# **Napkin -** SME Data Gathering, Lending and Risk Management Scope of Work

May 2023

# Contents

# The Opportunity

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# 1/ The Opportunity

## Napkin's Vision

- 1. We buy, build and optimize digital agencies with thousands of e-commerce brands, to create revenue sharing opportunities
- 2. We now plan to convert our customer GMV (gross merchant volume) into royalty streams that are investible and instantly liquid

## Executing the Vision: building SmartLend.AI, A Napkin credit product, machine learned (ML)

- Napkin is looking for a partner to help build SmartLend.AI: *Factoring Risk into Funding Opportunities.*
- The seven steps outlined in the SmartLend.AI document include:

| Num | Activity | WF Role | Comments |
|---|---|---|---|
| 1 | Gather Data | High | See slides |
| 2 | Determine Risk: Tolerance, Credit-worthiness, Ad Spend Loan Amount | High | See slides |
| 3 | Find the low-hanging Fruit to optimize each brand within the Portfolio | Medium | See slides |
| 4 | Advertise and Service account | Low | For discussion |
| 5 | Revenue Share | Low | For discussion |
| 6 | Automate for Scale via Built Platform | High | See slides |
| 7 | Data & Analytics Reporting to Firms, Funds, Banks etc | High | For discussion |
| + | Programme disciplines | Joint | See slides |
| + | Partnership Approach (design, workflow, wireframes, dev, build) | Joint | See slides |

# Proposed Approach: for Discussion

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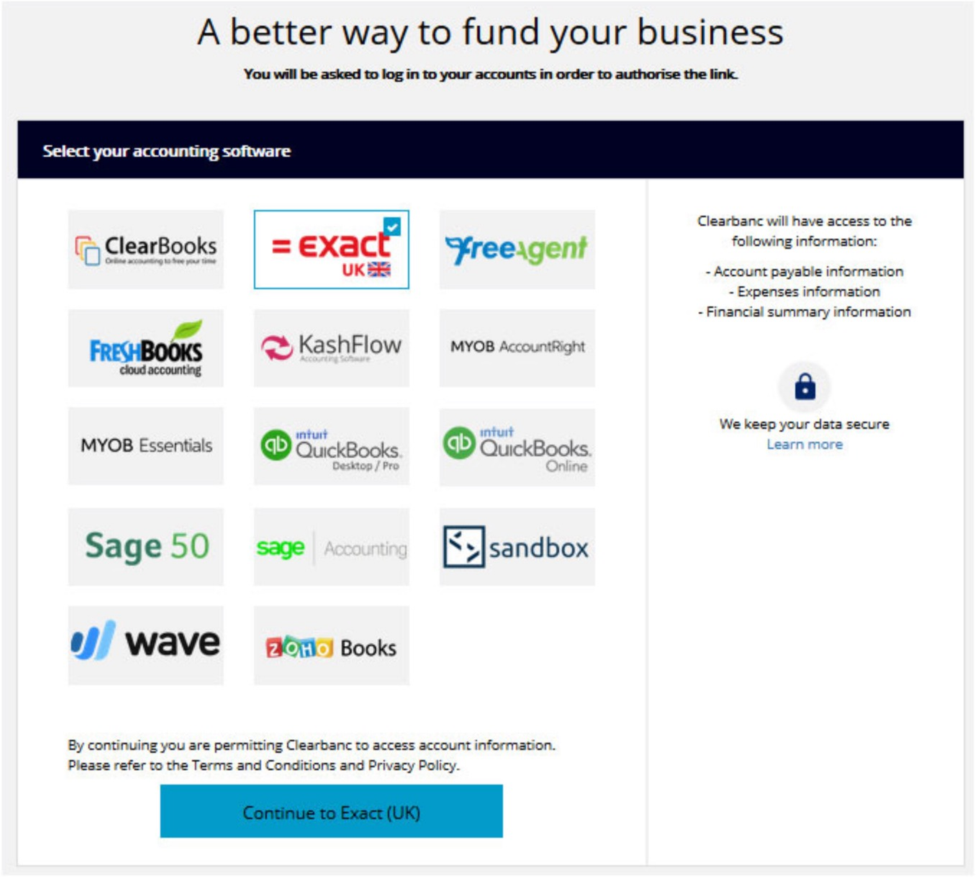
# 1/ Gather Data

## Assumptions:

- Data is required to credit assess private North American companies
- Data is required at “onboarding” and for “ongoing monitoring”.
- Real time, reliable data is a critical variable enabling Napkin to build the analytics and insight required to be successful
- FunnelDash is a benchmark example. They appear to be using Codat



# 1/ Gather Data – Codat and Wiserfunding integration

## We connect and sync data

## So you can embed and automate credit analytics

### Accounting

xero · qb · sage · ZOHO Books · FreshBooks · ClearBooks · FreeAgent · wave · kashoo

### Ecommerce

### Bank Accounts

PLAID · TRUELAYER

Sync

Sync

Sync

API

API

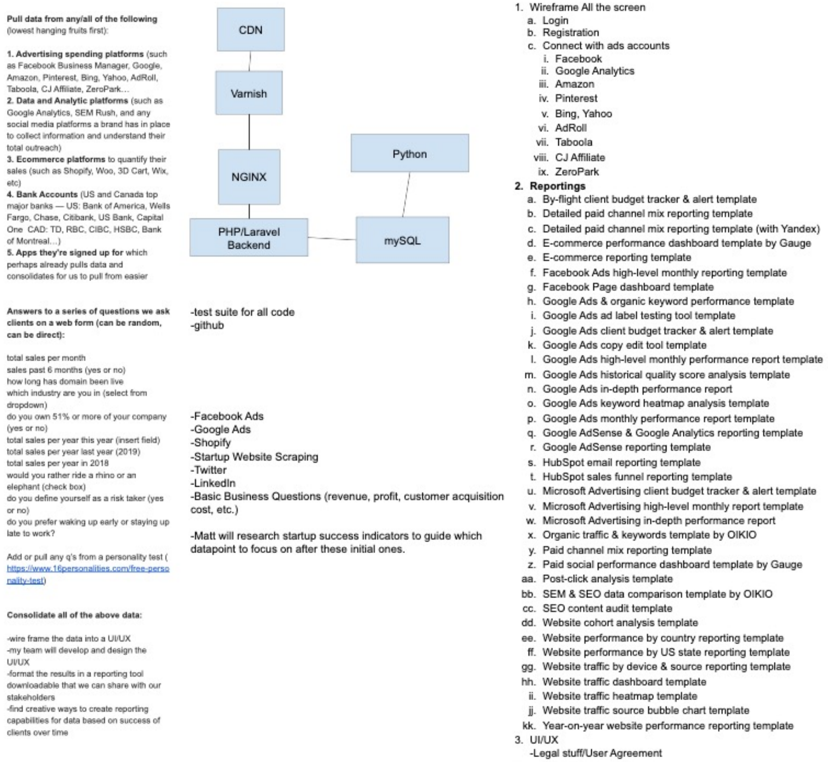
## Risk made easy

| API Integration | Easy Setup | Fast Response | Accuracy |
|---|---|---|---|
| **Cloud-based** platform with full **API** connectivity | Simple set up with implementation in under **one week** | Generate detailed risk assessment within 5 **seconds** | Default prediction accuracy **30% higher** than market standard |

