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Climate Change: Approach to quantify Climate Change Risk

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ABSTRACT: Climate change is no longer a distant threat but already has a definitive impact on the way we lead life. While the physical risk from climate change is omnipresent and being actioned on at macro level, it is the transition risk from climate change that this paper focuses on. The paper is targeted at the business and risk units of financial institutions who are responsible for lending out debt capital to customers from industries evolving or surviving in face of climate change risk- to assist them to make informed credit decisions to build a sustainable future.This paper uses industry level survival and adaptation data to quantify the time to failure of customers in face of climate change risk indicating that institutions need to wrap up capital from risky industries and invest in adaptive industries. Details on industry specific investment strategies in light of the climate change risk are provided together with emerging empirical examples to show the importance of tapping the new financial risk types as well as potential growth areas.

Keywords: Climate Change Risk, Portfolio Management, Investment Decisions, Survival Analysis, Time Series Forecasting, Probability of Failure

I. INTRODUCTION

Credit risk assessment has been an evolving area ever since its inception. There was a time when credit bureaus were the only source of customer credit information used for credit risk assessment. However, in the last ten years credit managers had to strengthen the information source by combining data from multiple sources, including non-conventional sources of data like airtime usage, mobile money usage, geolocation, bills payment history and social media usage for better credit decisions. Supplementing the conventional sources is the need of the hour to stay relevant as customer behavior is always changing overtime which drives new risk typologies. Now, commercial lending has also seen similar evaluation if not more. In the past, commercial lending was mainly driven by relationship managers/ experts' opinion. However, over the period of last 10-12 years, risk scorecards have secured its own place which are primarily built on consumer financials, expert assessment scores, utility bill payment status, adaptability to upcoming industry wide changes et cetera. These evaluations of credit risk drivers have been a combination of proactive and reactive approach due to crisis, regulation and more importantly change in customer behavior and accompanying emerging risk typologies. Moreover, credit risk should be viewed as function of almost all other risk types. Hence, it is imperative for portfolio managers to pre-empt the emerging risk typologies and plan the lending strategy accordingly.

Climate risk will have direct and indirect impact to almost every aspect of business; credit lending being one of the main areas in immediate need to integrate the climate related factors. Paris Agreement and the subsequent commitments (like in COP26) made on climate risk should definitely have a direct impact on the short and long term lending strategies of banks as they re-scheme in the quest to not only play its part as a social responsibility but also to minimize bad loans and make profitable investments. As every risk comes with new opportunity, it is also of paramount importance for portfolio managers to tap the new commercial opportunity where customers in a traditional industry are in dire need of financial support for changing fundamental business functions in order to be compliant with environmentally friendly policies.

At the COP26 summit [1], United States of America, Canada another 18 nations committed to stop financing for fossil fuel abroad by end of 2022 and instead steer their spending to clean energy. The President of United States in his concluding remarks at the summit asserted that US greenhouse gas emissions will be cut by well over a "gigaton" by 2030. More than 40 world leaders agreed that they will work together to turbo charge the uptake of clean technologies by imposing worldwide standards and policies. Other directives called for forming a working group to accelerate the development of "technologies that can capture, remove and store carbon dioxide as well as heating and cooling products that don't rely on highly potent greenhouse gases." Combating climate change was seen earlier as more of a CSR activity and "good to have" step for institution before PG&E corporation filed for Chapter-11 due to insolvency in face of climate change. It has been one of the first bankruptcies in history tied to climate change. Hence, taking care of climate/supporting green initiative is no more of a choice but a mandate. This in turn will drive lending strategy for financial institutions both in long and short term.

In this paper we have attempted to analyze the trends in various industries towards greener initiatives which will aid the banks to make timely, well-informed and better decisions for lending to any undertaking and accordingly structure investments which not only will help the firms adapt but also be a source of future profit for the bank.

Standing today, the incorporation of climate related factors in risk assessment is primarily focused towards scenario analysis/stress testing or at best adding a subjective questionnaire on the sustainability quotient of a firm. We have explored a different angle whereby the fund managers have an additional resource of "time to perish" of a traditional industry (and thus succumbing to ecologically sustainable alternatives) to rely on to evaluate the prospective firm under the lens of climate risk and make necessary restructuring in the current lending as relevant. Thus, estimation of "time to perish" will not only help estimate the risk characteristics of the customer, but also at the same time can be a useful information for tapping a new horizon of lending avenues - the lending requirement which supports green initiative to become compliant with environment friendly policies.

