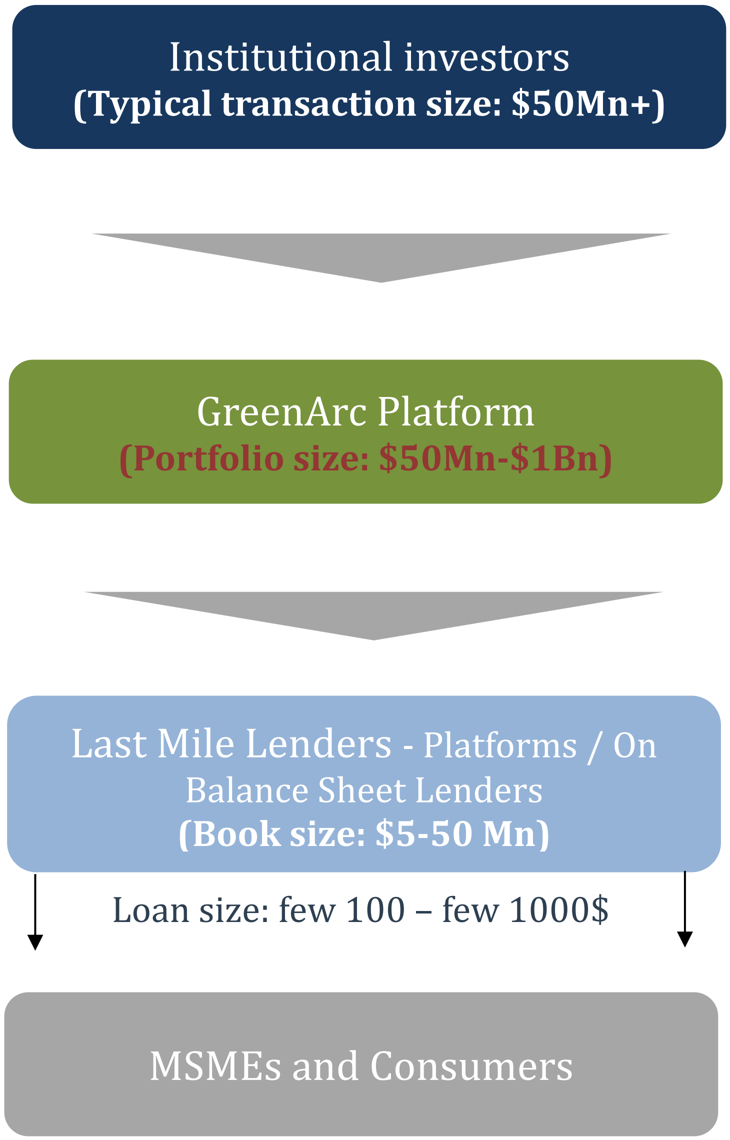
White Paper: GreenArc Platform

(Formerly Known As: Impact Loan Aggregation Platform "ILAP")

Date: 29 Jan 2021



1. The Challenge

$2.7 Trillion financing gap for SMEs and Individuals in Emerging Asia due to:

1) Underdeveloped Financial Institutions & infrastructure

2) Lack of credit information and eligible collateral for SMEs and Individuals

3) Last Mile Lenders' inability to scale due to lack of access to efficient debt capital

4) Institutional investors inability to access these loans due to industry fragmentation & high cost of underwriting / origination w.r.t. loan size

2. The Opportunity

Sustainable & Impact Financing is a rapidly expanding asset class looking for investment opportunities:

- From 2012 to 2018, total AUM in sustainable investment strategies grew from USD 11 Tn to USD 31 Tn (182% growth)
- By 2020, 50% of all investment industry assets ($40Tn), is expected to be run with an ESG mandate, up from 25 % in 2015
- Impact & Sustainable finance asset demand exceeds supply

3. Proposed Solution

GreenArc Platform:

- Lowers cost of capital by connecting Institutional & Impact investors to Last Mile Lenders
- Aggregates granular loan portfolios
- Provides integrated credit scoring and impact measurement modules
- Provides investors the ability to build and invest in SDG aligned thematic Impact Portfolios

EXECUTIVE SUMMARY

The Challenge and Opportunity

Small and Medium Enterprises (SMEs) are a major, yet often overlooked driver of the world economy, contributing up to 60% of total employment and up to 40% of GDP in Emerging Markets. But for SMEs, access to finance is frequently identified as a critical barrier to both entry and growth.

Similarly, unbanked individuals get locked out due to the lack of formal credit history or lack of data for traditional underwriting models to reliably assess the real risks. This has resulted in accessibility issues to even health care and insurance products.

The key reasons contributing to the financing gap are:
- Underdeveloped financial infrastructure
- Lack of credit information / eligible collateral
- Lack of access to efficient debt capital financing
- Inability of institutional investors to access asset class

On the capital supply side, sustainable & impact investments are an increasingly popular investment approach among institutional investors. These investments look for positive financial returns and measurable social or environmental impact. Impact investment market has been growing rapidly, with total assets under management increasing from USD 11 trillion to USD 31 trillion over the last 6 years.

Deploying an impact investment approach for the above challenge could address the financial exclusion problem of Emerging APAC SMEs and individuals, while satisfying the demand from global investors for scalable impact investment opportunities.

The Solution

The GreenArc Platform (formerly known as "ILAP"), is an impact credit platform for funding SMEs and individual loans with measurable impact, in Emerging Markets. The platform curates and aggregates these transactions targeted at socially responsible thematic impact investors.

The GreenArc platform partners with fintech LMLs that lend to SMEs and individuals. Loans from selected LMLs are aggregated via the GreenArc platform and then sold to institutional, private, and blended finance investors. Investors can customize risk / return preferences and tailor investments by Impact / SDG alignment and other relevant Impact metrics

Project Proposal

This proposed proof of concept project is intended to implement the key components of the GreenArc platform outlined in section 2.2. Through the implementation, we intend to test the efficacy of LML proprietary lender models which will help determine the downstream partners which have the most accurate predictive lender models.

