ISSN 2282-8168

CEFIN Working Papers No 94

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May 2024

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Circularity and Default Probabilities: an empirical investigation based on the 3R principles

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Abstract: This paper empirically investigates the role of Circular Economy (CE) in explaining firms' probability of default (PD) in the short and the medium term. Based on the 3R principles of CE, we identify three main dimensions of circularity whose mean represents an overall circularity score. The first, Reduce, measures the degree of reduction in GHG emissions with respect to the previous year, the second, Reuse, measures the share of renewable energy used and the third, Recycle, measures the share of waste recycled or recovered. We adopt and OLS regression over a sample of 108 European companies, from the STOXX Europe 600 Index over the period 2017 – 2021. Three main results emerge. First, both in the short and medium term circularity practices are associated to a lower PD even after accounting for usual economic – financial indicators. Second, among the three dimensions of circularity the really relevant one is Reduce. Third, when comparing the effect of circularity in the short term versus the medium term, it emerges that the negative relationship with the PD is more pronounced in the short term, suggesting that immediate benefits of CE (e.g. tax benefits, easier access to credit, better reputation) offset implementation costs, which instead can be amortized over years. These results are of interests both for managers, who may exploit the negative association of CE and PD, and for supranational institutions that via circularity regulation may also contribute to a more stable financial system.

May 2024

Keywords: Sustainability, ESG, Circular economy, default probability,
Jel codes: C23, G32, M14

1. **Introduction**

Corporate Social responsibility (CSR) practices have evolved into a focal aspect of contemporary business paradigms, reflecting a progressive recognition of the interconnection between corporate operations with social and environmental issues. Escalating environmental degradation and resource scarcity are increasingly compelling companies to adopt CSR practices in their business activities, to mitigate their environmental footprint while simultaneously enhancing economic efficiency and resilience. The European Commissions has given attention to environmental sustainability: for instance, in December 2019 it launched the Green Deal (European Commission, 2019), which represents a comprehensive strategy to make Europe climate-neutral by 2050.

Moreover, recent legislative developments at the European level have introduced a further nuance within the CSR, specifically the concept of Circular Economy (CE). This concept stands in opposition to the traditional linear "take-make-dispose" model of production and consumption, emphasizing the regenerative use of resources, waste reduction and the establishment of sustainable value chains (Keulen and Kirchherr, 2020). Within this new framework, it is possible to identify two main initiatives. First, the CE Action Plans (CEAP) adopted by the European Commission outline a series of concrete measures to promote the transition to a CE in Europe, with specific objectives and targeted actions (European Commission, 2015 and 2020). Second, in 2023 the European Financial Reporting Advisory Group (EFRAG) presented a set of standards for reporting sustainability, known as European Sustainability Reporting Standards (ESRS), where the ESRS E5 standard is entirely focused on the topic of CE (EFRAG, 2023).

As a response, in the last decades EU-27 member states have significantly increased their circularity rate, measured by the share of material recycled and fed back into the economy, which increased from just above 8% in 2004 to 11.7% in 2021 (European Court of Auditors, 2023). However, it remains a highly relevant and timely issue for years to come, as the Commission's 2020 CEAP objective is to double the 2020 circularity rate by 2030.

It is important to emphasize that, although the concepts of CSR, Environmental, Social, and Governance (ESG), and CE are interrelated and have been usually considered proxies for sustainability, they do not completely overlap. In fact, CSR, which dates back to the 1950s, refers to the voluntary commitment of companies to conduct their business ethically and responsibly, considering the impacts on the environment, stakeholders and, more broadly, on the society at large. Hence CSR serves as a precursor of corporate sustainability as it applies sustainable development principles at the business level and represents the capability to satisfy the needs of the firm's direct and indirect stakeholders without compromising the ability of future stakeholders to meet their own needs (Murmura et al., 2017). The acronym ESG for Environmental, Social and Governance was introduced by the famous UN Report "Who cares win" (Compact, 2005) indicating a set of criteria that investors and stakeholders use to assess a company's performance in environmental, social, and governance dimensions. Thus, ESG can be thought of as a metric for CSR (Muñoz-Torres et al., 2018; Gillan et al., 2021). Finally, CE, or circularity, is a model of production and consumption that aims to minimize waste, maximize resource efficiency, and create a closed-loop system where products, materials, and resources are kept in use for as long as possible. Over the years, different definitions of CE have been proposed (Geissdoerfer et al., 2017; Kircherr et al., 2017; Kircherr et al., 2023), without reaching a consensus (De Pascale et al., 2021).