A thorough article review revealed that a number of research have been undertaken in this field, in particular, speaking about potential disruption, financial implications and business adoptions due to climate change. They speak about associated physical hazards and socioeconomic impacts and establish the fact that climate risk is recognised as a financial risk and credit manager cannot ignore this risk type. An Oliver Wyman paper [2] "Climate change: Managing a new financial risk" stresses that with the growing recognition of business implications of climate change, external pressures in upcoming regulations, integrating climate risk into financial considerations and not just reputationally has become a pressing priority for banking institutions. Other notable articles by KPMG [3] and IMF [4]too emphasize on establishing economic and financial impacts of climate concerns and banks to action on it. Bloomberg [5] and Wall Street Journal [6] articles echo the same while reporting the PG&E bankruptcy case and apprehends that it would not be the last climate change related corporate casualty unless we act fast.

While these first set of papers concludes climate risk to have financial implications, another host of them concentrates purely on credit risk. An EDHEC- risk institute working paper on "Climate Change and Credit Risk" [7] establishes that the distance to default, is negatively associated with the amount of a firms carbon emissions and carbon intensity. Few articles like the McKinsey's on "Banking Imperatives for Managing Climate Risk" [8] and recognises the need to incorporate climate risk into its counterparty ratings and lays down the high-level steps by which a risk score can be defined like scenario analysis or the likely explanatory variables that can be explored. GARP Risk Institute's paper on "Climate Risk Management at Financial Firms" [9] summarises the results of a global survey on the actions banking institutions are currently adopting and opines that though there has been a good start there is a long way to go.

Further, Oguntuase[10] touches upon all the three dimensions of credit risk- a borrower's capacity to generate enough income to service and repay it debt as well as the capital and collateral that back the loan. It speaks of re-calibrating the risk weight factor for all categories of assets to identify the differential due to climate-related risks. The paper proposes to achieve it by recognising borrowers exposed to climate risk or utilising any climate risk related ratings but lacks in defining a clear methodology to quantify the same.
The below table summarises the themes of the paper we discussed so far:

Table 1.Literature review

Climate Risk Paper/Articles references/links	Identifies climate risk as a financial risk and discusses about the business impacts	Advocates to take actions and step towards the greener initiatives	Explicit quantification
Oliver Wyman Paper [2]	Yes	Yes	-
KPMG Article [3]	Yes	Yes	-
IMF Article [4]	Yes	Yes	-
Bloomberg Article [5]	Yes	Yes	-
Wall Street Journal Article [6]	Yes	Yes	-
EDHEC-Risk Institute Working Paper [7]	Yes	-	-
McKinsey [8]	Yes	Yes	-
GARP Risk Institute [9]	Yes	Yes	-
Oguntuase[10]	Yes	-	-

As noted in the table above, all the papers have detailed climate risk impact and advocated towards taking action but none of the papers have explicitly mentioned on the methodology to quantify the growth or decay of a particular industry such that a credit manager can plan the future investments accordingly which is becoming increasingly crucial day by day.

Given the times we are in, with climate related crisis looming and threatening the banking landscape, it is necessary to design an estimation approach that can effectively estimate the growth/ decay of a particular industry. This paper attempts to analytically formulate a structure to not only quantify an industry's distance to default but also connect it to assign a climate risk score for credit/lending decisions. This in turn would enable banks to identify potential investment opportunities and in addition to making financially successful ventures, aid the transition to green.

II. MATERIALS AND METHODS

1.1 Theoretical Framework and Design of Analysis

The synopsis of the paper lies in quantifying the climate change risk with statistical modelling tools whereby we arrive at the time to failure of an industry by looking at the sales/production statistics of the leading players in that industry. This is done through a Survival Analysis framework construction and also time series forecasting.

The paper focuses on two major industries- Automobile and Electrical Energy generation which are facing the most direct effect of Climate Change and has been the two most highlighted sectors in the COP26 summit. However, the analysis can be extended to other industries with the availability of required data and business requirement. The key steps followed are below:

1. Data collection: At the onset, we primarily collect data that showcase the declining trend of traditional industries in these sectors, e.g., decline in percentage sales of Internal Combustion Engine (ICE) cars among all cars sold due to the rise in eco-friendly electric vehicles.
2. Defining failure event: As we look at the trend of relative declining sales of ICE vehicles or the decline in the relative production of electricity using non-renewable sources like coal and crude oil, we define a failure event to happen when their relative productions/sales of the non-green product go below a certain threshold.
3. Determining the failure probabilities: Basis the failure event, we fit a survival curve to the failure time to obtain the failure probabilities at each time point.
4. Forecasting the future relative sale/production: With the failure probabilities for each industry on one side, we next focus on forecasting the future relative sale/production of the non-green industries. A high relative increase in the green industrial production would mean an ultimate downtime of the non-green industry in the face of climate change. Use of Holt-Winter's exponential smoothing approach is made to

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forecast the relative produce/sale of green industries compared to non-green industries.