# 2 / Determine Risk:  Tolerance, Credit-worthiness, Ad Spend Loan Amount

## Framework and Workflows:

- Wiserfunding can support and advise on the design and build of workflows and UI to ensure process and data gathering balance the competing demands of robust risk analytics and great UX
- We have developers but we are not a dev shop so would not build out wireframes, screens, workflow, etc.



**Pull data from any/all of the following** (lowest hanging fruits first):

**1. Advertising spending platforms** (such as Facebook Business Manager, Google, Amazon, Pinterest, Bing, Yahoo, AdRoll, Taboola, CJ Affiliate, ZeroPark...
**2. Data and Analytic platforms** (such as Google Analytics, SEM Rush, and any social media platforms a brand has in place to collect information and understand their total outreach)
**3. Ecommerce platforms** to quantify their sales (such as Shopify, Woo, 3D Cart, Wix, etc)
**4. Bank Accounts** (US and Canada top major banks — US: Bank of America, Wells Fargo, Chase, Citibank, US Bank, Capital One  CAD: TD, RBC, CIBC, HSBC, Bank of Montreal...)
**5. Apps they're signed up for** which perhaps already pulls data and consolidates for us to pull from easier

**Answers to a series of questions we ask clients on a web form (can be random, can be direct):**

total sales per month
sales past 6 months (yes or no)
how long has domain been live
which industry are you in (select from dropdown)
do you own 51% or more of your company (yes or no)
total sales per year this year (insert field)
total sales per year last year (2019)
total sales per year in 2018
would you rather ride a rhino or an elephant (check box)
do you define yourself as a risk taker (yes or no)
do you prefer waking up early or staying up late to work?

Add or pull any q's from a personality test ( https://www.16personalities.com/free-personality-test)

**Consolidate all of the above data:**

-wire frame the data into a UI/UX
-my team will develop and design the UI/UX
-format the results in a reporting tool downloadable that we can share with our stakeholders
-find creative ways to create reporting capabilities for data based on success of clients over time

CDN
Varnish
NGINX
PHP/Laravel Backend
Python
mySQL

-test suite for all code
-github

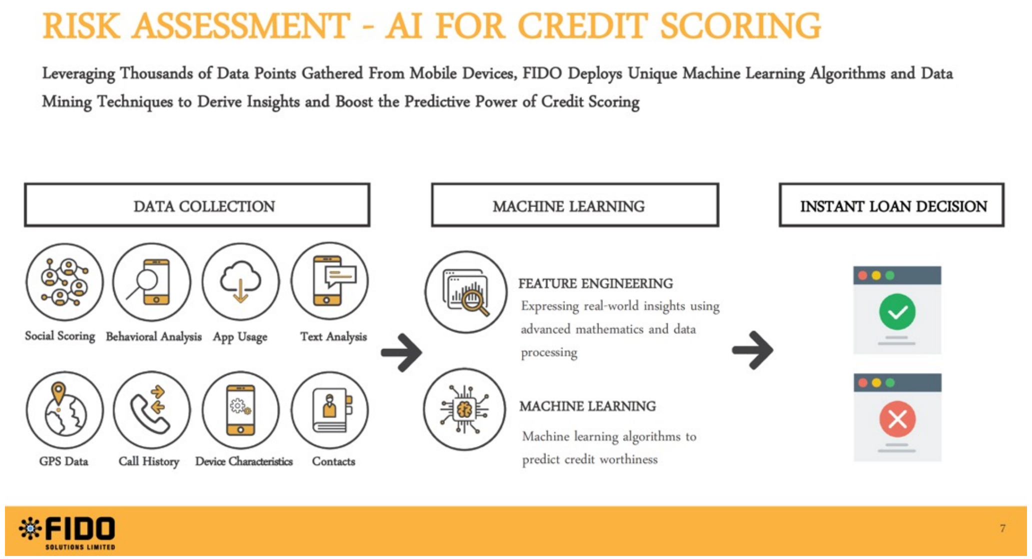
-Facebook Ads
-Google Ads
-Shopify
-Startup Website Scraping
-Twitter
-LinkedIn
-Basic Business Questions (revenue, profit, customer acquisition cost, etc.)

-Matt will research startup success indicators to guide which datapoint to focus on after these initial ones.

1. Wireframe All the screen
   a. Login
   b. Registration
   c. Connect with ads accounts
      i. Facebook
      ii. Google Analytics
      iii. Amazon
      iv. Pinterest
      v. Bing, Yahoo
      vi. AdRoll
      vii. Taboola
      viii. CJ Affiliate
      ix. ZeroPark
2. **Reportings**
   a. By-flight client budget tracker & alert template
   b. Detailed paid channel mix reporting template
   c. Detailed paid channel mix reporting template (with Yandex)
   d. E-commerce performance dashboard template by Gauge
   e. E-commerce reporting template
   f. Facebook Ads high-level monthly reporting template
   g. Facebook Page dashboard template
   h. Google Ads & organic keyword performance template
   i. Google Ads ad label testing tool template
   j. Google Ads client budget tracker & alert template
   k. Google Ads copy edit tool template
   l. Google Ads high-level monthly performance report template
   m. Google Ads historical quality score analysis template
   n. Google Ads in-depth performance report
   o. Google Ads keyword heatmap analysis template
   p. Google Ads monthly performance report template
   q. Google AdSense & Google Analytics reporting template
   r. Google AdSense reporting template
   s. HubSpot email reporting template
   t. HubSpot sales funnel reporting template
   u. Microsoft Advertising client budget tracker & alert template
   v. Microsoft Advertising high-level monthly report template
   w. Microsoft Advertising in-depth performance report
   x. Organic traffic & keywords template by OIKIO
   y. Paid channel mix reporting template
   z. Paid social performance dashboard template by Gauge
   aa. Post-click analysis template
   bb. SEM & SEO data comparison template by OIKIO
   cc. SEO content audit template
   dd. Website cohort analysis template
   ee. Website performance by country reporting template
   ff. Website performance by US state reporting template
   gg. Website traffic by device & source reporting template
   hh. Website traffic dashboard template
   ii. Website traffic heatmap template
   jj. Website traffic source bubble chart template
   kk. Year-on-year website performance reporting template
3. UI/UX
   -Legal stuff/User Agreement

## Our Approach to Risk and Analytics:

- Wiserfunding is built on 50+ years of pioneering academic research.  We blend traditional methods (Financial Statement analysis) with new techniques that result in 30% more accurate models than our competition
- We do not use behavioural data (behavioural biometrics, call histories, social scoring, etc) but we do incorporate bespoke data and use unstructured data in our models.



