	13.3%	11.8	83
2018/11/30	1.52M	3.25K	49.21K	1.73M	105....	85.6%	14.3%	80.0%	10.17M	0.43M	4.2%	28.1%	8.7	2.33M	22.9%	65.2K	75.4K	2.7%	3.8%	90.3%	55.8%	21.1%	16.2%	13.6	85
2018/12/31	1.22M	2.41K	47.29K	1.61M	88.5%	88.1%	9.6%	75.8%	9.45M	0.37M	3.9%	30.2%	7.8	2.42M	25.6%	211.9K	116.4K	7.1%	2.6%	77.0%	27.2%	22.7%	17.9%	14.3	83
2019/01/31	1.68M	3.66K	46.56K	1.54M	100....	90.6%	19.7%	77.7%	10.30M	0.38M	3.6%	22.4%	8.1	2.50M	24.2%	-127.2K	115.4K	2.5%	2.0%	109.6%	69.7%	22.8%	18.6%	12.9	96
2019/02/28	1.44M	2.65K	45.73K	1.50M	105....	87.1%	12.3%	75.1%	9.59M	0.34M	3.5%	23.5%	7.4	2.44M	25.4%	67.9K	117.9K	4.3%	2.1%	106.2%	57.5%	22.3%	19.6%	14.9	86
2019/03/31	0.97M	1.89K	44.79K	1.36M	98.1%	87.6%	10.0%	70.8%	9.10M	0.33M	3.7%	34.4%	7.5	2.50M	27.5%	94.7K	97.3K	3.6%	2.2%	82.8%	46.3%	25.0%	20.7%	16.7	82
2019/04/30	1.31M	2.62K	38.69K	1.28M	111....	89.4%	14.8%	76.2%	8.56M	0.31M	3.6%	23.4%	7.9	2.06M	24.1%	-466.0K	106.3K	1.9%	1.4%	87.6%	46.4%	24.7%	20.0%	15.8	84
2019/05/31	1.63M	3.17K	18.96K	1.22M	102....	88.1%	12.3%	75.0%	8.50M	0.31M	3.7%	19.2%	16.5	2.00M	23.6%	-35.7K	168.9K	2.9%	1.6%	88.7%	55.0%	23.9%	20.0%	14.9	85
2019/06/30	1.15M	2.17K	14.25K	1.14M	107....	91.7%	46.5%	92.0%	6.86M	0.29M	4.2%	24.9%	20.0	0.67M	9.8%	-1,325.3K	35.8K	2.8%	1.0%	84.5%	50.7%	6.5%	3.4%	15.6	85
2019/07/31	1.30M	2.52K	14.13K	0.64M	106....	92.1%	26.2%	90.5%	7.02M	0.30M	4.3%	23.3%	21.4	0.75M	10.6%	63.1K	10.6K	2.7%	1.0%	87.2%	52.5%	7.7%	4.0%	15.2	87

South_Africa

24.30%
Impairments vs. Revenue in last month

5.06%
% NPV of Group in last month

13.22%
% Sales of Group in last month

NOTES:
- The Credit Pack only includes the NPV and Provisions for Malawi - NFB due to data inconsistencies in the other fields that needs evaluation.
- Revenue numbers are only reporting lending revenue (i.e. revenue related to lending practices).

PRODUCT IRR (contractual)

Date	2019/05/31			2019/06/30			2019/07/31	
Name	Disbursed (in month)	% Disbursed of total	Product IRR	Disbursed (in month)	% Disbursed of total	Product IRR	Disbursed (in month)	% Disbursed of to
GB PAYROLL - 24 MONTH (> 11K)	500,304	31.1%	31.5%	372,828	31.6%	31.9%	416,939	31.5%
6 Month - Term Campaign Loan	444,333	27.6%	105.6%	274,247	23.3%	105.2%	335,468	25.4%
Mediclinic 24 M	212,140	13.2%	32.3%	186,321	15.8%	32.8%	170,929	12.9%
3 Month - Term Campaign Loan	106,811	6.6%	291.2%	79,280	6.7%	282.4%	92,171	7.0%
5 Month - Term Campaign Loan	43,801	2.7%	165.4%	32,676	2.8%	147.2%	38,560	2.9%
4 Month - Term Campaign Loan	36,827	2.3%	218.1%	22,440	1.9%	213.7%	31,927	2.4%
Tsogo Sun 12 MONTH (> 11.5K)	31,707	2.0%	37.0%	21,271	1.8%	35.3%	20,451	1.5%