Nonetheless, the definition most frequently referenced in academic studies is the one proposed by Murray et al., (2017) p. 371, according to which: "*By circular, an economy is envisaged as having no net effect on the environment; rather it restores any damage done in resource acquisition, while ensuring little waste is generated throughout the production process and in the life history of the product.*"

On the other hand, in the international regulatory and business context, a reliable frame of reference is represented by the Ellen MacArthur Foundation, a non-profit organization, which defines the circular economy as follows: *"The circular economy is a system where materials never become waste and nature is regenerated. In a circular economy, products and materials are kept in circulation through processes like maintenance, reuse, refurbishment, remanufacture, recycling, and composting. The circular economy tackles climate change and other global challenges, like biodiversity loss, waste, and pollution, by decoupling economic activity from the consumption of finite resources".*[1]

This latter definition is based on three key principles: eliminate pollution, circulate products and materials and regenerate nature.

Overall, the concept of circular economy embodies a holistic and systemic approach to economic development that prioritizes resource efficiency, environmental sustainability, and long – term perspective. Such a concept has been interpreted by the academic literature through the 3R framework of Reduce GHG emissions (the so-called Scope1), Reuse energy from renewable sources and Recycle of materials, in order to optimize production in a sustainable manner (Kircherr et al., 2017). The nature of the relationship between CSR practices and the resulting economic-financial impacts, specifically on creditworthiness, as measured by default probability (PD) has long been debated (Naili and Lahrichi, 2020; Kaur et al., 2023).

The existing literature focuses on the relationship between ESG or more generally sustainability factors and default probability (Meles et al., 2023; Do 2022; Li et al., 2022). Despite the growing importance of the CE in terms of policies and regulations, research on CE remains relatively scarce in comparison to studies on sustainability or on the ESG, suggesting that topic is still largely unexplored.

Against this backdrop, the final aim of this paper is to gauge the role of sustainability in explaining firms' PD, with a specific focus on circularity and its three dimensions (Reduce, Reuse, Recycle), i.e. the 3R framework. To this end, we have measured circularity score based on the Eco Efficiency Indicator proposed by Park & Behera (2014), which considers a threefold partition of CE based on CO2 emission, energy consumption, raw materials. The paper aims to address three main research questions: To what

[1] https://www.ellenmacarthurfoundation.org/topics/circular-economy-introduction/overview

extent does circularity influence companies' PDs? Do the 3R of circularity contribute in different ways to explain the PD? Does circularity affect PDs more in the short term or in the medium term?

The research is performed on a sample of 108 companies, belonging to the STOXX Europe 600 from 2017 to 2021. In order to assess the relationship between circularity practices of a firm and its probability of default, we estimate an OLS regression with fixed effects in which we regress PD on companies' circularity scores and economic/financial variables. Data on PD were obtained through the Bloomberg data provider, at 1-year and 5-year, to investigate the likelihood of default of the companies in the short and medium term respectively.

The present research contributes to a recent strand of literature on the relationship between CSR practices and companies' default risk in two main directions. First, it is a first attempt to assess circularity considering a threefold distribution based on its multidimensional nature that encompasses: greenhouse gas emissions, energy from renewable sources and waste reduction policies. Second our analysis is based on Bloomberg PD score while the most existing studies use other scores such as those by Credit Research Initiative, Risk Management Institute, Altman z – score or KMV model. This latter contribution is relevant given the current debate about the quality and divergence of different PD scoring providers.

Our study reveals that, even after accounting for profitability and other financial ratios, circularity, and particularly GHG reduction policies, significantly explains the PD by means of a negative association, which is more pronounced in the short term rather than in the medium term.

The reminder of this paper is structured as follows. Section 2 reviews the literature on the relation between sustainability and PD and Section 3 describes the dataset and the main variables used in the analysis. Section 4 illustrates the empirical model to test the effect of CE in explaining PD, Section 5 discusses results. Last Section concludes.

2. Literature review: the role of sustainability in explaining PD

The sustainable finance literature has been growing very fast following different strands. A first and very productive strand covers the field of sustainable assets such as green bonds (e.g. Zerbib, 2019; Bertelli et al., 2021) and sustainable portfolio strategies and performance (e.g. Friede et al., 2015; Revelli and Viviani, 2015; Cunha et al., 2021; Bertelli and Torricelli, 2022 and 2024). A second strand focuses on the implication of sustainability on the firms' credit worthiness, encompassing multiple aspects, including: credit ratings (Dorfleitner and Grebler, 2020; Zanin, 2021); credit risk from the perspective of credit default swap spreads (Bannier et al., 2022; Barth et al., 2022; Zhang et al., 2023), and firms' default risk (Pizzi et al., 2020; Atif and Ali, 2021; Do, 2022).