The 3 main objectives of this POC were to: 1) set up a credit module to create standardized scoring that institutional investors can comprehend 2) develop an impact measurement module and 3) develop a supervisory model to evaluate the efficacy of other LML lender models.

Implementation

GreenArc platform was set up as planned (details in section 2.2) – with a focus on the Credit Risk and Impact Modules.
Credit scoring module was developed with a combination of NUS-CRI's forward intensity model for SME loans and a dataset of over 45,000 individual loans from 6 countries. A supervisory model was implemented by training Logistic Regression (LR) and Machine Learning (ML) models on the individual loan dataset. Our model utilized the Area-Under-Curve (AUC)[1] and GINI index[2] metrics to measure the ability to separate 'default' and 'not default' loans.

The impact module was designed using UN SDGs, IMP's 5 dimensions of impact and GIIN's IRIS+ metrics. A rule-based impact score was implemented allowing loans to be rated based on their social impact.

Findings

Objective #1: For each loan we were able to assess the probability of default and subsequently put them into rating groups and risk levels. However, testing alone does not inform us as to which PDs fit into

[1] AUC is a performance measurement for classification problems of the False Positive Rate and True Positive Rate

[2] GINI index is a measure of inequality, where 0 represents perfect equality and 1 is perfect inequality.

which ratings groups. For example, if a few loans have a PD of .25% to 1%, determining the cut off points between AAA or AA ratings will be a business decision. For further improvement, the ratings groups could use more data to calibrate the groupings.

Objective #2: Our platform successfully implemented a rule-based impact score and metrics associated with a Philippine based lender. Through the course of implementation, 1) we observed that the lender may not have the resources or processes on the ground to collect and provide the information required for the scorecards. This was overcome partially by re-using loan tape data for impact scoring, hence reducing the additional data collection burden on lenders. Furthermore, 2) we identified that beyond the differences in SMEs and Individual loans, different scorecards were needed for assessing impact measurement of different sectors, such as education and consumer loans.

Objective #3: The results suggest that it is possible to construct a supervisory model that can be used to assess the efficacy of underlying LML models' predicative ability. For the metrics, the closer that the AUC and GINI scores are to 1, the better the models are at sorting between 'default' and 'not default'. The performance of the LR model was an AUC of .62 and a GINI of .23, whilst the ML model produced an AUC of .63 and GINI of .25, indicating a reasonable improvement by deploying ML. In theory, with the same set of variables used in our models, our results can evaluate the predictive power of other LML risk models by testing the LML's data on our models and evaluating them using the AUC and GINI scores. At the same time, we recognize that our model will require additional variables and an increased number of observations to continually improve upon accuracy.

Next Steps

In this first iteration, GreenArc platform has addressed the credit and impact measurement challenges within EM APAC private loan market. There is room to extend this to cover additional financial products (structured notes, funds etc.). The credit module could be fine-tuned further with additional data features as well as training with more data sets. On the impact module, there is room to improve accuracy and efficiency by a) using big data methods to gather benchmark data and b) moving to a machine learning based impact calculation approach. Finally, there is an opportunity to add an impact audit module to identify data discrepancies and improve the integrity of impact data which in turn could potentially help prevent 'Impact Washing'.

1. PROJECT BACKGROUND: THE CHALLENGE AND OPPORTUNITY

1.1 The Financial Exclusion Problem

Approximately two billion people worldwide are excluded from the banking and financial system, averaging 50% unbanked in Emerging Asia, and up to 80% unbanked in certain countries like the Philippines.

This financial exclusion problem results in many individuals and SMEs lacking access to credit. Credit markets in developing countries are characterized by market failures and imperfections, including information asymmetries, inadequacy or lack of recognized collateral, high transaction costs of small-scale lending, and perceptions of high risk. These market characteristics result in reduced access to credit for SMEs and individuals.

1.1.1 Target End Customer

This project proposal targets two main segments:

1. Small and Medium Enterprises (SMEs) are a major, yet often overlooked driver of the world economy; contributing up to 60% of total employment and up to 40% of GDP in Emerging Markets. For SMEs, access to finance is frequently identified as a critical barrier to growth. The problem is even more severe in developing countries where 65 million or 40% of formal SMEs have unmet financing needs.

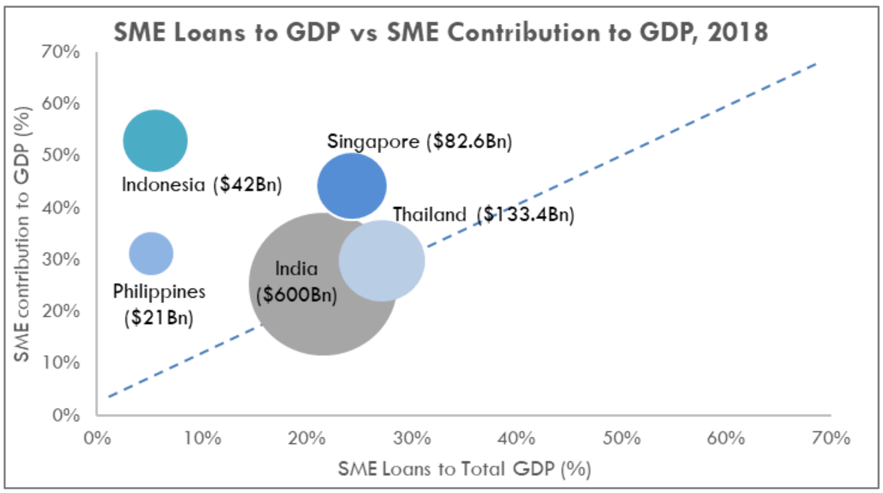


Figure 1: SMEs unserved or underserved by credit services
(Source: McKinsey Global Institute "Digital Finance For All", World Bank, UNESCAP, UOB, OECD)

2. Similarly, unbanked individuals get locked out due to a lack of formal credit history or lack of data for traditional underwriting models to reliably assess the real risks. As a result, these individuals have traditionally relied on local networks of personal money lenders who charge high interests and suffer from poor risk assessment.