Risk - Credit

Botswana_CC
Botswana_GB
Botswana_TU
Br.Net_Zambia
Br.Net_Zimbab...
Capfin
FairGo
Group
Haraka
Kenya
Malawi
Mozambique
Namibia
South_Africa
SALES TARGET REACHED IN LAST MONTH
108.1%
SALES & COLLECTIONS
Sales EUR
Collections EUR
COLLECTIONS
1st strike
In-contract
Out-of-contract
TOTAL
NPV & PROVISIONS
NPV
Provisions (EUR)
Provisions vs NPV
SALES COUNT & ACTIVE LOANS
Sales Count
Active loans
WRITE-OFFS
CD0 to CD1 (early) & CD3 to CD4 (final)
CD0 to CD1
CD3 to CD4
DISBURSED IRR (expected & actual)
Sales EUR
IRR Expected
IRR Actual
DISBURSEMENTS - LOAN SIZE, INSTALLMENTS & TENURE
Tenure (Months)
Average monthly installment
Average monthly loan size
PAR 30 & PAR 90
PAR30
PAR90

Risk - Capital

Botswana_CC | Botswana_GB | Botswana_TU | Br.Net_Zambia | Br.Net_Zimbab... | Capfin | FairGo | Haraka | Kenya | Malawi | Mozambique | Namibia | NFB_Malawi