5. Establish downtime of the non-green industry: By comparing the increasing probability of failure (with respect to time) with the forecasted values of relative growth in green industries, we can zero down on a time horizon which will establish the ultimate downtime of the non-green industry.
6. Validation: We further validate our data and statistical analysis driven claim with opinion on the same industries from leading consultancy firms and experts [11].

This paper provides a quantification of the impending climate change risk and will prove to be a handy guidance to portfolio managers, credit approvals and risk managers in making wise investment decisions, i.e., by not only basing the decisions on the idiosyncratic factors of the obligors alone but by also looking at the climate change risk faced by the lending transaction and hence its chances of survival in the lifetime of the credit obligation. As an example, lending a large advance to a diesel vehicle engine manufacturing entity due to be repaid in the next 5-7 years might not be the most informed/rational decision. However, a similar lending to an electric car battery manufacturer which currently may not be of the same stature as the diesel engine manufacturing firm might turn out to be a better decision for future. On the contrary, if the same diesel vehicle engine manufacturing has proven creditworthiness and is looking for funds in order to change the business process to become climate friendly, it is a potential customer for sustainable financing.

With the theoretical framework thus defined, we move onto the data analysis stage where we further discuss the details of the analytical framework and granularly explain the quantification of the climate change risk.

It is worth noting here that due to limitations on open-source data, we could not extend the empirical study to a multivariate structure with additional exogenous variables predicting climate change score. The section: Further Enhancement of The Framework speaks of ways the structure can be extended with the availability of more data.

1.2 Data Collection

Given the current market dynamics, the two of the most booming industries where we are seeing the shift towards green, sustainable alternatives gradually kicking in are automobile and energy. We have also attempted to target these two sectors, as a starting point, wherein by studying the past 10 years trend, we forecast the magnitude of paradigm shift in the coming years and estimate a time of death for the polluting sector to perish to the greener alternatives.

For the automobile industry, United States of America has been chosen as the country for the analysis due to easy availability of open-source data coupled with it being a leading manufacturing hub of automobiles. The top 20 car manufacturers are picked and we have collated their total vehicle sales [12] from 2011 to 2019. Corresponding to each of them, sales of Plug-In-Electric vehicles (PEV) are obtained from US department of Energy [13].The data for PEV is collected for leading car brands and we have consolidated them by car manufacturers to obtain a total sample of 13 companies. Finally, the ratio of sales of electric vehicles to total sales (consists of electric and traditional internal combustion engine (ICE) vehicles) is considered which forms the basis of the survival analysis and the time series forecasting thereafter.

The next industry segment in spotlight is the energy sector. Numerous studies have pointed energy sector to be one of the biggest contributors of greenhouse gases and economies are constantly pursuing and exploring to tap the immense potential of renewable alternatives. Country wise data on electricity production from renewable sources of energy as percentage of total electricity production (combining both from renewable and non-renewable sources of energy) spanning years 2000 to 2015 from the World Bank data archives [14] has been used for this purpose. Energy consumption is closely related to a country's GDP and we have focused our study to those countries that are among the top 25 nations with the highest per capita GDP in 2019 [15]. With this criterion, good quality data (in terms of non-missing cases) could be obtained for 18 nations. The percentage of renewable energy consumption from 2000 to 2015 has been directly used for further analysis. Refer to the Appendix A for detailed tables of automobile and energy sector.

1.3 Survival Analysis Framework

The crux of a survival analysis framework lies in fitting a suitable survival curve to the failure event marked data. The first step is to define the failure points in the data and then define the "time to failure".

For the automobile data we have the percentage of sales of electric vehicles relative to the total sales of automobiles. We consider 5% sales of electric vehicle relative to the total sales as the cut-off point to define a failure in the traditional fossil fuel vehicle industry. As the data is limited to only 10 years, hence a stricter cut off could not be defined.