As for the literature on firms' default risk, most papers essentially investigate the role of sustainability issues (represented by either ESG ratings or CSR practises) in explaining probability of default or financial distress measures by means of a regression analysis except from Zeng et al. (2022) that include ESG ratings in PD prediction.[2]

A substantial body of research has employed a single country as a reference point. Rizwan et al. (2017) explore the impact of CSR engagement for 1,119 non-financial US-listed companies between 2000 and 2012.[3] They rely on Merton model (1974) for the estimation of distance-to-default, a reverse measure of default risk, and find evidence that companies with greater CSR commitment are exposed to a lower default risk. Another analysis on the US stock market was conducted by Boubaker et al. (2020), who showed that, in the period 1991-2012, companies with high CSR, measured by MSCI ESG rating, are subject to lower financial distress risk, proxied by the Z-score of Altman (1968). In particular, this result is mainly driven by the governance component of sustainability. The negative association between sustainability issues and default risk is confirmed also by Atif and Ali (2021) by considering US non-financial companies from 2006 to 2017 and finding that ESG disclosure, calculated by Bloomberg as a score from 0 to 100, has a positive relationship with Merton's distance-to-default and a negative one with credit default swap spread. Shifting emphasis towards Asian markets, Li et al. (2022), based on a five-year time frame from 2015 to 2020, provide evidence that Chinese companies with higher ESG ratings show lower company's default risk.[4] Specifically, the impact of this relationship is even stronger for non-manufacturing companies than for manufacturing companies. Remaining within the Asian market, a recent study conducted by Okimoto and Takaoka (2024) and focusing on Japanese bonds from 2007 to 2018 confirms that ESG performance, provided by Refinitiv, acts also in mitigating corporate bond credit spreads.[5]

On the other hand, there are studies based on multi-country data. By focusing on the environmental aspects only, Kabir et al. (2021) measure the effect of carbon emissions on Merton's distance-to-default.[6] In the period 2004-2018 they find a negative impact of emissions on worldwide companies' distance to default, moreover environmental commitments and initiatives can act as mitigators of this effect. Likewise, Meles et al. (2023) investigate the explanatory power of green innovation, retrieved by the Thomson ASSET4 database, on a sample of European firms from 2003 to 2019 and reveal that green innovation is negatively related to companies' default risk, based on both

[2] Zeng et al. (2022) use a KMV methodology, which relies on Merton's model (Merton, 1974) for default risk estimation, to compute the distance to default and the expected default probability of a sample of Chinese internet finance firms from 2016 to 2020. Then, they correct such estimates in order to integrate ESG ratings into the evaluation model.

[3] CSR engagement score is based on the KLD Research and Analytics database, which ranks companies in various dimensions of CSR. A total of 13 dimensions are considered: community, diversity, governance, employee relations, human rights, environment, products, alcohol, gambling, firearms, military, tobacco and nuclear energy. Of these dimensions, the first seven present data in the form of strengths and concerns, while the remaining six are dichotomous variables with a score of 1 if the company is engaged in one of the above activities and zero otherwise.

[4] Company's PD data are retrieved from Risk Management Institute database, while ESG ratings are retrieved from Sino – Securities Index Information Service database.

[5] Data are obtained from Japan Standard Bond Price Thomson Reuters Eikon database.

[6] They considered four different measurements of carbon emissions: total carbon emissions, direct carbon emissions, indirect carbon emissions, and Scope 3 carbon emissions.