# 2/ Determine Risk: Credit Rating Models – An overview

## How Credit Rating Models operate

- A credit rating model assesses the financial strength of a company by analysing a series of financial variables and assigning an overall score (usually between 0 and 1000, or in alphabetic notation such as CCC- to AAA+);

- The selection of what financial variables are chosen to assess individual companies is typically determined using a logistic function on a sample of companies. The logistic function assesses how different combinations of different financial ratios fair when identifying whether or not a company will default. The function does so by assigning betas to each of the ratios and assessing combinations of ratios with combinations of weights.

- The probability of a company defaulting is therefore given bye a function of β values, corresponding to the weights to be applied to each financial input $x$:

$$PD = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots\ldots + \beta_N \cdot x_N)}}$$

- The company risk rating corresponds to the sum of the company financials weighted by the model parameters:

$$Company\ Risk\ Score = \sum \beta_1 \cdot x_1 + \beta_2 \cdot x_2{}^{(1)}$$

- A key measure of the accuracy of a logistic model is given by how the predicted probability *PD* compares to the real observed default frequency in the sample (ODF).

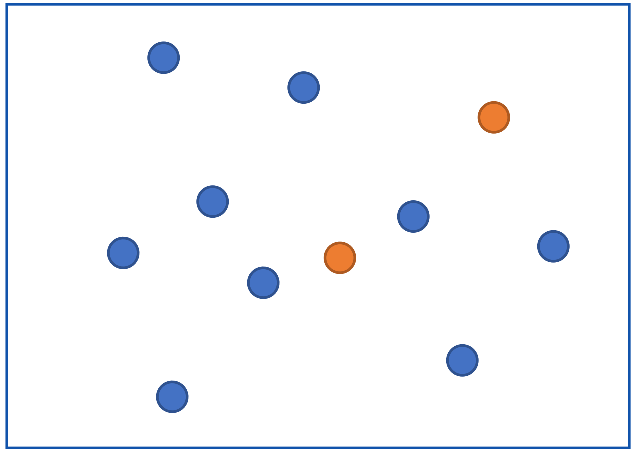


Fig. 1 - A representative view of a credit portfolio: If orange circles correspond to defaulted companies, by knowing their characteristics prior to default it should be possible to predict which companies default

In a credit rating model, financial ratios viewed or analysed in isolation do not provide sufficient insight to adequately rate companies, it is when these financial ratios are viewed as a group that companies can be rated.



(1) With β's having their signals inverted so that higher scores correspond to higher probabilities of default (see negative exponent in PD expression)

# 2/ Determine Risk: Financial Variables used by Wiserfunding Models

## Overview

- Please see below some of the financial variables leveraged by the Wiserfunding models in order to generate its proprietary risk metrics, as per Wiserfunding documentation – the weight list is of course proprietary and cannot be here replicated.

| Category | Variable | Reasoning |
|---|---|---|
| Leverage | **Equity (Book Value) / Total Assets** | Ratio between equity and total assets of a company, indicative of its capital structure. The lower the ratio, the higher the higher the proportion of liabilities against assets. **For long term contracts such as PPAs, this can be used as an indicator of company robustness.** |
| | Net Debt/EBTIDA | This metric will estimate how much of the debt which cannot be covered by cash and cash equivalents can be paid for with the current earnings. The higher the ratio, the lower the financial robustness of the company. |
| Liquidity | **Current Assets/Current Liabilities (current ratio)** | Short term liquidity can be key assessing the year on year risk of potential offtakers. Looking at the historic fluctuation of this ratio can provide insightful data into the capacity of the potential customer to deal with short-term economic downfalls. **Lower ratios indicate reduced liquidity, which when covering critical costs is significant for the company performance.** |
| Profitability | **Return on Equity (ROE)** | The ability of a prospective offtaker to manage invested capital effectively indicates a robust management and profitable business model. **A high ratio will indicate a robust profile and as such a lower risk of insolvency.** |
| | EBITDA/Total Assets | This metric measures the efficiency of a company in capitalising upon its assets. Higher ratios indicate a higher return on the companies assets and as such a more efficient use of these. |
| Coverage | EBITDA/Interest Expense | This metric displays a companies ability to repay the interest expense on outstanding debts. The lower the ratio, the higher the risk implied, given that the company will struggle to pay the interest rates on its loans. |
| Activity | Account Receivables/Liabilities | This metric estimates the ability of a company to pay its debts solely from future economic income expected to be received within the following 12 months. |

# 3/ Determine Risk: Credit Rating and PPAs

## Financial variables to look out for

- In addition to financial inputs already involved in Wiserfunding models, the following aspects can be considered for an analysis of the **offtaker's resilience:**

| Category | Variable | Explanation |
|---|---|---|
| Margin | EBITDA / Revenue | The EBITDA margin is a measure of a company's operating profit as a percentage of its revenue and is a performance metric that measures a company's profitability from operations and has been found to correlate with resilience.(2) **Lower ratios indicate reduced profitability, which when covering critical costs is significant for the company performance.** |
| Optionality | Retained earnings | Retained earnings (RE) is the amount of net income left over for the business after it has paid out dividends to its shareholders. Companies have been leaving less optionality today as a consequence of the ongoing pandemic, but resilient companies are able to maintain their values.**For long term contracts such as PPAs, this might be used as an indicator of company robustness.** |

## Non-financial variables to look out for

- Below are additional variables which have been identified by the Wiserfunding team as especially relevant within the context of PPAs – these are the result of the discussions which narrowed down the original list during engagements #1 and #3:

  1. **Existing Legal Events and payment remarks from electricity providers (qualitative):** These are the number of remarks against the off-taker made by other electricity providers. The larger the higher the probability of a default occurring.
  2. **Volatility in electricity consumption within the previous 3 years (quantitative):** These are the risks to which XYZ is exposed should the off-taker not consume enough electricity or demand to consume more.