Further, 5% is more of an early warning sign of the potential growth of the electric vehicle industry at the expense of decline of the traditional vehicle industry. Lastly the choice of 5% is driven by the fact that all of these entities had absolutely 0% sale of electric vehicles at the start of the time series in 2010. Growth to 5% is a significant point to consider the changing pattern of the market. However, survival probabilities can be explored by iterating the 5% cut off. In our data for automobiles, we wait for the 5% trigger and if not observed until 2019, we consider the data right censored at 2019. Thus, we obtain a right censored data set denoting the time-to-failure of automobile companies, the right censor point being at:

$t = 9$, where year 2010 is marked $t = 0$

For the data on the percentage of electricity production from renewable sources to the total energy production, we observe that different countries are at different stages of implementing the change to electricity generation from renewable sources. However, countries touching 30% on the ratio of electricity from renewable resources to non-renewable resources have steadily increased the proportion thereafter. Thus, we define a failure for the non-renewable energy industry when the ratio touches 30%. We have data between 2000 to 2015 and hence the data is right censored at $t = 15$, where year 2000 is marked $t = 0$. As mentioned earlier, institution can vary this cut-off basis their risk appetite and define failure accordingly. Here the ratio more than 30% means that the survival curve will have a very small gradient indicating a very late change in the energy industry, which practically might not be the case as per experts of this field.

The second step of the survival analysis is to determine a suitable survival curve. As per leading articles in Climate Change Risk, the risk to failure of non-green industries will gradually increase with time. This in terms of survival analysis indicates a dying process where the probability of failure increases with time, i.e., the hazard rate (instantaneous probability of failure) increases with time. In such scenarios the Weibull distribution is a good and most general approximation of the failure probability. The probability density function of the Weibull distribution is given by:

$$f(x, \lambda, k) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}$$

For $x \geq 0$ and $k > 0$ is the shape parameter and $\lambda > 0$ is the scale parameter.

1.4 Time Series Forecasting Framework

While the Survival Analysis framework forms the base of failure probability estimation and interpretation into 'time to perish', given the low volume of data on which the survival probabilities has been built, an independent Time Series estimation is used for both industries to forecast future sales decline / decline in consumption and ratify the results against the outcome of the survival analysis framework.

Plots of sales percentage of ICE automobiles and percentage consumption of green electricity from individual companies or countries (in Section 3.2) indicate that an additive model can be used to forecast the values as the random fluctuations do not seem to increase the level of time series. Holt-Winters are an appropriate approach in this case which uses an exponential smoothing technique to make short term forecasts. For that, we use exponential smoothing method which forecasts on a weighted average of past observations, with more weight being put on more recent observations. It accounts for trend and seasonality as well and estimates the level slope of trend and seasonal component at a particular time point. The model equations are as follows:

$$\hat{y}_{t+h|t} = l_t + hb_t + s_{t+h-m(k+1)} \quad (1)$$
$$l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \quad (2)$$
$$b_t = \beta * (l_t - l_{t-1}) + (1-\beta)b_{t-1} \quad (3)$$
$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \quad (4)$$

Where y_t is the corresponding time series value at time t, l_t is the level equation with smoothing parameter α. b_t refers to the trend of the series with β as the slope parameter. Lastly there is a seasonal variation incorporated by s_t in additive form where m is the frequency of number of periods in a year. hthe number of steps ahead forecast we want to estimate. Further, to smooth out the large variations in the series and linearize it logarithmic transformation is taken before forecasting. Holt-Winters function in the R package "Forecast" is used to generate the estimates.

III. RESULTS

1.5 Results from the Survival Analysis and its interpretation

The Weibull Distribution is used to model failure times and is selected for the survival analysis due to the flexibility to simulate Normal or an Exponential distribution based on the parameters. Weibull Distribution is interpreted in terms of its scale and shape parameters. A shape parameter value > 1 indicates that the hazard rate increases with time which is the expectation from the data. Use of SAS version 7.1 procedure PROC RELIABILITY is used to fit the right censor data of "time-to-failure".

The following are the parameter estimates obtained for the two industries in focus:

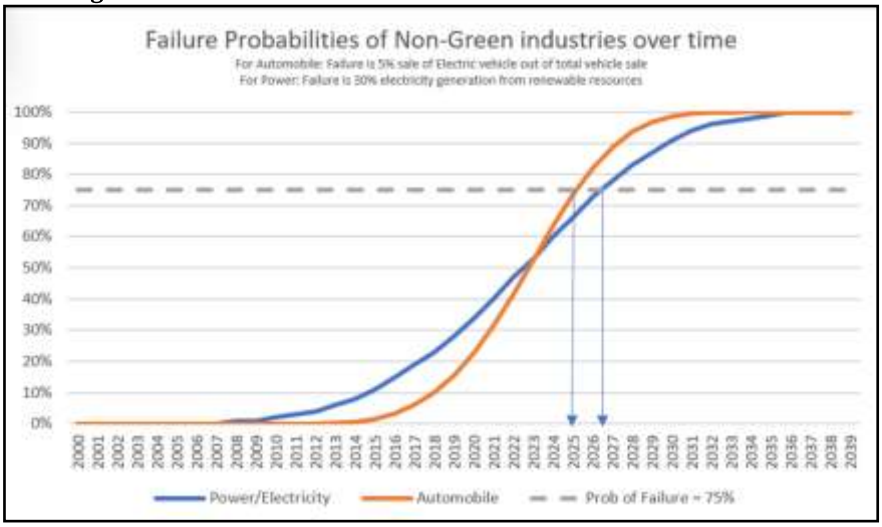
Table 2.Weibull parameter estimates for the two industries