market-based and accounting-based indicators. Further, Mirza et al. (2024), by focusing on a European sample over the period 2012-2022, find that higher emissions are positively associated to default risk, whereas higher environmental score has a mitigating effect. By shifting from an environmental perspective to an overall ESG consideration, Badayi et al. (2020) use Thomson and Reuters Datastream ESG data as a proxy for CSR and investigate their effect on the PD, proxied by Altman Z – score, of 496 firms from 17 developing countries in 2010-2017. Results show that CSR practices reduce the PD in Asian, Latin American, and European regions, with the exception of the African and Middle Eastern region. When dealing with mandatory ESG disclosure, Do and Vo (2023) adopt a difference-in-difference model on firms in 17 emerging countries over the period 2000-2018 and show that companies situated in countries with mandatory ESG regulation have increased their distance to default (provided by Credit Research Initiative (CRI)) compared to firms not subject to mandatory ESG disclosure. Regarding the family firm's context, Maquieira et al. (2024), by examining a worldwide sample over 6 years between 2015 and 2021, reveal that there is positive relationship between ESG and Altman Z-score.[7] Furthermore, by looking at the separate ESG pillars, the result is confirmed for both E and S. Finally, Do (2022) empirically find a negative relation between CSR and the PD of firms from 36 countries in 2002-2016. Firm-level CSR performance is derived from Thomson Reuters ASSET4, while default probability is considered over different time horizons ranging from 1 month to 5 years and is obtained from the CRI.

Overall, very little has been said about the role of CE-based activities, which can be considered a proxy for environmental sustainability, in explaining companies' probability of default. Nevertheless, we are particularly interested in investigating the role of CE on PD, because, as Kumar et al. (2023) pointed out, CE and finance are not totally detached concepts from each other. Contrarily, these two concepts exhibit an interconnected relationship wherein they mutually foster and influence each other.

To the best of our knowledge, only Zara and Ramkumar (2022) empirically investigate the role of CE practices in explaining firms' PD. Specifically, they perform an OLS regression analysis, based on 222 European firms in the period 2013 – 2018. However, the authors use a broad concept of CE: the circularity score used in their estimates is based on 140 ESG indicators (covering the three ESG pillars) that are considered relevant for CE and among them they select the industry material ones according to the materiality framework proposed by the Sustainability Accounting Standards Board (SASB). The authors find that circularity practices exert a de-risking strategy both in the short and long term, even after including economic and financial control variables in the analysis.

In summary, despite the rapid growth of CE practices, there is a lack of empirical research in the in the literature on the relationship between CSR practices and firms' PD. As a matter of fact, Agrawal et al. (2023) identify as a promising field for future research understanding the extent to which circular

[7] Both ESG and default risk data are collected from Thomson Reuters Eikon database.

companies are profitable and capable of meeting their economic obligations, thereby challenging the assumption that these companies are not economically viable due to higher initial costs.

To fill this gap, this paper aims to investigate the extent to which CE, from the 3R perspective, can be considered a determinant of companies' PD.

3. Dataset and descriptive statistics

In this section we illustrate the dataset used and the variables considered. First in Section 3.1 we describe the sample selection process and the main economic-financial variables used in the analysis. Then, in Section 3.2 we discuss the theoretical motivation behind the setup of circularity score and we clarify its computation.

3.1 Dataset and economic-financial variables description

For our sample we consider the 925 stocks that were part of the STOXX Europe 600 Index from January 2016 to December 2022.[8] We focus on the period subsequent to the enter into force of the UN 2030 Agenda and we include also Covid-19 pandemic outburst. Yearly circular economy and financial variables of companies are retrieved for the period 2017-2021 from Bloomberg, which draws on companies' reports and communications, and, in cases of missing circularity data, we examined companies' websites and all publicly disclosed information.[9] We consider only non-financial companies, because of the distinct nature of financial ones, for which circularity has less impact on business activities and decisions. Moreover, in order to have a balanced and reliable dataset, we exclude companies for which circularity variables are not available or inconsistent for all the years considered. This process brings to a significant reduction in the sample size due to three main reasons. First, there is a lack of standardization both between companies and within the same company over time. Second, circularity information exhibits different granularity and disclosure levels given that some companies provide more detailed and comprehensive information about circularity practices, while others offer only limited or surface-level insights. The final issue refers to missing data for earlier years due to incomplete historical records or change in measurement practices, especially for specific environmental indicators (e.g. consumption of renewable energies and amount of recycled waste).

Hence, the final sample includes 108 companies and consists of a balanced panel containing 540 firm-year observations. Despite the limited number of components, it is quite representative of the overall market in terms of industry and country as reported in Table 1 and Table 2 respectively. The two most represented industries are Industrials and Materials, which represent one third of total companies considered. The latter, together with the other most significant sectors (Consumer Discretionary,

[8] The STOXX Europe 600 Index is a stock market index composed of 600 leading companies by capitalization of the European market and it offers a comprehensive coverage in terms of industry and country.
[9] From the analysed period we exclude 2016 due to incomplete data concerning companies' environmental performance and 2022 since, at the time the analysis was conducted, many data were not yet available.