South_Africa

2019/07/31

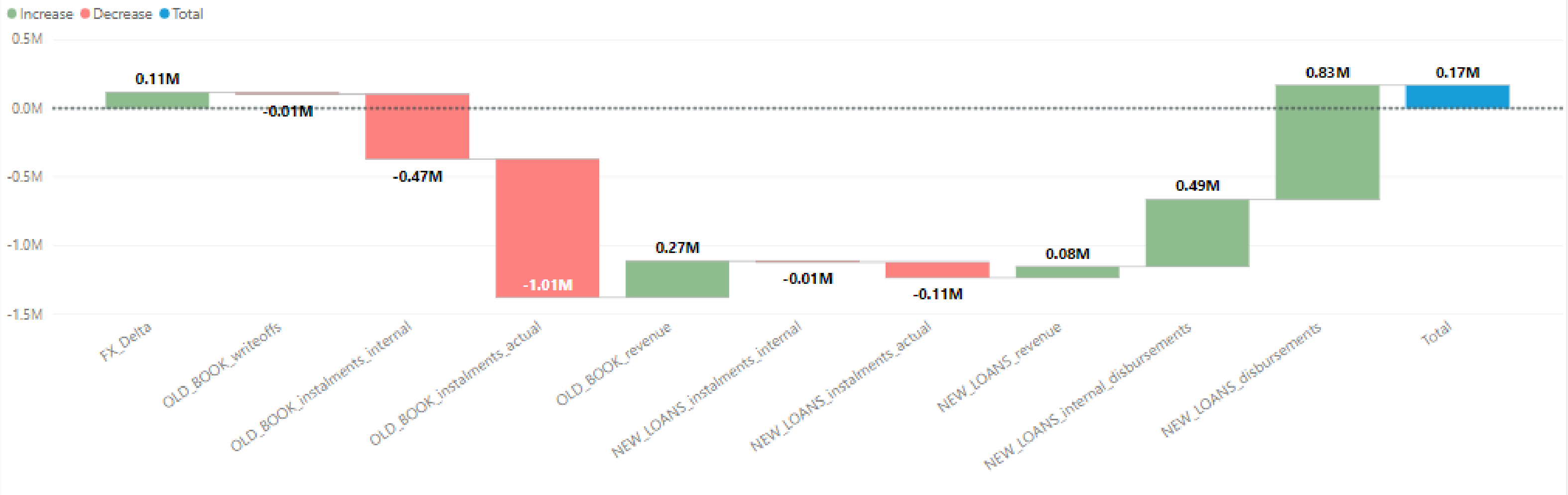
NPV IN-AND-OUT OVER LAST 13 MONTHS

Date	Opening_ Balance	NEW_LOANS_ disbursements	NEW_LOANS_internal _disbursements	NEW_LOANS _revenue	NEW_LOANS _instalments_ actual	NEW_LOANS _instalments_ internal	OLD_BOOK _revenue	OLD_BOOK_ instalments_ actual	OLD_BOOK_ instalments_ internal	OLD_BOOK _writeoffs	FX_Delta	Closing_balance _theoretical	Closing_balance _actual
2018/07/31	9.69M	1.86M	0.85M	0.25M	-0.37M	-0.02M	0.46M	-1.48M	-0.56M	-0.11M	0.44M	11.02M	11.02M
2018/08/31	11.02M	1.24M	0.75M	0.13M	-0.21M	-0.02M	0.41M	-1.58M	-0.64M	-0.06M	-1.09M	9.95M	9.95M
2018/09/30	9.95M	1.20M	0.66M	0.12M	-0.21M	-0.01M	0.40M	-1.55M	-0.60M	-0.06M	0.35M	10.24M	10.24M
2018/10/31	10.24M	1.19M	0.69M	0.11M	-0.15M	-0.02M	0.38M	-1.48M	-0.66M	-0.09M	-0.17M	10.05M	10.05M
2018/11/30	10.05M	1.03M	0.61M	0.08M	-0.10M	-0.01M	0.40M	-1.56M	-0.60M	-0.09M	0.64M	10.46M	10.44M
2018/12/31	10.44M	0.77M	0.48M	0.05M	-0.02M	0.00M	0.34M	-1.30M	-0.48M	-0.14M	-0.50M	9.65M	9.64M
2019/01/31	9.64M	1.16M	0.67M	0.09M	-0.10M	-0.01M	0.39M	-1.41M	-0.66M	-0.12M	0.82M	10.48M	10.48M
2019/02/28	10.48M	0.89M	0.48M	0.08M	-0.07M	0.00M	0.34M	-1.26M	-0.48M	-0.13M	-0.52M	9.81M	9.81M
2019/03/31	9.81M	0.58M	0.38M	0.05M	-0.05M	0.00M	0.32M	-1.17M	-0.39M	-0.11M	-0.12M	9.31M	8.84M
2019/04/30	8.84M	0.83M	0.50M	0.08M	-0.10M	0.00M	0.30M	-1.11M	-0.49M	-0.14M	0.06M	8.77M	8.77M
2019/05/31	8.77M	1.00M	0.61M	0.09M	-0.13M	-0.01M	0.29M	-1.05M	-0.60M	-0.18M	-0.09M	8.69M	8.69M
2019/06/30	8.69M	0.72M	0.44M	0.06M	-0.07M	0.00M	0.27M	-1.06M	-0.45M	-0.04M	0.10M	8.67M	6.86M
2019/07/31	6.86M	0.83M	0.49M	0.08M	-0.11M	-0.01M	0.27M	-1.01M	-0.47M	-0.01M	0.11M	7.03M	7.03M