Industry	Weibull Shape	Weibull Scale
Automobile	4.02	13.99
Electricity/Power	4.34	24.5

As expected from climate risk change literature, the shape parameter of both the Weibull distributions is greater than one, indicating that the probability of failure increases with time.

The curves of failure probabilities overtime are represented in the graph below:

Figure 1: Failure Probabilities of Non-Green Industries over time



As can be seen from the figure above, the shape of the probability of failure curves are quite similar for both industries. However, the time to failure is quite different and this makes us believe the industry of the institution's client will play a major role to determine its survival in the face of climate change.

The non-green automobile industry is projected to fall by at least 5% around 2025 whereas the power industry based on non-renewable sources will reach a 70% downfall by 2027. The fact that the curve for the electricity generation is flatter is also logical as electricity generation from renewable sources only might not be sufficient for the exploding population and hence some reliance on non-renewable sources of energy will remain. However, the same is not valid for automobiles as electric vehicles are turning out to be exact replacement of diesel/petrol vehicles and as a result will enforce the complete downfall of the traditional non-green vehicles in the near future.

While the data time series is limited in this paper, it needs to be kept in mind that collection of green versus non-green data has only started very recently (late 2000s) as collecting such data was not in priority for all countries/ companies for the majority of the 21st century. Hence, for any analysis the data will remain limited and data driven inference needs to be complemented with expert views on the topic to accurately predict the future outcomes and be best prepared to face the consequences. Now that the failure probabilities have been estimated, we focus on the second part of this statistical analysis based on time series forecasting using the same data. The output of the time series forecast will be interpreted together with the failure probabilities to finally arrive at the tentative timeline when these industries will fail (cross the threshold).

1.6 Results from The Time-Series Forecasting framework

Given the comparatively small sample of our data, to validate the findings of the survival analysis, an independent time series forecasting is carried out

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and coherence of the two results is checked. The plots of percentage sales for the two sectors for the 10 years period we have gathered are provided below:

Figure 2: Percentage sales of electric vehicles in US

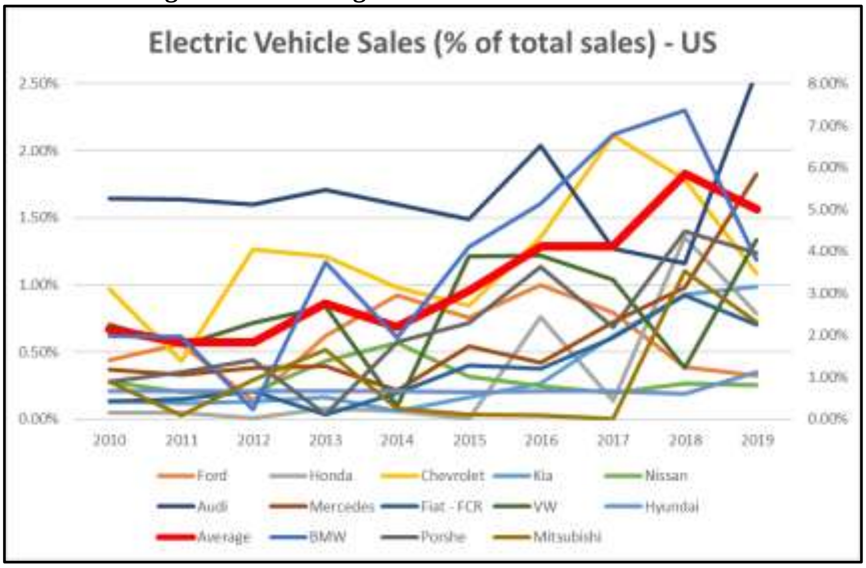
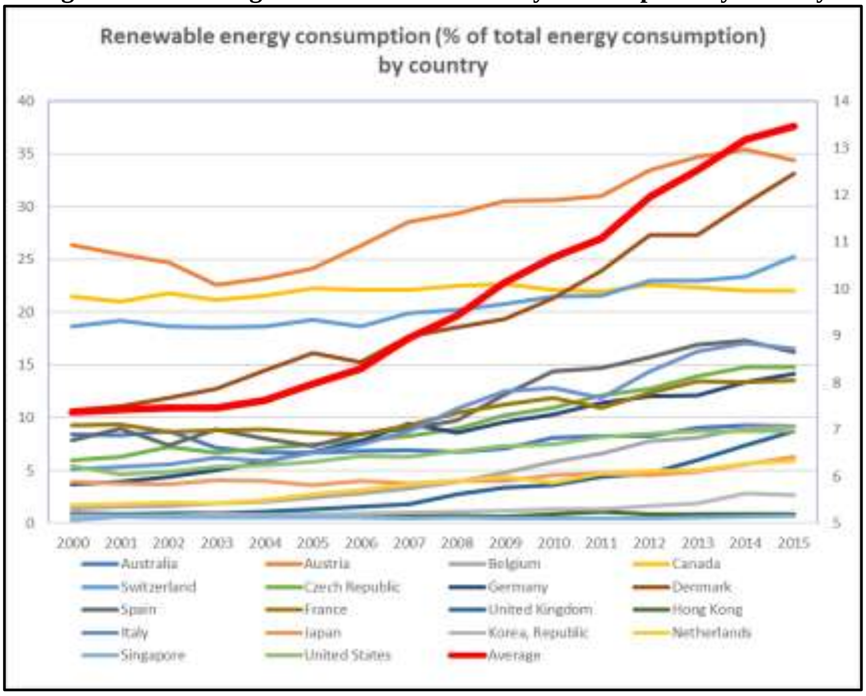