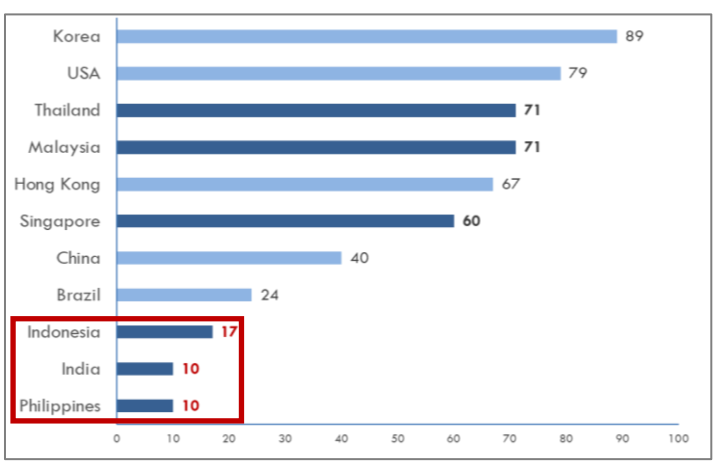


Figure 2: Credit to households as a % of GDP
(Source: The World Bank, Axis Bank, CEIC Report, Macquarie Research, May 2018)

Furthermore, the typical loan requirements in Emerging markets range from a few hundred dollars for individuals to a few thousand dollars for SMEs. As a result, the origination fee that can be earned from one SME or Individual under the traditional loan origination process is too low compared to those from one corporate client. In the case of loan underwriting, the typical costs could exceed the value of a loan. Thus, institutional investors have no incentive to lend to SMEs and Individuals.

1.2 The Opportunity

Impact investments are investments made with the intention of generating positive and measurable, social and/or environmental impact alongside a financial return. Impact investing is a small but growing segment of the broader sustainable and responsible investing universe. The impact investment market demand is growing rapidly. Between 2012 and 2018, total assets under management in sustainable investment strategies grew from USD 11 trillion to USD 31 trillion (182% growth rate). By 2020, half of all investment industry assets ($40tn), are expected to be run with an ESG mandate, up from just 25 per cent as recently as 2015. Deutsche Bank projects 95% of investment strategies will be ESG oriented by 2030.

The social impact – new jobs created, women employed, increase in wages, number of children educated etc. – that can be obtained by addressing the financing gap of these segments, is very significant and can be mapped to 8 of the UN Sustainable Development Goals (SDGs).

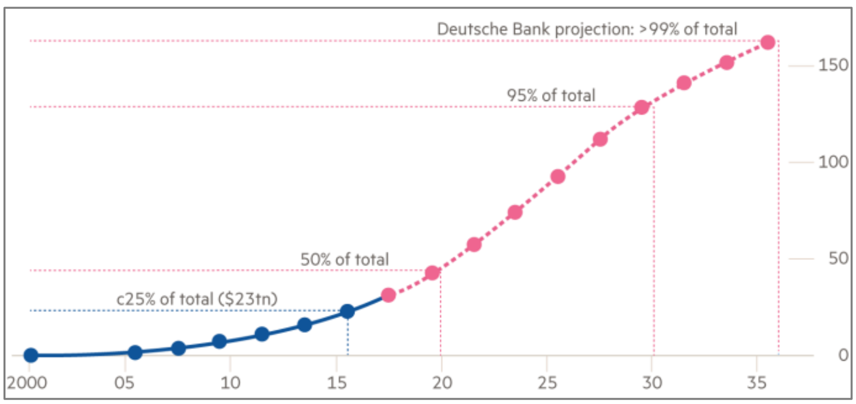


Figure 3: Assets under management with an ESG mandate ($Tn)
(Source: FT: Deutsche Bank, Global Sustainable Investment Alliance)

There is currently a shortage of high-quality investment opportunities in the impact investment space to meet investor demand.

For institutional investors, the key is to be able to see measurable incremental impact in addition to obtaining market returns. By definition, impact investment solutions must have transparent and measurable impact metrics. Therefore, deploying a scalable impact investment approach could address the financial exclusion problem of Emerging APAC SMEs and individuals, whilst satisfying the demand from investors for impact investment opportunities.

2. PROPOSED SOLUTION

2.1 GreenArc Platform

The GreenArc Platform is an impact platform for funding SMEs and individual loans in Emerging Markets. The platform curates and aggregates transactions targeted at mainstream institutional investors as well as socially responsible thematic investors.

- The platform partners with fintech LMLs that lend to SMEs and individuals

- Loans from selected LMLs are aggregated via the platform and then sold to institutional, private, and blended finance investors

- Investors can customize risk / return preferences and tailor investments by SDG alignment and other relevant Impact metrics