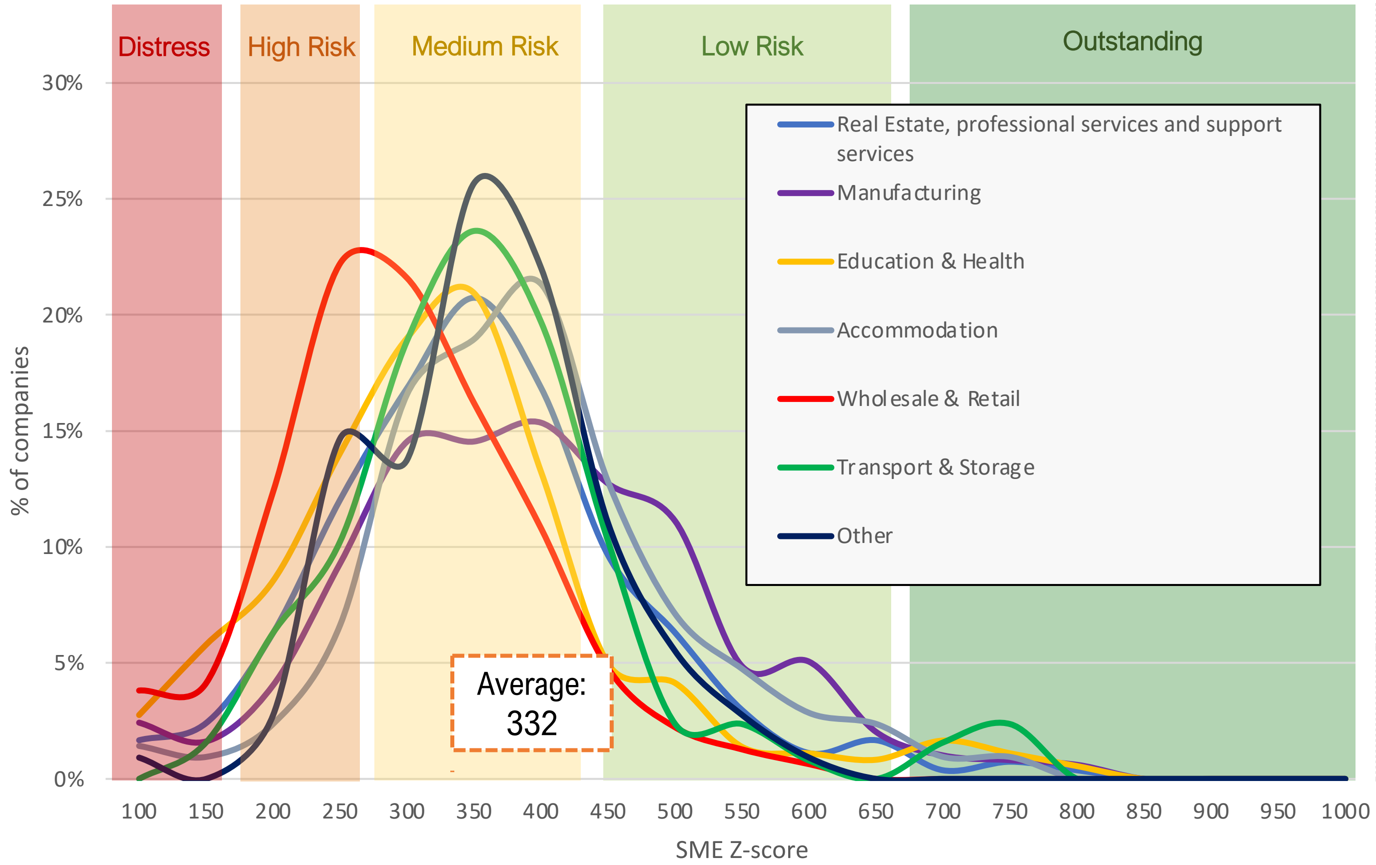


(2) Based on the work presented in "New risk challenges and enduring themes for the return", McKinsey on Risk 2021

# 2/ Determine Risk: SME Z-Score Distribution Across industries

## Overall considerations

- The table displayed presents Equifax's Score Check which, as suggested by XYZ, has been used to derive a traffic light system in order to assess the viability of applicants. **XYZ will only target companies with a score of D+ or higher.**
- The Wiserfunding team has estimated that a score of a D+ or higher corresponds to an SME Z-score of 250 or higher. However, an accurate mapping of the Equifax Score Check with Wiserfundings SME Z-score will be carried out in due course.




| Category | Traffic Light Categories | Category | Traffic Light Categories |
|---|---|---|---|
| A+,A,A- | Excellent | G | Serious Gazette code present |
| B+, B, B- | Very good | I | The company is technically insolvent |
| C+, C, C- | Above average | O | The company is late in filing its latest accounts at Companies House. |
| D+, D, D- | Average | NT | The company's accounts state that the company does not trade |
| E+, E, E- | Below Average/Poor | N | Companies House classifies the company's accounts as "dormant company accounts". |
| F+, F, F- | Very Poor | NA | The company has not yet filed accounts |

# 3/ Find Low Hanging Fruit: Minimum score for acceptance

## Defining a minimum score for credit worthiness

- As described, assuming the portion of new companies being given credit follows the target portfolio distribution the final expected loss is below the projected values by XYZ over the years. However, this does not correspond to a realistic or viable scenario, as contracts with deteriorating credit performance would increase the percentage of companies in higher risk levels. **The minimum acceptable risk score is that at which all predicted new companies could be accepted generating a loss lower than the projected admissible value.**
- This corresponds to assuming a full onboarding situation, where all predicted new customers are onboarded at once and share the same risk characteristics. **Results indicate that for the first operating year this corresponds to the risk threshold of a Z-Score of 250, usually associated with the beginning of the high risk region.**

| Average values as obtained from target portfolio | | | | | Expected loss assuming all new contracts fall in each risk band (full onboarding) | | | | |
|---|---|---|---|---|---|---|---|---|---|
| SME Z-score | Avg SME-Z score | PD | LGD | EL | Y.1 | Y.2 | Y.3 | Y.4 | Y.5 |
| 0-50 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 |
| 50-100 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 |
| 100-150 | 123 | 123 | 123 | 123 | 123 | [illegible] | 123 | 123 | 123 |
| 150-200 | 123 | 123 | 123 | 123 | 123 | [illegible] | 123 | 123 | 123 |
| **200-250** | 123 | 123 | 123 | 123 | 123 | [illegible] | 123 | 123 | 123 |
| 250-300 | 123 | 123 | 123 | 123 | 123 | [illegible] | 123 | 123 | 123 |
| 300-350 | 123 | 123 | 123 | 123 | [illegible] | [illegible] | 123 | 123 | 123 |
| 350-400 | 123 | 123 | 123 | 123 | [illegible] | [illegible] | 123 | 123 | 123 |
| 400-450 | 123 | 123 | 123 | 123 | [illegible] | 123 | 123 | 123 | 123 |
| 450-500 | 123 | 123 | 123 | [illegible] | [illegible] | 123 | 123 | 123 | 123 |
| 500-550 | 123 | 123 | 123 | [illegible] | [illegible] | 123 | 123 | 123 | 123 |
| 550-600 | 123 | 123 | 123 | [illegible] | 123 | 123 | 123 | 123 | 123 |
| 600-650 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 |
| 650-700 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 |
| 700-750 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 |
| 750-800 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 |
| >800 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 | 123 |
| Projected Values - Admissible Expected Losses [MM £] | | | | | 123 | 123 | 123 | 123 | 123 |