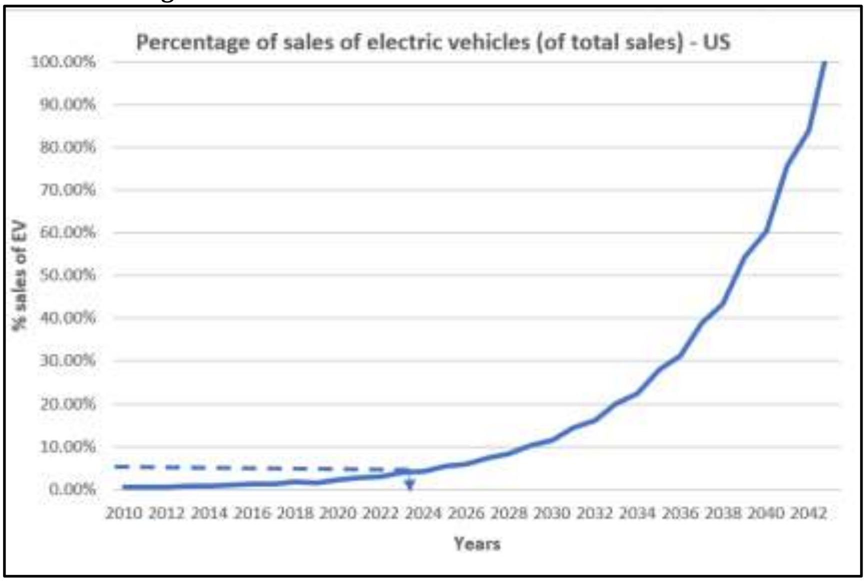
Figure 2: Percentage of renewable electricity consumption by country



3.2.1. Time Series Results for Automobile

The data consisted of percentage of electric car sales for 13 manufacturers from 2010 to 2019. To iron out minor missing values in the data a forward looking 3 year moving average is used. As explained earlier, we have focused on US for the assessment on automobiles. The consolidated sales percentage for US is obtained by averaging the numbers across all manufacturing companies. We have forecasted the sales percentage for the next 30 years.