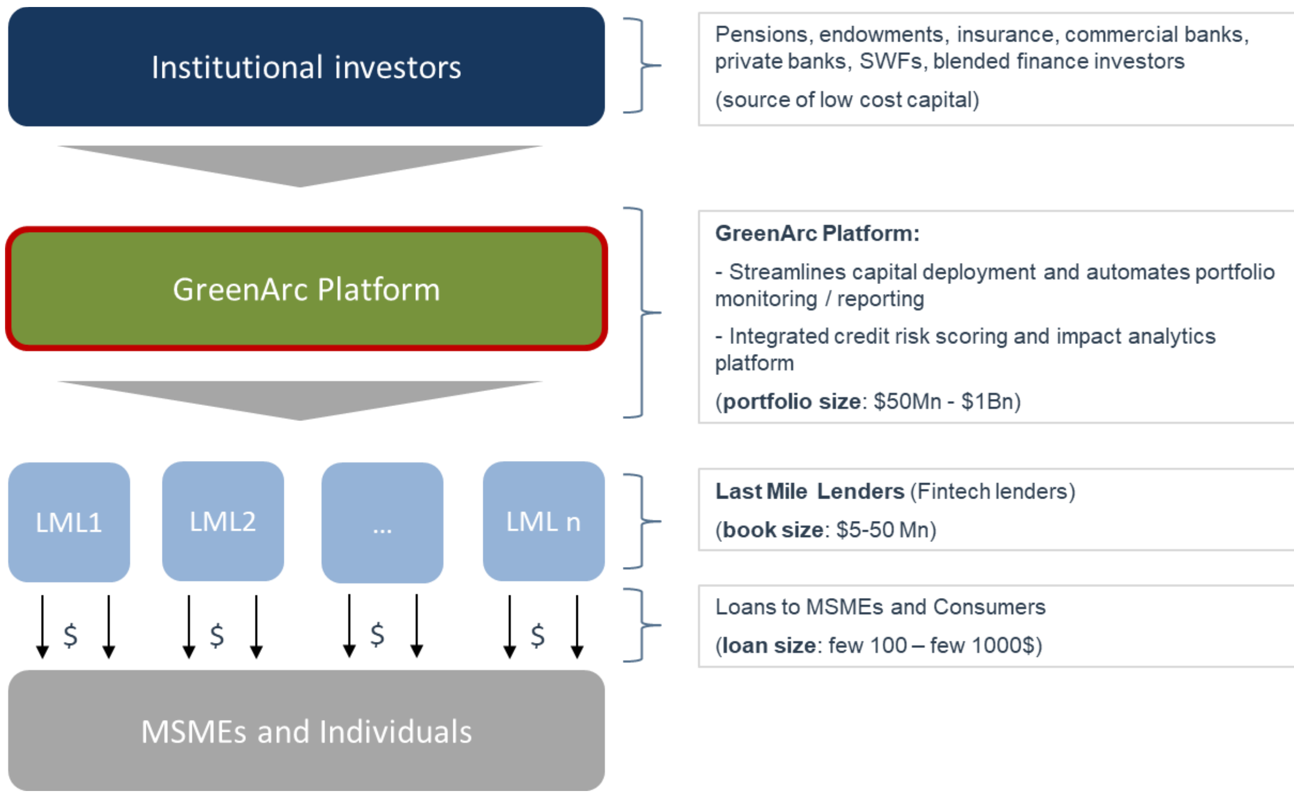


Figure 4: Base of Pyramid Lending Landscape in South and South East Asia

The GreenArc Platform allows SMEs and individuals to access larger pools of credit financing from institutional investors and addresses the following key obstacles:

2.1.2 Challenges	2.1.3 Solutions
Underdeveloped financial infrastructure: In Emerging Asia, banks are the dominant source of financing. However, they tend to lend only to large enterprises because of better financial transparency and risk management and reject SMEs and Individuals. Financial institutions also cannot afford to monitor small borrowers closely and continuously due to lack of information infrastructure. Without the tools and capabilities, financial institutions have little incentive to develop infrastructure and risk management systems to cater to this segment.	GreenArc Platform facilitates institutional capital to SMEs and Individuals, which fills the credit financing gap that financial institutions have not been able to provide. With a loan data architecture and credit scoring module, GreenArc Platform maintains the necessary information infrastructure for institutional investors cost-effectively access and monitor loans.
Lack of credit information and eligible collateral for SMEs and individuals makes it hard to assess their ability to repay and manage borrower risk. Thus, traditional lenders are less willing to lend given the uncertainties.	The credit scoring module combines loan level data from LMLs with institutional credit risk practices to assess and monitor asset class credit risk.
Lack of access to efficient debt capital financing for Last Mile Lenders (LMLs): In the last decade, there has been an explosion in mobile penetration and the advent of big data has led to the emergence of "non-traditional" data points for credit risk scoring. Resulting in the proliferation of Alternative Finance activity (through Fintech last mile lenders - *LMLs*). However, because of the small sized loans and lack of credit history, these loan portfolios are still un-attractive to institutional investors. Hence the LMLs raise capital through retail investors (p2p) and equity via VC / PE	A supervisory model, part of the Credit Scoring Module consolidates the "non-traditional" data points and further reduces the need for a credit history. Loan aggregation enables institutional investors to curate portfolios at scale, enabling the provision of efficient capital for LMLs.

sources which results in high cost of capital. This restricts LMLs from lending to large number of SMEs and Individuals, limiting LML's lending scale.	
Inability of Institutional investors in accessing this asset class due to industry fragmentation and high cost of underwriting / origination with respect to small loan size. Institutional investors typically have limited direct access to SMEs and Individuals. Accessing them through intermediary channels is also difficult, because there are too many small players in the market (500+ platforms in South and Southeast Asia). Conducting due diligence on a few small players is still necessary, but very time-consuming and cost ineffective for institutional investors.	By partnering with established LMLs, investors can access loan portfolios efficiently through GreenArc Platform. For LMLs, the access to lower cost capital incentivizes them to open their loan books to the platform. As illustrated in Figure 4, through the aggregator approach, GreenArc Platform curates loan portfolios of desired financial and impact metrics for institutional clients.

By aggregating capital from institutional investors and allocating to LMLs in small loan sizes, the GreenArc Platform reduces the cost of capital for LMLs. Hence, LMLs can afford to lend to larger pools of SMEs and Individuals, thus improving lending scalability.

2.2 TECHNICAL ARCHITECTURE

GreenArc Platform architecture consists of 5 key modules:

- Data infrastructure
- User Interface
- Loan Management System
- Credit Scoring Module
- Impact Measurement Module