DATA ANONYMISED

# 1/ The Opportunity

## Napkin's Vision

- "We buy, build and optimize digital agencies to grow e-commerce brands and promote revenue sharing

## Executing the Vision: building SmartLend.AI

- Napkin is looking for a partner to help build SmartLend.AI: *Factoring Risk into Funding Opportunities.* The seven steps outlined in the SmartLend.AI document include:

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| 1 | Gather Data | High | See slides |
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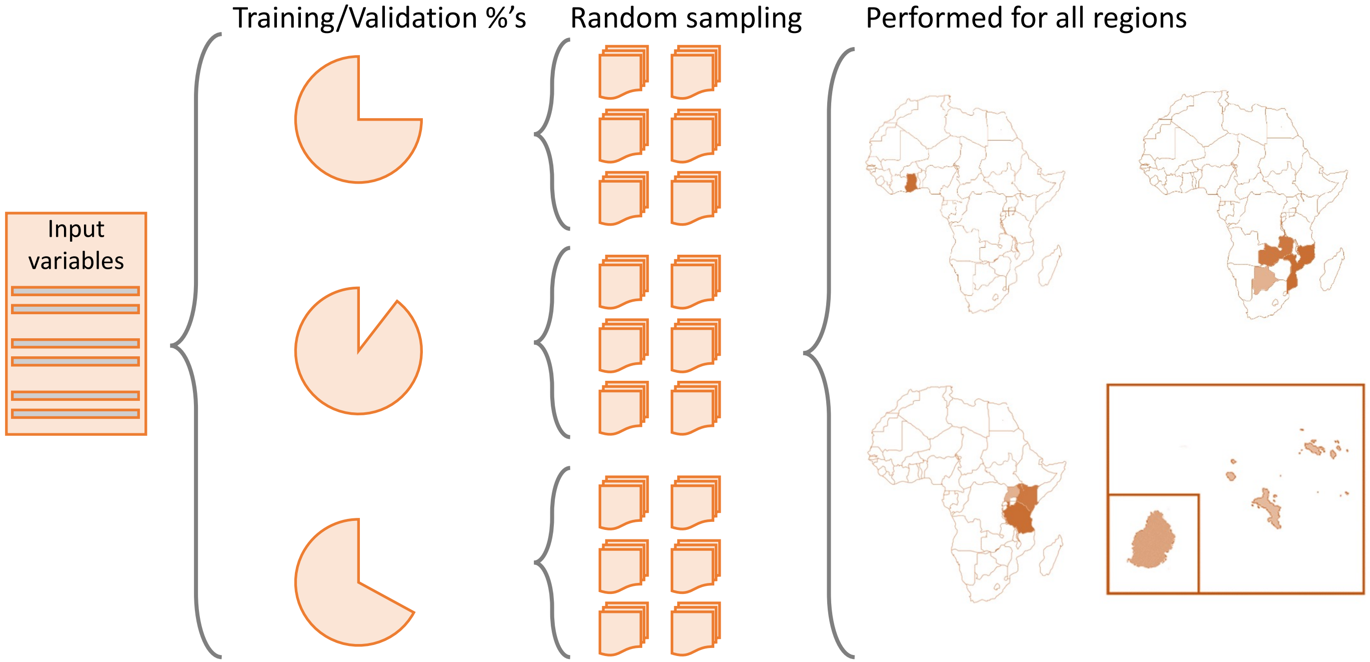
| 5 | Revenue Share | Low | For discussion |
| 6 | Automate for Scale via Built Platform | High | See slides |
| 7 | Data & Analytics Reporting to Firms, Funds, Banks etc | High | For discussion |
| + | Programme disciplines | Joint | See slides |
| + | Partnership Approach (design, workflow, wireframes, dev, build) | Joint | See slides |

# 6/ Automate for Scale via Built Platform: Precision and performance by region – Methodology (1/5)

## Model calibration: Dynamic Sampling

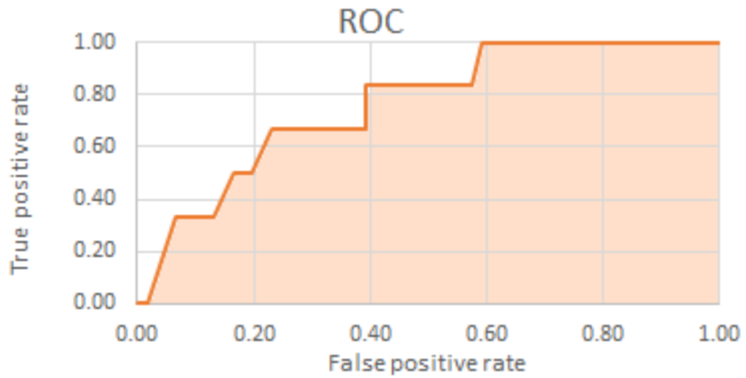
- The implemented calibration used a portion of the sampling as a training sample, on which the model was trained, and then a validation sample, over which the models were run and their precision evaluated.
- Typical splits for logistic models consider an 20%-80% split, for the models in analysis different sampling percentages were tested in order to find the best precision possible. Given the small sample sizes the validation sample always included the whole sample (100%).
- The variables currently in use were tested for different training sample percentages, with different random selection methods. For each of the four regions, the selected models were those for which the precision (AUC) was the highest.