Figure 4: Forecasted share of electric vehicles in US

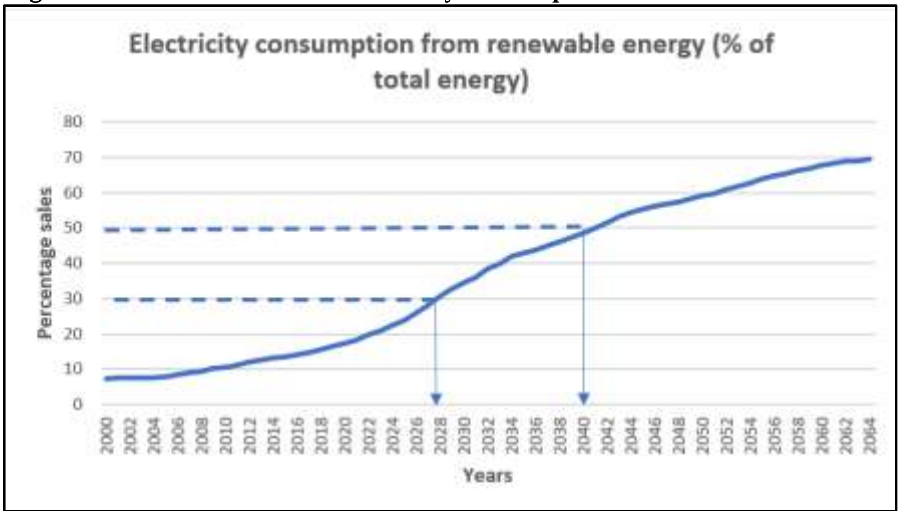


From the above forecasted plot, we can see by 2025, the share of electric vehicles in US will be 5% and will grow exponentially to be the major player in 2038. The above estimates foresee a complete perish of the traditional combustion engine vehicles by 2042.

3.2.2. Time Series Results for Energy

The energy data is at country level to begin with and thus there is no need to aggregate it by taking average. For each of the 18 countries, separate Holt-Winters equation is estimated, and the share of renewable energy consumption over the course of 40 years is forecasted.

Figure 5: Forecasted share of electricity consumption from renewable sources



As evident from the graph, by 2042, the power sector will be dominated by renewable sources, with the traditional alternatives decaying by the end of 2065.

The estimated level parameter for most cases is close to one reflecting higher weight is placed to recent observations which is logical given the fact it is only until recent times that countries have started to take steps clear in ameliorating the growing environmental concerns.

IV. DISCUSSION

Interpretation of the failure probabilities and time series forecast

So far, we have separately obtained a failure probability of two industries and the time-series forecast of the transformation to greener alternatives. In this section, we draw parallels between the two approaches and validate the forecasts.

For the automobile industry, the failure event is defined as a 5% share of sale of electric vehicles out of total sales. We find a 75% probability of failure (i.e., 75% probability that be possible fuel vehicles industry drops to 95%) around 2025. from the time series forecast, we also see that the forecasted values of 5% share of electric vehicles is around 2025. This indicates that the failure event definition and the time series forecast both point towards 5% decline by 2025. Defining a failure event about 5% from the limited data is not possible, however now that we know the time series to be fairly accurate, we can look at further forecasts of the same period. To draw data evidence in most of our arguments, we find the electric vehicle sales will have a majority share of the market by 2039.

For the electricity generation power industry, the failure event is defined at 30% share of electricity production from renewable sources relative to the total electricity production. We find that by 2027, the failure event will have a probability of 75%. Separately from the time series forecast, we see that the share of electricity generation through renewable sources of energy will have a forecasted value of 30.7% in 2028. Again, it is evident that the survival failure event curve and the time series forecast is aligned closely. Due to limited data, defining a failure event after 30% is not possible at the moment, but given the parallels between the survival and time series approaches, we can trust the time series forecast based on data evidence and can safely forecast the electricity generation from renewable sources will have the majority share in the market by 2041.

It is interesting to see that the survival curves and time series forecasts from two disjoint industries follow similar pattern with a half-death of non-green resources by 2040. However, it is common knowledge that the death will not be a point in time event, rather the decay has started to happen and will gain speed exponentially. Hence, trusting the data driven inference, the financial institutions need to act urgently now to re-strategize lending decisions and continue to be vigilant about the trend with more and more data in hand.

Stepwise summary of the framework:

To conclude, in a nutshell the high level steps a portfolio manager is to follow to come up with this additional metric are summarized below:

Step 1: Collect year-wise sales trend of the concerned industry the entity belongs to, as a proportion of total sales (comprising both traditional and greener alternative).

Step 2: Determine our “cut-off” based on the industry, past trends, subjective judgement and future expectation which will be a good enough benchmark to reflect a tilt in the scale towards the greener alternatives. The cut-off can also be set considering it to be more of a sign/ an early warning often accelerated future decay.

Step 3: Look at the year at which the probability of the industry's sales proportion causing the predefined threshold is high (says 75%). Tally this output of the survival analysis with the time series forecasted numbers to validate the conclusion.

Step 4: The year at which the traditional industry decays and the sector transitions to ecologically better alternatives is to be used as an input in the credit decision-making process. Moreover, the trend needs to be followed for customized credit decisions.

Further Enhancement of the framework

While in this paper we provide the analytical framework of an amalgamation of survival curve based increasing probability of failure with the forecast of relative declining change in the non-green industries, a further step ahead can be to actually forecast a climate change risk adjusted probability of failure based both on the climate change factors (e.g., time to failure of the industry) and also the other idiosyncratic factors for the client. In this section, we mention certain more climate change risk factors that can be considered to model the probability of failure and come up with a scaled climate change adjusted rating for every client. The model can be any supervised learning techniques where the target will be the relative decline in sales/ production / income /profit of that client attributed to climate change risk.