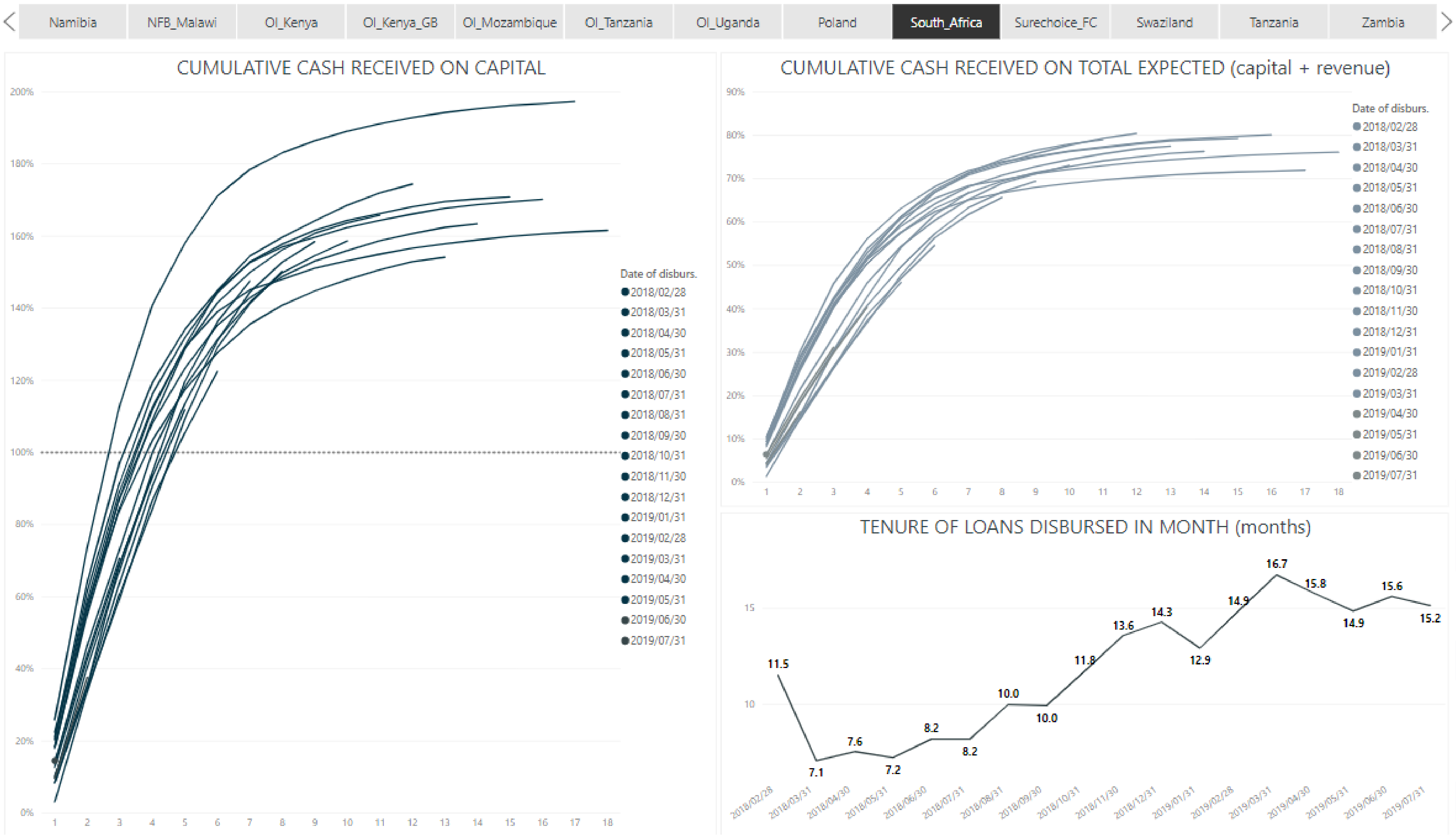
DATE SELECTION

- 2018/07/31
- 2018/08/31
- 2018/09/30
- 2018/10/31
- 2018/11/30
- 2018/12/31
- 2019/01/31
- 2019/02/28
- 2019/03/31
- 2019/04/30
- 2019/05/31
- 2019/06/30
- 2019/07/31

NPV IN AND OUT FOR SPECIFIC MONTH



Risk - Liquidity



Risk – IFRS 9 Provisions

1. Centralised Group Function
2. Background IAS39 vs IFRS 9
3. Macro-economic forward-looking
4. Model Governance / Audit
5. Reporting

Our team

The team

Gunther Marais | Managing Director

Gunther has 9 years' experience in banking risk management with a focus on stochastic modelling, counterparty risk and derivative valuations. He joined MyBucks in 2015 as a credit risk analyst and in 2019 took up the role of group CRO overseeing all risk reporting as well as the IFRS 9 modelling for the group. Gunther holds an MSc in Applied Mathematics

Leilanie Uys | CDO

Holds a Master's Degree in Computer and Electronic Engineering which was focused on the automatic classification of digital signals. Completed her master's degree at the CSIR's. She has been working in the FinTech industry since, specialising in credit risk modelling and data engineering.