Consumer Staples and Health Care), reach two third of the total sample and represent manufacturing companies for which circularity plays a crucial role due to the substantial energy and raw material requirements, as well as the significant waste generated. In terms of geographical distribution, Britain, Germany, and France stand out as the most represented countries, collectively accounting for half of the sample.

Table 1. Companies by sector

	N	**(%)**
Communications	5	4.630
Consumer Discretionary	14	12.963
Consumer Staples	11	10.185
Energy	7	6.481
Health Care	11	10.185
Industrials	15	13.889
Materials	21	19.444
Real Estate	11	10.185
Technology	8	7.407
Utilities	5	4.630
Total	108	100.000

Notes: the table reports sector breakdown in absolute terms (second column) and in percentage (last columns) according to the Bloomberg Industry Classification System (BICS) level 1.

Table 2. Companies by country

	N	**(%)**
Austria	1	0.926
Belgium	3	2.778
Britain	20	18.519
Czech	1	0.926
Denmark	2	1.852
Finland	4	3.704
France	16	14.815
Germany	18	16.667
Italy	9	8.333
Netherlands	7	6.481
Norway	2	1.852
Poland	1	0.926
Portugal	1	0.926
Spain	5	4.630
Sweden	8	7.407
Switzerland	10	9.259
Total	108	100.000

Notes: the table reports country breakdown in absolute terms (second column) and in percentage (last columns).

To empirically test the relationship between circularity and the PD in the short and in the medium term, as dependent variable we consider both 1-year PD and 5-year PD. Such measures are retrieved from Bloomberg and are calculated by the Bloomberg Issuer Default Risk model which is based on an equity perspective. Table 3 presents descriptive statistics of both 1-year and 5-year probabilities of default which results to be on average small (0.2% and 1.8% respectively) with little variation (1.2% and 2.8% respectively), hence we use their log transformation in order to usefully increase the range of PD values.

The explanatory variables we focus on in the present analysis are the circularity one, but we also consider as controls the financial and performance ratios normally used in the PD estimation literature. As for circularity, we measure it both with a comprehensive score and its three main components presented and computed in Section 3.2. As for the control variables, we include profitability ratios to control for income performance from an equity and total asset perspective by considering *Return on Equity* (*ROE*) and *Return on Assets* (*ROA*) respectively; *Interest coverage ratio*, calculated by dividing company's earnings before interest and taxes (EBIT) by its interest expenses, to assess a company's ability to pay interest expenses on its outstanding debt, hence controlling for liquidity risk; *Current ratio* is a ratio between current assets and current liabilities and controls for company's ability to meet short-term obligations with its short-term assets; *Net debt to EBITDA* (Earnings Before Interest, Taxes, Depreciation, and Amortization) is a financial ratio to assess company's financial leverage and ability to repay its debt obligations, thus it controls for company's solvency; *Market capitalization to total assets* is a ratio that measures the company's market value relative to the value of its total assets, hence controlling for company's market size. From Table 3 it emerges that the companies in the sample show a certain variability in terms of control variables. For instance, ROE exhibits a larger standard deviation and a wider range of values with respect to ROA, suggesting that the companies in the sample might be characterized by different financial structures or by a financial structure that significantly changed over the years. Interest coverage ratio assumes both negative and (very) positive values implying that the ability to generate enough operating income to cover the interest on debt is different between companies and within the same company over the year. In particular the highest Interest coverage ratios are associated to 2017 and 2018, years of normal market condition, whereas the lowest values are mainly referred to 2020 when the Covid-19 pandemic hit companies by reducing their revenues while maintaining rigid financial commitments.

Table 3. Descriptive statistics of dependent and control variables

	N	Min.	Median	Mean	Max.	St. Dev.
Dependent variables						
1-year PD	540	0.000	0.000	0.002	0.184	0.012
5-year PD	540	0.000	0.010	0.018	0.321	0.028
log 1-year PD	540	-23.026	-10.085	-10.632	-1.693	3.899
log 5-year PD	540	-8.204	-4.582	-4.671	-1.136	1.177
Control variables						
ROE	540	-197.143	12.952	12.917	126.416	20.364
ROA	540	-21.637	4.930	5.531	41.460	5.746
Interest cov. Ratio	540	-31.237	9.033	21.533	704.143	52.977
Current ratio	540	0.135	1.258	1.451	17.135	1.195
Net debt to EBITDA	540	-6.944	1.594	2.557	52.319	5.341
Mkt cap. to tot. Assets	540	0.043	0.883	1.270	8.435	1.146

Notes: the table presents minimum, Median, Mean, Maximum and Standard Deviation (St. Dev.) of dependent and control variables. 1-year PD and 5-year PD are not reported in percentage. Log 1-year PD and log 5-year PD represent the natural logarithm of 1-year PD and 5-year PD respectively. ROE and ROA are expressed in percentage.