The first factor can be driven from the analytical framework of this paper. It can either be the industry of the entity or the time to failure of the industry. This will vary between industry and the major driver behind the risk due to climate change.

It is common knowledge that not all the countries have taken the proactive corrective actions to face climate risk. Developed economies like the USA, majority of western European countries and some of the Middle East countries have stringent policies to tackle climate change risk and hence the firms from these countries have already started to adopt to the Go-Green initiative and hence are much better prepared for the imminent change. On the other hand, the countries that are still at very nascent stage to check the industries with high level of carbon emission face a much higher risk to fail when the policies are put in force at a very short notice and demand for this product decline drastically living the firm little chance to adapt. The financial institutions financing this firms will also face the heat. As an example, single use plastics have been banned in advanced economies or available at a very high price to discourage the demand. Therefore, industries producing plastic for means of storage or transportation have started to move to biodegradable options serving the same purpose. However, in Southeast Asian countries of developing economies, single use plastics are still in abundant use. Countries in this belt are currently putting in policies to immediately stop the use of the same under global pressure which means that the plastic producing firms get almost no time to adapt to the change and hence face a crisis that can lead to abrupt shutdown of the firm and consequently huge losses for the bank that had advanced loan to these industries. Hence it can be understood that the country of an obligor places a vital role in determining the riskiness of default/ shut down/ losses of an obligor in the face of climate change risk.

The third factor of importance can be ordinal/scaled value on the adaptability of the firm with the climate change risk. On a scale of 1 to 10 (10 being the best), a firm can be rated on how much the firm has already adopted/ invested on infrastructure to Go-green in line with the policies. For example, among automobile manufacturers in the USA where there are stringent policies around the pollutant level on the exhaust from cars, firms like Tesla have heavily invested on electric vehicles and is leading the sales of electric vehicles in the country, where as a firm like Toyota which has a huge market in the USA is still relying on ICE cars for its' majority of sales. Hence, Tesla can be rated better with respect to Toyota on the adaptability to Go-Green initiative scale.

A classification framework based on these 3 primary factors can indicate the riskiness of the obligor under scanner, where the dependent variable needs to be the observed decline/ascent in their sales or profit over the last decade (where we assume that between comparable forms the decline/ ascent is due to the firm complying with Go-green initiatives).

The dependent variable can also be a binary factor where the rate of return on quality of the firm is compared against the portfolio average rate of return (the average being taken on the firms with similar total turnover in the same country and industry) and marked as "1" (indicating worse outcome) if the rate of return is lower and where there is a reason to believe that such low rate of return is due to lack of "Go-green" initiative in the face of rising cost of high pollutant raw material or decline in sales of conventional high pollutant finished product. Financial institutions can use portfolio expert's view to assign this dependent variable as well.

The accuracy of the climate sensitive risk can be validated by the climate specific stress testing/ scenario analysis that the institution is performing in the long run. As an instance, a customer belonging to an industry with imminent perish will have pooper climate risk rating compared to a customer belonging to a more ecologically balanced industry.

V. CONCLUSIONS

Investment strategy for every institution will be positively biased towards "Go-Green" initiatives to achieve "NET ZERO" vision over next few years. However, whether it involves some other emerging risk typologies is worth preempting like unwanted concentration risk. The only option is to adapt risk identification methodologies with emerging risk typologies.

A recent study conducted by Moody's [16] global project finance deals reveal the following:

1. There are three categories of projects which can be defined as: 1) Green, 2) No-green and 3) Third category (other than greenness)
2. Default rate is lowest in the third category (2.9% globally) followed by "Green" (5.7%) and "No-green" (8.5%)
3. The "Green" versus "No-green" default rate is significant in developed economies as compared to emerging market economy.

The output of the study gives a clear picture of investment towards "Go-green" initiatives globally, however, it also leaves an open question on why default rate observed is lowest in one special category (use-of-proceeds could not be determined) which can't be categorized as "Green" or "No-green". The study suggests that the difference could be due to sample characteristics other than Greenness. Does that mean this category mainly consists of industries which are not directly impacted by climate change risk like IT services industries? Intuition says it is not, because in that

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case the default rate would have been between default rate of “Green” and “No-green”.
This leaves us in front of a couple of unanswered open questions like: is it related to international policies or some other causal factors that is not working in favor of some specific industries which are yet to be discovered or the actual reason is swept under the carpet? We may want to explore further in our next study.

Appendix A
Automobile:


Automobile sector

Energy:


Electricity sector

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