Kobus van der Merwe | CTO

Holds an Honours degree in Computer Science, specialising in Software Engineering. Experienced Software Engineer in the Data Science. has broad, in depth experience on all aspects of software development, system architecture and robust design principles.

Dirk Postma | CRA

Trained chemical engineer with a MSc with 18 months experience as a credit risk analyst. He brings the engineering- and problem-solving mindset to the department. Dirk is in-part responsible for the group impairment (expected loss) modelling under IFRS9, as well as the credit risk reporting.

The Board

Timothy Nuy | Founder

Timothy Nuy founded Finclusion in July 2018 with a vision of enabling financial inclusion through data driven lending. In March 2019, Timothy Nuy was asked to return as MyBucks S.A. (a German listed, Luxembourg based African bank holding company) Chief Executive Officer to lead the Company's financial restructuring. Under his leadership - the Company executed a c. EUR64m Debt Recapitalization, a complete overhaul of governance frameworks across the Group and a retrenchment of over 100 staff members and disposal of non core assets leading to the Company's return to positive equity.

Timothy has over 10 years of international experience across Europe and Sub-Saharan Africa in management, investment and advisory capacity. During his previous tenure with MyBucks from 2014 until 2018, Timothy was most notably involved with the group's acquisitions of banks in Malawi, Mozambique and Uganda as well as its listing on the Frankfurt Stock Exchange.

Prior to MyBucks, Timothy was an Investment Director with ADC African Development Corporation AG and an Assistant Manager in KPMG's Transaction & Restructuring team in Hamburg. Timothy holds a BSc from Maastricht University and is a CFA Charterholder.

Mark Young | Director

Mark is the CEO of the GetBucks South Africa Group and a founding director of Fractal Labs, with over 25 years experience in the African financial services landscape Prior to joining MyBucks, he was the founder and CEO of Ideation, a specialist lending and insurance consulting company with clients in South Africa, Nigeria, Kenya and Malawi with a focus on credit risk, capital raising, and value chain transformation. Mark was previously the Deputy CEO and CRO for Bayport SA and the CRO of Old Mutual Finance. He has served as the chair of these organisations credit committees as well as serving as a non-executive director of Mazwe Financial Services, Old Mutual Investment Administrators and a trustee and chair of the Board of Trustees of the Fairbairn Capital and BoE retirement funds.

Tamuka Mpofu | Director

Tamuka Mpofu has over a decade of experience in the finance sector. He completed articles training with KPMG Chartered Accountants Zimbabwe with a specialty in Banking & Financial Services. He has successfully led audits of the largest listed and non-listed banking institutions in the country in addition to insurers and other financial service providers. He previously was an Audit Manager with MooreStephens International before joining GetBucks Microfinance Bank Limited as its Head of Internal Audit. Tamuka has taken on the role of Group Finance Manager for MBC Holdings Limited, a bank holding company, where he focused on financial reporting and management. Tamuka is a strong believer in innovation through technology having spearheaded implementation of several e-platforms to improve efficiency.

Tamuka Mpofu holds a Bachelors of Accounting Sciences (BCompt) from the University of South Africa (UNISA). He also holds a post-graduate CTA (Certified Theory in Accounting) Level 1 from UNISA with emphasis on Financial Accounting, Management Accounting, Audit and Taxation. He is a Certified Expert in Microfinance with the Frankfurt School of Finance & Management.

Tamuka Mpofu is an avid First Aider and is passionate about emergency response. He is also a qualified and accredited trainer facilitating several professional training courses including those for the Institute of Internal Auditors (IIA).

Thank you

Fractal Labs

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