## Model calibration: Testing

- All generated prototype models were evaluated for precision and goodness of fit using the following key factors:

1. **Hosmer-Lemeshow:** The test assesses whether or not the observed event rates match expected event rates in subgroups of the model population
2. **Pearson Chi Square:** Applied to sets of categorical data to evaluate how likely it is that any observed difference between the sets arose by chance. It tests a null hypothesis stating that the frequency distribution of certain events observed in a sample is consistent with a particular theoretical distribution.
3. **AUROC:** Area under the ROC Curve, measures how accurately the model distinguishes between defaulting and non-defaulting contracts. This score gives us a good idea of how well the classifier will perform. (see example below)



# 6/ Automate for Scale via Built Platform: Precision and performance by region – Western Region (2/5)

## Overall considerations

- For the western region (Ghana) approx. 60% of the defaults correspond to SME companies – this is in line with original ABSA expectations
- The observed default frequency for SME companies is indeed higher, meaning this trend is not consequence of the number of companies in each segment.
- The obtained precision of approx. 0.88 corresponds to the maximum observed result.

| AUROC | Hosmer - Lemeshow | Pearson Chi Sq |
|---|---|---|
| 123 | 123 | 123 |

| Country | # companies | % companies | # defaults | % defaults | ODF* | Average PD |
|---|---|---|---|---|---|---|
| Ghana | 123 | 123 | 123 | 123 | 123 | [illegible] |
| Overall | 123 | 123 | 123 | 123 | [illegible] | [illegible] |

DATA ANONYMISED

| Segment | # companies | % companies | # defaults | [illegible] | [illegible] | Average PD |
|---|---|---|---|---|---|---|
| BB | 123 | 123 | 123 | [illegible] | 123 | 123 |
| CIB | 123 | 123 | 123 | 123 | 123 | 123 |
| SME | 123 | 123 | 123 | 123 | 123 | 123 |
| Overall | 123 | 123 | 123 | 123 | 123 | 123 |

(*) Observed Default Frequency

# + Programme Disciplines: Project Overview

## PROJECT BACKGROUND

In addition to the ongoing stress-testing and portfolio monitoring, Wiserfunding also worked with SBI to build bank-specific exclusive SME Credit risk models using SBI company data. These models were developed to be entirely representative of the bank's portfolio

## PROJECT FRAMEWORK (HIGH-LEVEL)

- **Phase 1:** Evaluating SBI's existing framework and data. We tested Wiserfunding's generic models with SBI company data to develop statistically significant benchmarks.

- **Phase 2:** Developed customized SME Credit risk models for SBI segmented by industry

- **Phase 3**: Validated, tested and compared the performance of the customize models with Wiserfunding's existing models using the previously generated benchmarks to ensure that prediction accuracy was at par or higher than generic models

- **Phase 4**: Re-calibrate, test and improve models as part of quarterly maintenance

## ANNUAL STRESS-TESTING OF THE PORTFOLIO

Wiserfunding has been working with SBI since March 2020 to stress-test the entire portfolio (bottom-up) by applying industry-wide stresses to every company, the results of which are shared in the board meeting and appreciated by the Chairman of the bank

# + Programme Disciplines: Tentative calendar

## Timeline

| Phase | Description | Start Date | End Date | SX Estimated Time | Status |
|---|---|---|---|---|---|
| Phase 1 | Understand the Power Purchase Obligation:<br>a) Purpose<br>b) Amounts<br>c) General Terms & Conditions<br>d) Discussion with Client | 1/06/2023 | 3/06/2023 | 2 day | Planned |
| Phase 2 | Identify the necessary parameters which a potential lender should consider from the aspects identified | 4/06/2023 | 06/06/2023 | 2 day | Planned |
| Phase 3 | i Discuss with XYZ the comparison between the current parameters considered by underwriters and the ones recommended by WF in previous stage<br>ii Produce qualitative description of the underlying rationale behind the chosen parameters used to assess potential customers | 07/06/2023 | i. 11/06/2023 (discussion)<br>ii. 21/07/2023 (delivery deadline) | 14 day | Planned |
| Phase 4 | i Develop a scorecard based on the findings and outcomes of phases 2 & 3 which can map each prospective company rating to an expert PD.<br>ii Convert phase 3 into a quantifiable measure of the company's risk | Continued Discussion | | | |

# + Programme Disciplines: Introduction

## Plan and Objectives

- The exercise consisted in applying the general Wiserfunding Z-Score model over the portfolio of existing companies with relevant data (5230), in order to carry out a benchmark of the Z-Score distribution across XYZ's portfolio. This will enable to determine the risk profile and plan out the requirements for the calibration of the ABSA specific models.

| Project Phases | Overall Description | Status |
|---|---|---|
| 0 Data Collection | • Definition of target sample<br>• Data Quality Analysis<br>• Data Remediation<br>• Data signoff | ✔ |
| 1 Calculation of benchmark scores with general SME model | • Application of Wiserfunding Z-Score model to the overall portfolio<br>• Analysis of risk profile by region and country | ✔ |
| 2 Review of XYZ's ratings/rating scale | • Comparative analysis between default distribution and Z-Score by region and country<br>• Comparative analysis between ABSA scores/risk bands and Z-Score by region and country | In progress* |
| 3 Analysis of Qualitative Data | • Identification of relevant qualitative factors to consider in the model recalibration | In progress |
| 4 Model recalibration per region | • Recalibration of the Z-Score model considering the ABSA portfolio<br>• Validation | In progress |

* - Requires ABSA scores for comparison against Wiserfunding benchmark and completion.

# + Partnership Approach: Overview

Project Plan Snapshot

| Sub-phases | Description/Approach | Core Deliverables | Timeline | Status |
|---|---|---|---|---|
| 0 Project set-up | • Agree on project plan<br>• Set up questions / requests log<br>• Set up workshops / meetings | N/A | Week 1 | |
| 1 Define use-cases | Design risk assessment journey which caters for different customer-types. | Risk assessment journey map | Week 1-2 | |
| 2 Development of judgemental / expert scorecard | • Determine risk factors & weightings<br>• Scorecard validation | Expert scorecard | Week 2-4 | |
| 3 PD Methodology & Calculation | Determine PD methodology and calculation | PD methodology | Week 4-5 | |
| 4 LGD Methodology & Calculation | Determine secured LGD methodology and calculation | LGD methodology | Week 6-8 | |