3.2 Circularity score

Since Circularity score represents the focus of our analysis, in its setup we aim to consider all the main features that characterize a circular economy. In doing so we combine a qualitative definition of circularity with quantitative indicators to measure firms' circularity involvement. First, the interpretation of the main features of circularity (i.e. eliminate pollution, circulate products and materials, regenerate nature) passes through the 3R paradigm which consists in Reducing GHG emissions, Reusing energy from renewable sources and Recycling materials. Second, we consider the Eco-Efficiency Indicator, originally proposed by Park & Behera (2014), which has been described by De Pascale et al. (2021) as a possible indicator for measure CE at meso level.[10] The Eco-Efficiency indicator is based on the World Business Council for Sustainable Development (WBCSD) definition of eco-efficiency, a concept that applies to any types of company and focuses on achieving more value with fewer resources and less environmental impact, hence optimizing resource use and reducing waste and pollution. Among the various ways described by the WBCSD to reach eco-efficiency and different indicators to measure it, Park & Behera (2014) select four sub-indicators to build their Eco-Efficiency Indicator: an economic indicator and three environmental indicators represented by raw material consumption indicator, energy consumption indicator, and CO2 emission indicator (WBCSD 1993 and 2000; Verfaillie and Bidwell, 2000).

In order to set up a circularity score for each company in the sample, we combine the 3R (Reduce, Reuse and Recycle) paradigm for CE with a measurement approach as the one represented by the three environmental indicators of the Eco-Efficiency Indicator. Even if Park & Behera (2014) propose

[10] Such an indicator has been classified among the meso level indicators since it has been originally proposed with the aim to simultaneously quantify the economic and environmental performance of industrial symbiosis networks.

measurement at meso level, while our analysis is at companies' level, we get inspiration from their work to identify metrics for measuring circularity objectives, adapting these metrics based on publicly available information from companies. Therefore, we select three main dimensions, that in line with the 3R paradigm we call Reduce, Reuse and Recycle, which are computed as follows:

$$Reduce_{i,t} = -\frac{\frac{GHG_{i,t}}{TA_{i,t}} - \frac{GHG_{i,t-1}}{TA_{i,t-1}}}{\frac{GHG_{i,t-1}}{TA_{i,t}-1}} \times 100 \tag{1}$$

$$Reuse_{i,t} = \frac{RenewEnergy_{i,t}}{TotEnergy_{i,t}} \times 100 \tag{2}$$

$$Recycle_{i,t} = \frac{RecWaste_{i,t}}{TotWaste_{i,t}} \times 100 \tag{3}$$

where:

$GHG_{i,t}$ = scope 1 greenhouse gas (GHG) emissions of company *i* at time *t*, measured in thousands of metric tonnes of carbon dioxide equivalent (CO2e)

$TA_{i,t}$ = total asset of company *i* at time *t*

$RenewEnergy_{i,t}$ = energy consumed by company *i* at time *t* that was generated by a renewable energy source

$TotEnergy_{i,t}$ = total energy consumed by company *i* at time *t,* including energy directly consumed through combustion, through chemical and energy consumed as electricity

$RecWaste_{i,t}$ = waste recycled or recovered by company *i* at time *t*

$TotWaste_{i,t}$ = waste, both hazardous and non-hazardous, discarded by company *i* at time *t*

Reduce represents the degree of reduction in GHG emissions with respect to the previous year, Reuse can be interpreted as the share of renewable energy used and Recycle the share of waste recycled or recovered. To account for all the three dimensions equally, circularity score for company *i* at time *t* is the arithmetic mean of $Reduce_{i,t}$, $Reuse_{i,t}$ and $Recycle_{i,t}$:

$$C_{score_{i,t}} = \frac{Reduce_{i,t} + Reuse_{i,t} + Recycle_{i,t}}{3} \tag{4}$$

The circularity score is, hence, measured in percentage and its descriptive statistics are reported in Table 4. Circularity score ranges from -45.349% to 68.122% with an average value of 34.548%, very close to the median one (34.880%). There are some negative circularity scores since the Reduce dimension shows also values below zero in cases where a company increases the amount of GHG with respect to the previous year. On the contrary, Reuse and Recycle exhibits only positive values in the ranges 0.005% to 96.038% and 1.362% to 100% respectively, with average values of 30.230% and 66.799% respectively. All 3R have a standard deviation around 20% and it reduces to 14% when considering circularity score.