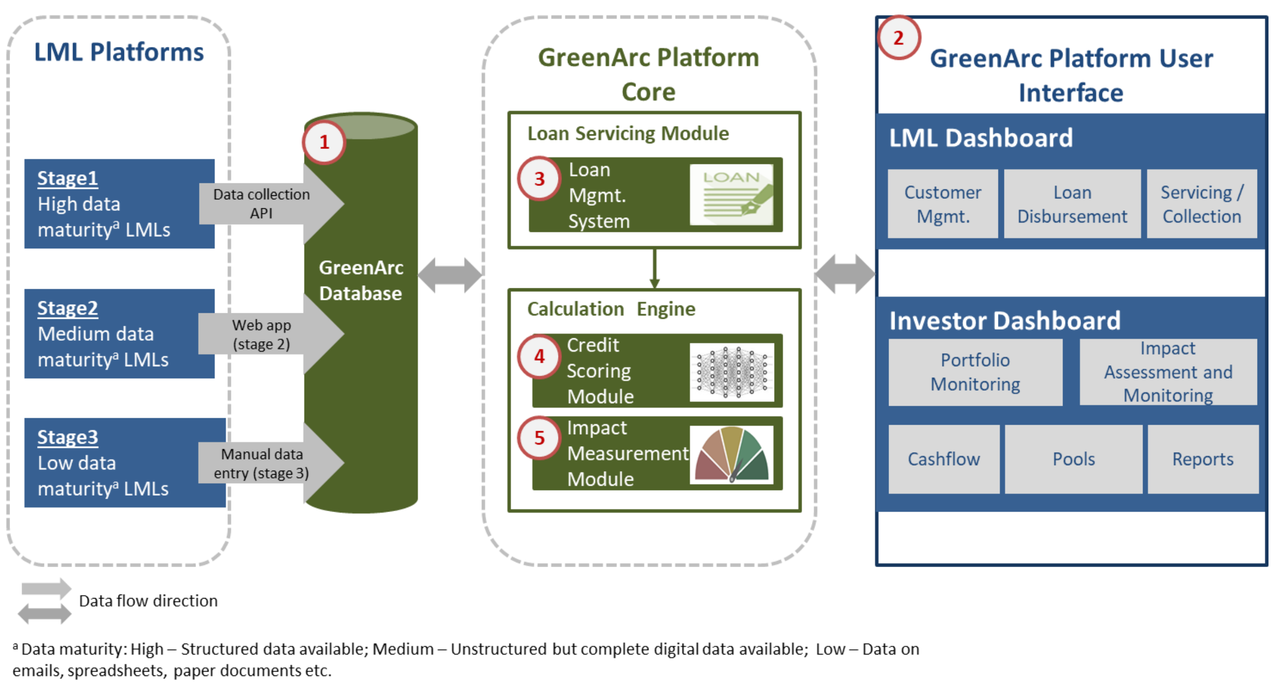


Figure 5: GreenArc Platform Technical Architecture
a: Data maturity: High – Structured data available; Medium – Unstructured but complete digital data available; Low – Data on emails, spreadsheets, paper documents etc.

2.2.1 Data Infrastructure

The data infrastructure consists of:

(1) data collection tools: for the pilot, GreenArc Platform targets <u>only high data mature LMLs</u> and per the due diligence that the GAC team has completed,

it has been confirmed that the target population of LMLs have the ability to provide loan level data for SMEs and individuals.

(2) data transformation tools: required in scaling stage (post pilot) if other data sources (spreadsheets, flat files etc.) need to be processed, and

(3) storage infrastructure: a NoSQL database that allows running analytics tools on the loan / impact data

2.2.2 GreenArc Platform User Interface

This is the interface that allows LMLs and Investors to interact with GreenArc Platform. The Investor Dashboard allows institutional investors to:

(1) Evaluate impact investment opportunities across a wide range of alternative loan origination platforms

(2) Monitor investments with portfolio management tools that help streamline risk monitoring, financial performance, and automate reporting

(3) Track and assess impact performance of their investment

2.2.3 Loan management system

The Loan administration and servicing module is an operational function that automates loan booking and administration.

2.2.4 Credit Scoring Module

The challenge with SME lending is that there is a dearth of digital data, other than their repayment history, that can be used to determine credit worthiness. Given that SMEs have very few avenues to borrow, this results in these entities not having a credit history / credit score.

GreenArc Platform proposes to overcome this challenge by implementing the below credit methodology:

- Once an LML is onboarded to GreenArc Platform, an internal credit rating is assigned to each end-borrower (SME / consumer) based on (a) The LMLs credit assessment of the loan, the LML's loan-level data that includes historical and current financial data collected directly from loan applicants (b) GreenArc Capital's (GAC's) assessment of the LMLs credit scoring methodology, (c) Country & Industry specific third-party credit data. Note that the LMLs in Emerging Markets typically assess end-borrowers using standard credit methodology (e.g. credit bureau reports, FICO / equivalent scores of key individuals and alternative credit scoring).
- GreenArc Platform validates estimated a priori obligor ratings and evaluate the predictive ability of ratings by observing actual loan performance at maturity (repayment at maturity, delinquency, or default) and by using actual loan performance data to dynamically calibrate expected and actual loan performance by assigned ratings over time. Hence, the platform re-calculates / validates the assigned ratings of obligors over multiple investment cycles given key data inputs a priori.

This methodology allows GreenArc Platform to scale portfolios in the asset class efficiently – allowing institutional investors ease of credit due diligence with the platform credit methodology validated with multiple transaction data points.

Moreover, as a credit aggregator, GreenArc Platform standardises scoring data across LMLs which deploy different proprietary scoring mechanisms, hence making the final obligor credit ratings more understandable for investors. With access to different platforms, transactions and rating systems, the platform monitors credit scoring data horizontally and validates how LMLs manage their loan books. By creating its own standalone credit metrics and ongoing tracking and analysis, GreenArc Platform can compare LMLs performance through time cohorts, regional and industry trends and across similar LMLs.

The intent is to combine this with industry data sourced as part of an engagement with Asian Institute of Digital Finance, formerly known as NUS Credit Research Initiative (CRI). With this rich dataset, GreenArc Platform can apply machine learning over time, allowing to generate accurate predictive models.

2.2.5 Impact Measurement Module

The Impact Measurement Module allows a) creation of *Thematic Impact Portfolios* and b) monitoring of impact performance of GreenArc Platform portfolios through the *Impact Scorecard*.

a) *Thematic Impact Portfolios*: GreenArc Platform analyses LML datasets to select loan portfolios aligned to Investors' impact preferences / SDG alignment. Based on this analysis, the platform allows investors to invest in prebuilt portfolios or create theme based customised portfolio based on Impact / SDG alignment and investment objectives. Each portfolio is made of up of a basket of LML sourced loans

b) *Impact scorecard*: Provides a real time view of impact performance of investors' portfolios using a methodology developed based on the GIIN IRIS methodology and IMP Impact framework.