Complete

In Progress

Not Started

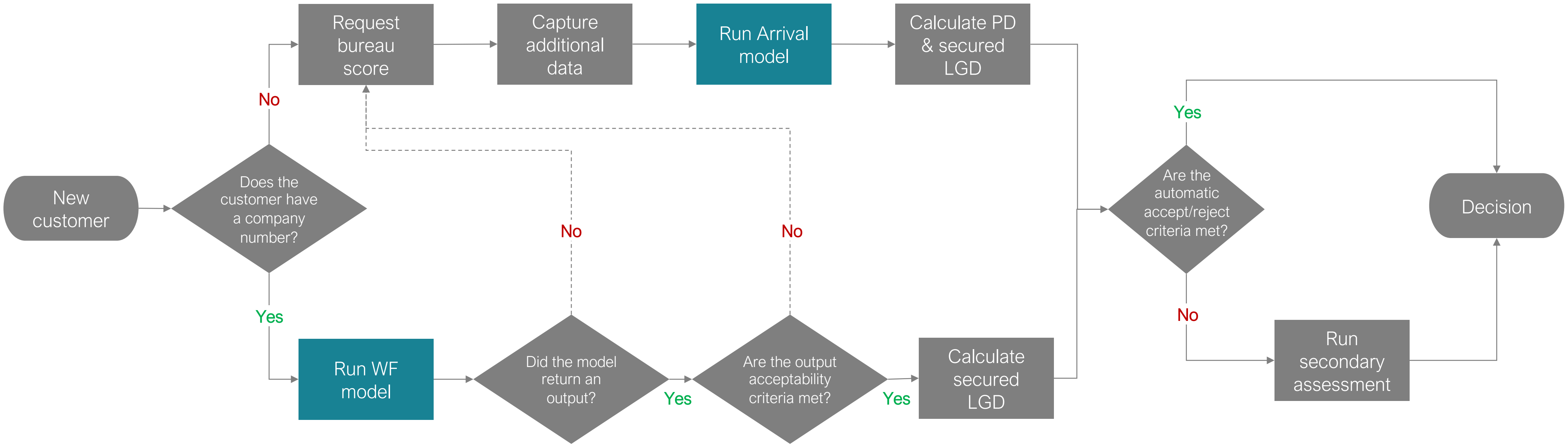
Notes:

- This document represents the deliverable for the first sub-phase of this project.
- A draft of this document was presented in the 'Use-Cases Workshop'
- Business rules for certain aspects of the process are yet to be fully defined.

Assumptions:

- It was agreed that segmentation of process flows by customer-type (new or existing) and by country, is appropriate.
- Furthermore, it was also agreed that no segmentation is required by product-type.

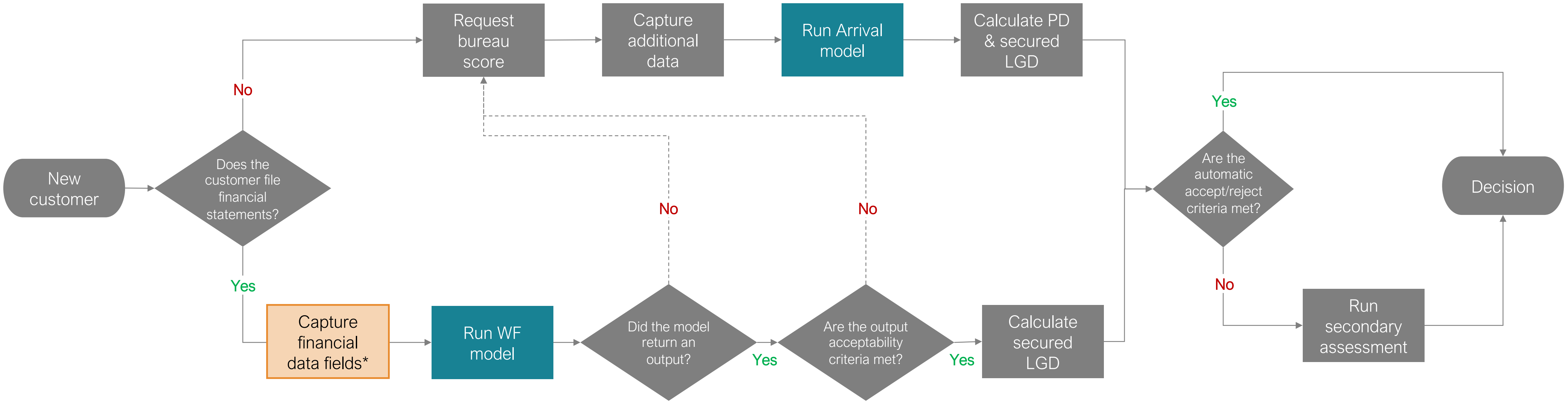
# + Partnership Approach: Use-cases ("New Customer; Europe")