Table 4. Descriptive statistics of circularity score and its components

	N	Min.	Median	Mean	Max.	St. Dev.
Reduce	540	-233.140	6.577	6.616	82.838	19.641
Reuse	540	0.005	24.392	30.230	96.038	25.141
Recycle	540	1.362	68.641	66.799	100.000	23.001
Circularity score	540	-45.349	34.880	34.548	68.122	14.935

4. Empirical analysis

In this Section we define the empirical model to be estimated and we conduct some preliminary analysis in order to deal with multicollinearity and the choice between fixed and random effects model specification.

In the analysis, aimed to investigate the effect of circularity in explaining companies' probability of default, we estimate the ordinary least square (OLS) model in equation (5). This approach, widely adopted in the literature on PD determinants, effectively captures the continuous nature of the dependent variable and facilitates the interpretation of the association between circularity and the PD. Moreover, the choice of OLS is justified since our dependent variable, the probability of default (PD), is a continuous variable whereas we do not consider a dichotomous variable indicating whether a firm has defaulted in the analysed period, given that our sample does not include defaulted companies.

$$logPD_{i,t} = \beta_0 + \beta_1 circularity_{i,t} + controls_{i,t} + \alpha_i + \lambda_t + u_{i,t} \tag{5}$$

where:

$logPD_{i,t}$ = log of Probability of Default (1 or 5 years) of company *i* at time *t*

β_0 = constant term

$circularity_{i,t}$ = overall circularity score of company *i* at time *t* or 3R: Reduce, Reuse and Recycle of company *i* at time *t*

$controls_{i,t}$ = vector of control variables for company *i* at time *t*: ROE, ROA, Interest coverage ratio, Current ratio, Net debt to EBITDA, Market capitalization to Total assets

α_i = company fixed effect

λ_t= year fixed effect

$u_{i,t}$= error term of company *i* at time *t*

In the model we consider both 1-year PD and 5-year PD in order to investigate separately the effect of circularity on short-term and medium-term PD. Moreover, circularity is both considered at the aggregate level (by means of the circularity score) but we also focus on its dimensions (Reduce, Reuse, Recycle) in order to see whether they impact PD differently. By introducing both company (α_i) and year

(λ_t) fixed effects we control for variables that are constant over time but differ across companies and for variables that are constant across companies but evolve over time respectively. Finally, in order to account for heteroskedasticity and autocorrelation in the error term $u_{i,t}$ we cluster standard errors at the firm level. Hence, we allow that the regression errors can be correlated over time within a company.

We begin the empirical analysis by examining correlation and the variance inflation factor (VIF) to ensure that multicollinearity is not an issue between the independent variables of regression in (5). Not surprisingly, the circularity score is highly correlated with its three components, especially reuse and recycle, as it is an arithmetic mean of the three (Table 5). However, there is no issue of multicollinearity in the model, as we conduct separate regressions where circularity is represented either by the circularity score or by its three components. ROA shows a moderate correlation with ROE (65.3%), given that they both represent profitability ratios, and with Mkt capitalization to tot. Assets, probably because they share the same denominator, and their numerators (i.e. net income and Mkt capitalization respectively) are quite correlated. However, Table 6 demonstrates that multicollinearity is not a concern in our analysis since VIF values, which quantifies how much the variance of an estimated regression coefficient is inflated due to multicollinearity, are below 10 (also below the more conservative threshold of 5) and tolerance (1/VIF) is always above 0.2 (Numan et al., 2022; El-Bannany, 2017).

In order to find the model specification more appropriate for our model, we perform a Hausman test (Hausman, 1978) and it confirms that a fixed effects model is preferred. Moreover, a fixed effects model is preferred also because in our context it is plausible that companies' characteristics might affect the regressors.