Loans originated by LMLs on GreenArc Platform are classified into Impact sectors such as SME lending, Tertiary Education loans amongst others. Relevant metrics (mapped to UN SDGs) in these sectors are selected to measure impact. Relevance is determined by 1) sector in which LML operates, 2) the major social issue that the LML / loan aims to address or the UN SDG it contributes towards, and 3) LML's vision, mission and values.

Metrics are classified as *output metrics* - measure of activity in numbers, and *outcome metrics* - changes in people's lives (positive & negative).

3. PROOF OF CONCEPT PROJECT

3.1 PROJECT OVERVIEW AND OBJECTIVES

The Proof of Concept (POC) project is intended to test the key components of the GreenArc Platform technical architecture that are essential for the pilot financial transaction.

Objective	Benefit
1. Set up GreenArc Platform Credit Scoring Module	By scoring loans according to credit standards understood by institutional investors, *Emerging Market Impact Loans will become more standardized* and hence more attractive to institutional investors. This will allow making the asset class *more accessible to institutional investors* hence *allow* scaling the asset class and *reducing cost of financing for SMEs and Individuals.*
2. Set up Impact Measurement Module	Based on GreenArc Capital's research, there are no technology platforms that allow thematic impact investment in APAC Emerging Markets private debt. *Being able to measure impact generated* / SDG alignment, *allows* institutional / impact investors to allocate *more capital to EM Impact Loans*, hence *reducing cost of financing* for the SMEs and Individuals. This is relevant from an investor perspective too, given the focus on SDG / Impact alignment.
3. Determine efficacy of predictive lender models and have the ability to validate LML's losses for a given credit band of accounts	Last mile lenders have proprietary credit scoring algorithms that they use for lending to SMEs and individuals. Determining efficacy of these downstream models *allow institutional investors to better allocate capital to loans* (through LMLs) with the most predictive models

3.2 IMPLEMENTATION AND RESULTS

The GreenArc platform was built per specifications defined in the technical architecture section (2.2). While there is very detailed documentation available on the platform features, technology architecture and processes, for the purpose of this white paper, we will focus on the 3 objectives of the project.

3.2.1 Credit Risk Module and Lender Model Efficacy (Objectives #1 and #3)

For all loans, Probability of Default (PD) is the core credit measure of the GreenArc risk module.

For SME loans, PD is measured using the Asian Institute of Digital Finance (AIDF) corporate default prediction system, built on the forward intensity model of Duan *et al.* (2012)[3]. This model produces forward-looking PD-term structures of public firms based on dynamic learning from the macro financial and firm-specific data. The data is constituted of sixteen input covariates (or default predictors) from both market-based and accounting-based firm-specific attributes, as well as macro-financial factors. Currently, 34,000 publicly listed firms from 128 economies are used in this dataset and updated daily to generate prediction horizons from 1 month to 5 years.

For individual loans, approximately 45,000 loans from 6 countries were used for modelling, training, and testing the risk module. Most of these loans came from Indonesia and Kenya (32,000), administered over a two-year period. For the feature selection (independent variables), typical loan tape data was used – such as installment amounts, loan usage, loan size, and number of installments. The dependent variable selected was 'Loan Default' i.e., whether or not the loan had defaulted. We tested various modeling techniques, including linear models (such as Logistic Regression [LR]), and non-linear machine learning (ML) models (such as Decision Tree, Random Forest, Support Vector Machines, and Neural Networks). For each method, a 10-fold cross-validation technique was utilized to prevent overfitting on the input parameters.

3.2.1.1 Testing

For SME loans, data was processed through the CRI's forward intensity model. The data was derived from anonymized borrowers from Indonesia and Singapore. The information was generated using a combination of historical financial data (elements from balance sheets, profit/loss statements and cashflows) and industry/country specific data. For each SME loan, the data was put through the CRI prediction system to generate a PD. The PD percentages were bucketed into rating groups (AAA, AAa, Aaa, etc.), which were then assigned to low-, medium- or high-risk categories on the platform.

Individual loans were tested by either using a 20% hold out from a specific country's dataset or on loans from all other countries. For example, for a model trained on Indonesia dataset, we used a hold out of 20% from Indonesia, all Kenya loans, and all other countries. In total, we trained 8 models and conducted 24 tests (3 for each model). The metrics used were the Area-Under-Curve (AUC)[4] and GINI index[5] to determine the ability for our models to separate the loans that 'default' from those that will 'not default'. Once the default probability was calculated, this was translated to a risk rating group similar to the SME loans classification.

3.2.1.2 Findings

STANDARDISED CREDIT RISK MODEL (Objective #1)
Our results indicate that it is possible to create rating groups based on the probability of default of both SME and individual loans for institutional investors. For each loan we were able to assess the probability

[3] Duan, J. C., Sun, J., and Wang, T. (2012). "Multiperiod Corporate default prediction – A Forward Intensity Approach", *Journal of Econometrics*, 179, 191-209.

[4] AUC is a performance measurement for classification problems of the False Positive Rate and True Positive Rate

[5] GINI index is a measure of inequality, where 0 represents perfect equality and 1 is perfect inequality.

of default and subsequently put them into rating groups and risk levels. However, testing alone does not inform us as to which PDs fit into which ratings groups. For example, if a few loans have a PD of .25% to 1%, determining the cut off points between AAA or AA ratings will be a business decision. For further improvement, the ratings groups could use more data to calibrate the groupings. For this POC, we translated PDs into standardized ratings that institutional investors can comprehend.

SUPERVISORY MODEL (Objective #3)
Below are the results from Receiver Operating Characteristics (ROC) curves that were used to evaluate model performance.

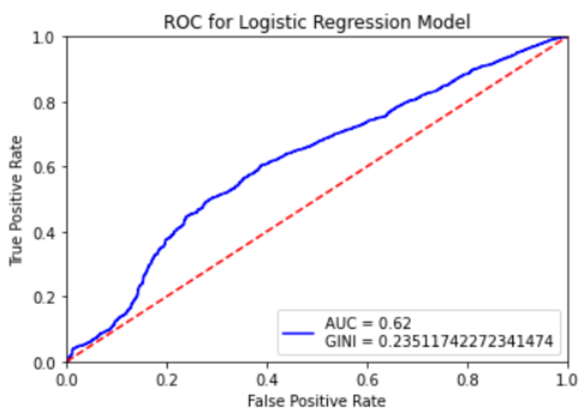


Figure 6: Logistic Regression method - ROC curve of GreenArc supervisory model trained on Indonesia and Kenya and evaluating efficacy of out sample of the same countries.