Process

Models

# + Partnership Approach: Use-cases (“New Customer; Outside of Europe”)

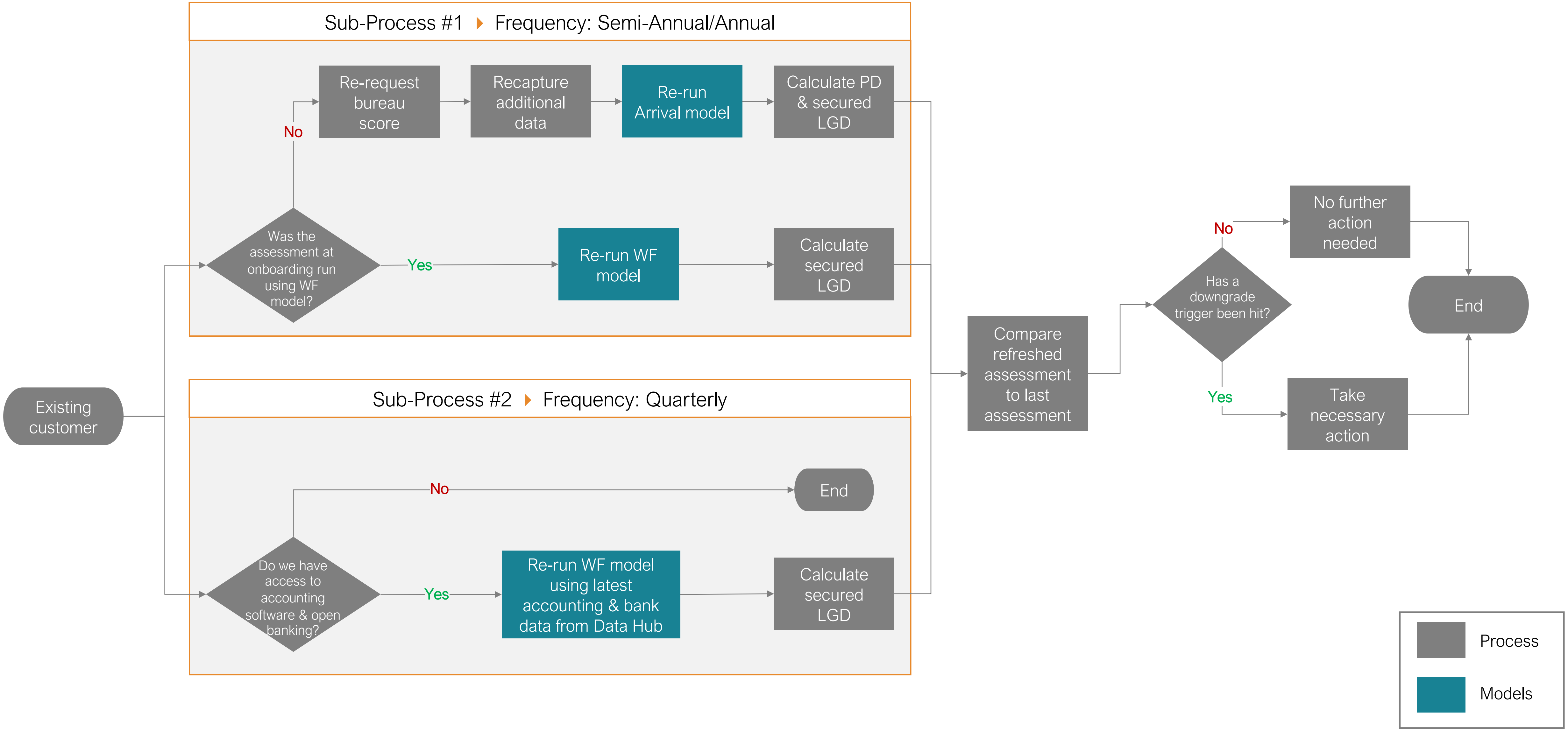



*Note: The only difference to the previous slide is that financial data would need to be fed into the WF model for non-European customers.

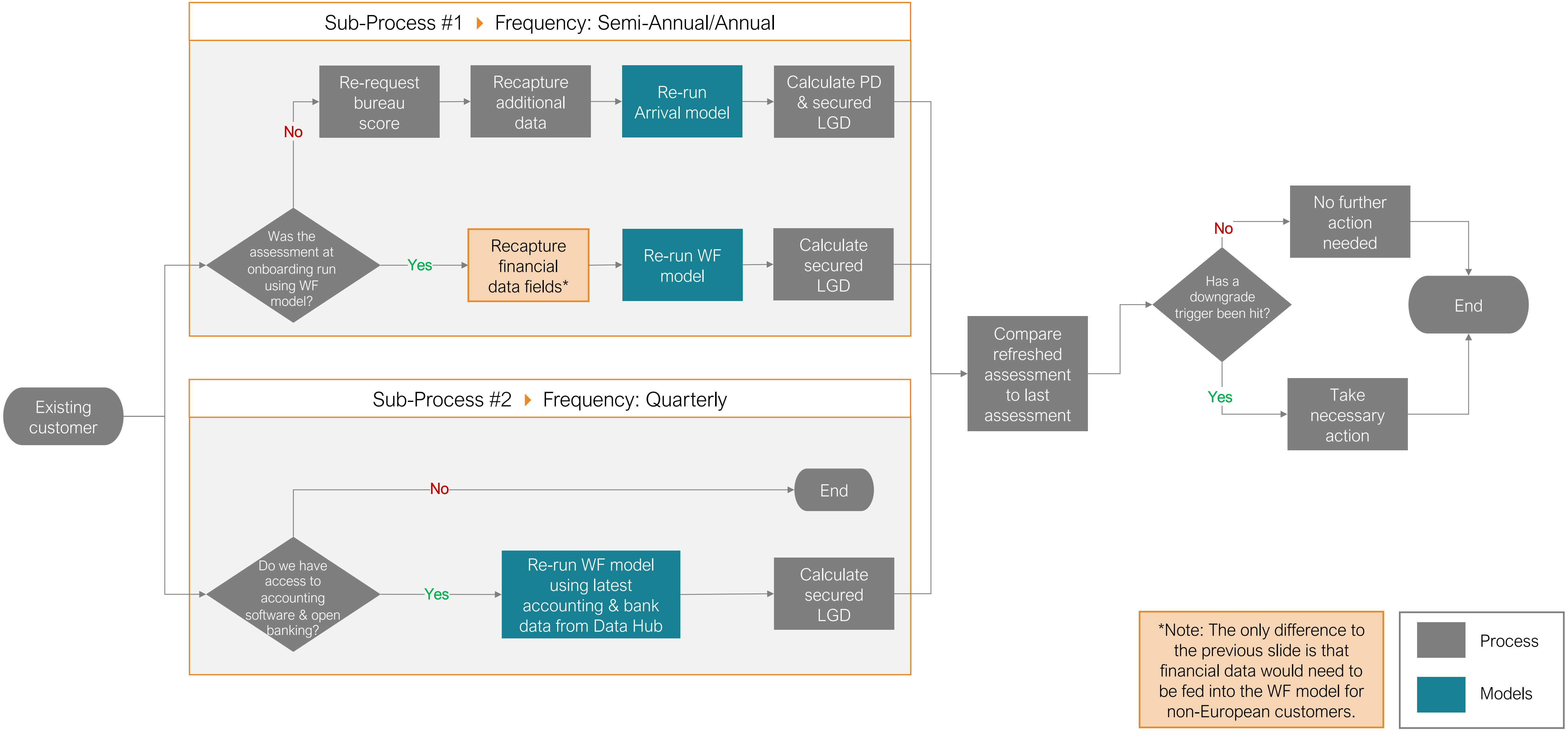
Process

Models

# + Partnership Approach: Use-cases ("Existing Customer; Europe")



# Partnership Approach: Use-cases ("Existing Customer; Outside of Europe")



# Next Steps

3

# Deep Risk Expertise Applied to Emerging Spaces

## New Bank License Application

*Built and stressed a virtual portfolio to support banking license application*

- Designed virtual portfolio reflecting the Bank's target market, sourced market data
- Assessed portfolio risk profile on multiple dimensions using Wiserfunding models
- Stressed the virtual portfolio following PRA specifications, rooting the exercise in macro-economic forecasts.
- Integrated results in 1st year ICAAP, as required for license application. Resulted in positive PRA response.

## Bespoke Risk Analysis for Alternative Lenders

*Embedded credit risk analytics into business models across multiple asset classes*

- Reviewed credit and investment decision criteria, evaluated origination process
- Identified leverage points where risk analytics could improve quality and speed of origination
- Integrated risk analytics in origination process through bespoke risk assessment including layering in unique data points
- Credit and Investment decisions and process improved by embedding risk analytics

## Holistic Risk Models for Renewable Energy

*Measured risk in renewable energy power purchase agreements, including qualitative and quantitative variables*

- Analysed energy consumption and volatility over a 3-year period
- Incorporated prospect and client payment data as unique risk factors.
- Integrated qualitative data (eg. property ownership, subsidiary status) with quantitative variables
- Integrated PPA variables with Wiserfunding's Z-Score for a bespoke and holistic asset evaluation.