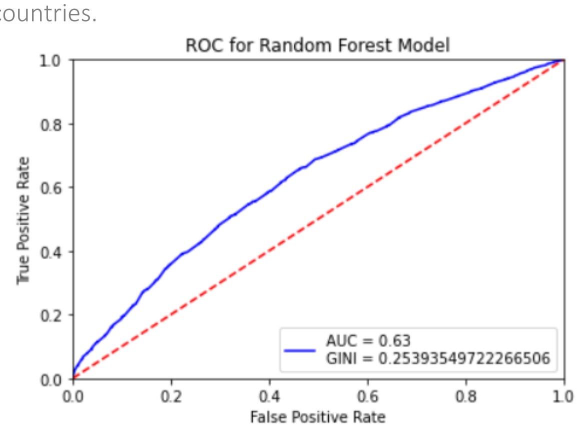


Figure 7: Random Forest method - ROC curve of GreenArc supervisory model trained on Indonesia and Kenya and evaluating efficacy of out sample of the same countries.

For the metrics, the closer that the AUC and GINI scores are to 1, the better the models are at sorting between 'default' and 'not default'. Illustrated in the graphs above, the performance of the LR model was an AUC of .62 and a GINI of .23, whilst the ML (Random Forest) model produced an AUC of .63 and GINI of .25, indicating a reasonable improvement in the GINI index.

The results suggest that it is possible to construct a supervisory model that can be used to assess the efficacy of underlying LML models' predictive ability. With the same set of variables used in our models, our results can evaluate the predictive power of other LML risk models by testing the LML's data on our models and evaluating them using the AUC and GINI scores.

We recognize that our model will require additional variables and an increased number of observations in future iterations to continually improve upon accuracy. As the platform begins to be rolled out to more lenders and more SMEs and individuals, we will acquire greater volumes of data that can be utilized for such purposes.

3.2.2 Impact Module (Objective #2)

Underpinning the entire impact module is our Theory of Change which states that providing more access to credit finance through loans has a positive impact on many micro-economic & socio-development indicators. As beneficiaries can positively utilize this financing to increase their income levels and/or access services that are otherwise unavailable (i.e. for individuals - food, education, healthcare and for SMEs – working capital, investing in tech etc.) thereby improving their quality of life.

From this starting point, the impact module was designed using the Impact Measurement Project's (IMP) five dimensions and Global Impact Investing Networks (GIIN) IRIS+ metrics.

For the IMP framework, the 5 dimensions are:
WHAT is the problem?
WHO are the target stakeholders?
HOW MUCH impact are we having?
CONTRIBUTION
RISK

For our two main categories of loans (SMEs and Individuals), each loan type was defined along these dimensions to derive more specifics on the intended impacts of these loan interventions. With this understanding, specific indicators were chosen from IRIS+ for measurement. The selection required a fine balance among data that was obtainable, measurable, and accurately representative of the impact of these interventions.

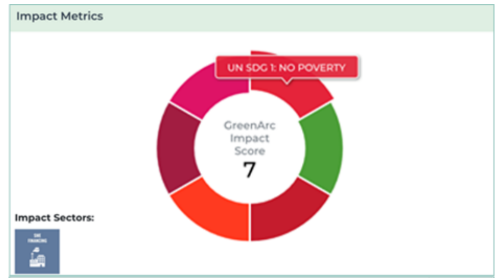
From these metrics, a scorecard was developed to create a rule-based impact score (from 1 to 10) for each loan. The scorecard method was chosen specifically because it consolidates all the metrics and assigns weights to them according to IMP's 5 dimensions and our impact focus. The benefit of the score is that the investor is provided with an easy-to-understand value that can be used to compare investment opportunities (loans).

3.2.2.1 IMPLEMENTATION

As part of the system build, the impact scoring module was implemented using python scripts. These scripts invoked through a data ingestion module which loads data from lenders in a pre-defined format. For testing purposes, the score produced by the platform was manually verified by the QA team using spreadsheets by running the algorithm manually.

3.2.2.2 FINDINGS

Provided below is a screenshot from the GreenArc platform that provides the impact score and metrics associated with a Philippine based lender. The score of 7 (on a scale of 1 to 10) in Figure 8, indicates a very high impact loan which an impact investor could potentially purchase.



Metric Name	Value
Semi Annual Revenue (USD)	$136,508
Months in Operation	8
Employees: Total	44
Proportion of Female Employees (% of total)	43
Proportion of Full-Time Employees (% of total)	50
Average Wage Rate p.m. (USD)	$194
Female-led MSME?	Yes

Figure 8: GreenArc Impact Score and Impact Metrics

During data gathering we observed that LMLs may not have the resources or processes on the ground to collect and provide the information required for the scorecards. So, the input data format was designed so that about 70% of the data is gathered from the loan tape and the remaining information provided by the lender.

Furthermore, during implementation, we identified that beyond the differences in SMEs and Individual loans, different scorecards were needed for assessing impact measurement of different sectors, such as education. As impact measurement has multiple metrics to evaluate efficacy of any given intervention, it is even more important to measure industries using different indicators. For example, the impact of education loans may be to increase literacy in a community and be measured by the number of children that are able to attend school, whereas an individual loan impact may be to improve health and be measured by the amount loans spent on more food.

3.2.3 Bring It All Together: Loans Marketplace

GreenArc platform was designed to partner with fintech LMLs to aggregate loans disbursed to SMEs and individuals. These aggregated loans are sold to institutional, private, and blended finance investors, who can customize risk / return preferences and tailor investments by Impact / SDG alignment.

This vision is achieved through the Loans marketplace feature – illustrated in Figure 9. An impact investor can use the interface to create a custom loan portfolio by selecting a desired impact score 1, risk rating 2 and other financial metrics (interest rate, loan term, currency etc.) to obtain a thematic portfolio 3 aligned to SDGs. All these financial and impact metrics are determined by the GreenArc platform based on underlying loans. By standardizing the risk and impact measurement and aggregating loans to institutional size, we aim to make the EM private debt asset class more accessible to institutional investors hence allow scaling the asset class and reducing cost of financing for SMEs and Individuals.

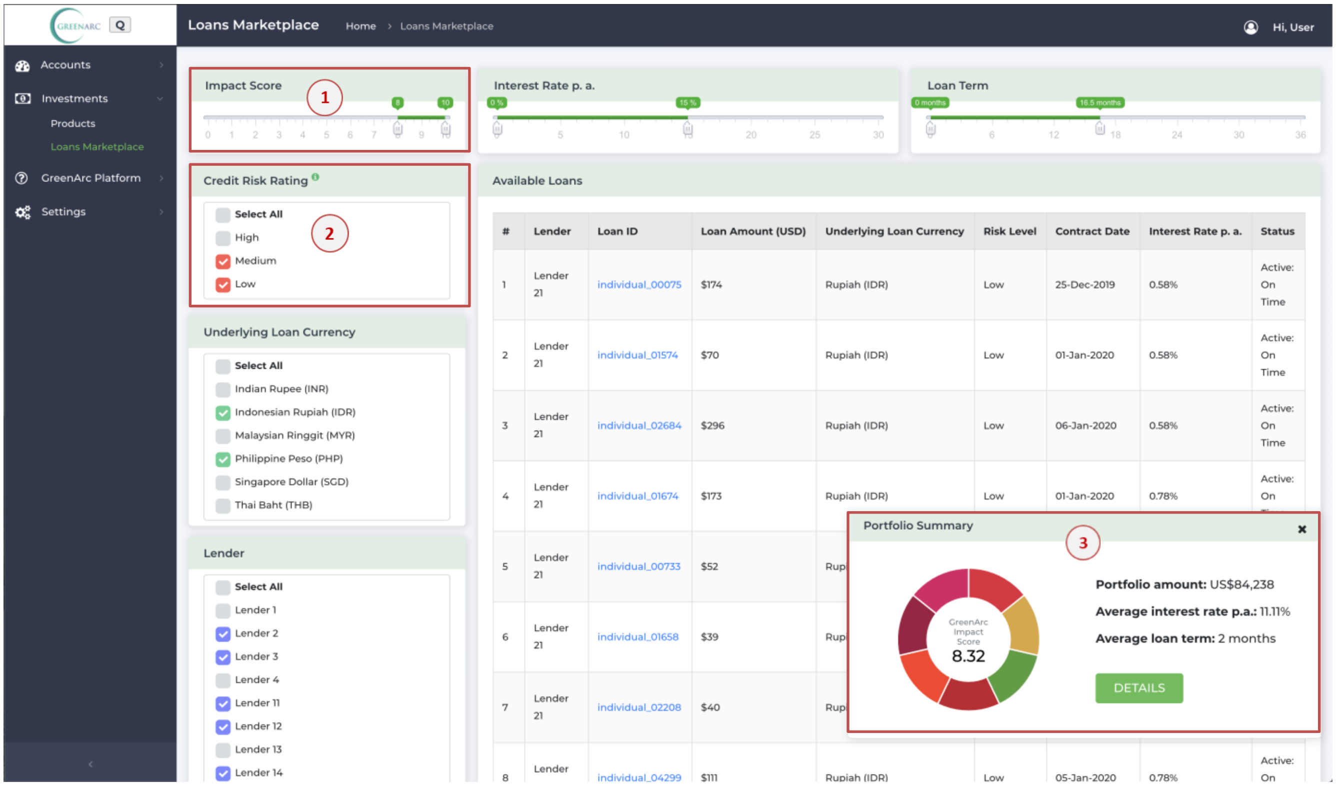


Figure 9: GreenArc Platform – Loan Marketplace

4. CONCLUSION and NEXT STEPS

This POC has successfully implemented the 3 objectives of the project i.e. set up a credit module, implement an impact measurement module and determine the efficacy of last mile lenders. Through this, the GreenArc Platform provides an avenue for impact investors to evaluate Emerging Market Private Debt (loans) based on institutional risk and impact metrics and invest in the asset class by creating custom impact loan portfolios. Based on initial client conversations, the GreenArc impact score has been received very well by institutional investors with whom we have been running pilot projects.

<u>Next Steps</u>

GreenArc Capital has just received an in-principle approval to operate the platform for accredited investors. Over the next quarter, we will be activating the platform by implementing the license specified controls.

On the technology side, for the credit risk module, while coherent and reasonable PDs were created for SME and individual loans, the thresholds setting for each rating level (AAA, AAa etc.), could be calibrated further based on more loan data. We also recommend (subject to data availability) expanding the number of variables used in the model, including education level, marital status, household size etc. which could potentially give more accurate insights into default probability. This could be potentially expanded to cover impact variables for risk hypothesis testing for e.g. Do education loans default more than SME loans?

On the impact module, we believe refining the scoring methodology beyond a rules-based model to a machine learning based model will allow the creation of a more accurate data-based score which can be customized by geography, sector etc. Further, we recommend obtaining benchmarks from sources such as multilateral databases and national statistics directories using big data techniques to allow managing data efficiently, and with minimal manual error.

Finally, there is no efficient mechanism in place (for base of pyramid microloans) to ensure the integrity and accuracy of the data self-reported by lenders. This results in relying on annual or even less frequent manual data audits using time consuming and costly on the ground surveys. The difficulty in conducting data checks and the need for greater capital, is an incentive for lenders to potentially provide fraudulent impact information. To address this issue, we recommend an impact audit system that can flag potentially fraudulent impact claims and improve ground level data veracity.

BNP Paribas has been following the development of the GreenArc platform very closely and is optimistic about the potential of the platform to attract private and institutional impact investors to the target Emerging Market private debt asset class.

As a next step, as part of BNP Paribas' co-create program under the Singapore Green Finance Center initiative, the bank is considering extending the engagement with GreenArc Capital to develop the impact module in line with the recommendations provided in this section.