Table 5. Correlation among dependent variables

	Reduce	Reuse	Recycle	Circular. score	ROE	ROA	Int. cov. Ratio	Current ratio	Net debt to EBITDA	Mkt cap. to tot. Assets
Reduce	1									
Reuse	0.020	1								
Recycle	0.107	0.298	1							
Circolar. score	0.504	0.723	0.727	1						
ROE	0.078	0.095	0.136	0.157	1					
ROA	0.153	-0.007	0.047	0.087	0.653	1				
Int. cov. Ratio	0.043	0.048	0.048	0.070	0.172	0.391	1			
Current ratio	0.010	-0.119	-0.136	-0.132	0.037	0.148	0.031	1		
Net debt to EBITDA	-0.096	0.085	0.080	0.047	-0.174	-0.360	-0.162	-0.077	1	
Mkt cap. to tot. Assets	0.066	0.078	-0.006	0.070	0.335	0.620	0.460	0.106	-0.284	1

Table 6. variance inflation factor (VIF) for multicollinearity

	Circularity represented by circularity score		Circularity represented by 3R	
Variable	VIF	1/VIF	VIF	1/VIF
ROA	2.920	0.343	2.840	0.353
ROE	1.850	0.539	1.830	0.546
Mkt cap. to tot. Assets	1.850	0.542	1.810	0.552
Interest cov. Ratio	1.320	0.760	1.310	0.761
Net debt to EBITDA	1.180	0.846	1.170	0.854
Recycle	1.150	0.868		
Reuse	1.140	0.877		
Circolarity score			1.050	0.948
Current ratio	1.060	0.947	1.050	0.952
Reduce	1.040	0.960		
Mean VIF	1.500		1.580	

5. Results

Regression results based on fixed effects specifications are reported in Table 7 for log 1-year PD and in Table 8 for log 5-year PD. In both tables circularity is represented by a single aggregate measure (Model 1 and Model 2) and through its three components Reduce, Reuse, and Recycle (Model 3 and Model 4). Moreover, we include time fixed effects because, by doing so, we allow time contribution to explain the variation in the dependent variable. The latter is particularly true for year 2020 in which Covid-19 pandemic affected the whole economy with an effect also on companies' probability of default. Coefficients for year dummies are always statistically significant but are not reported in the tables for the sake of brevity.

In Table 7 - Model 1 the circularity coefficient (-0.031) indicates a statistically significant negative association with the 1-year PD, suggesting that higher overall circularity is associated with a lower probability of default within one year. Specifically, when circularity score increases by 1 percentage point, the associated difference in log 1-year PD is -0.031, which mathematically corresponds to multiply 1-year PD by 0.969 ($= e^{-0.031}$). Hence, expressed in the percentage metric, a 1 percentage point increase in the circularity score is associated with a 3.052% decrease in 1-year PD. With the inclusion of economic and financial control variables (Table 7 - Model 2), which allows a more comprehensive understanding of the factors influencing default risk, the coefficient of circularity score remains significant even if it slightly decreases to -0.027, implying that a 1 percentage point increase in the circularity score is associated with a 2.664% decrease in 1-year PD. Such a reduction with respect to 3.052% shows that part of the initial contribution of the circularity score in explaining the probability of default is shared with ROE, ROA, Net Debt to EBITDA, and Market Cap to Total Assets which show statistically significant coefficients. In particular, ROA and Market Cap to Total Assets have a negative relationship with PD, whereas ROE and Net Debt to EBITDA have a positive one. While it is expected that a higher leverage is positively associated with companies' default risk, ROE positive coefficient equal to 0.013 (corresponding to an increase of 1.308% of 1-year PD as ROE increases by 1 percentage point) might appear counterintuitive. However, a higher ROE may be achieved through an increased leverage making the company more vulnerable to economic downturns or higher interest rates, thus showing a positive relationship with the probability of default. Further, firms with high ROE might be focusing on short-term profitability at the expense of medium-term stability, hence increasing short-term PD. On the other hand, when circularity is represented by the 3R, only Reduce has an association (-0.011) which is statistically significant (Table 7 - Model 3 and Model 4), implying that a 1 percentage point increase in Reduce is associated with a 1.094% decrease in 1-year PD. After the inclusion of control variables (Table 7 - Model 4), the role of Reduce remains quantitatively invariant, differently form the case in which the overall circularity score is considered. This phenomenon might be attributed to the fact that, in comparison to the circularity score, Reduce shows a lower correlation with statistically significant economic and financial variables, except of ROA (Table 5). Finally, in all models in Table 7, although the constant term is large and negative, its effect on PD is negligible give the log transform of the same: for instance, when constant is -12.002 (Model 1), its effect is close to zero (6.132E-06 $= e^{-12.002}$).

Table 8 reports result for 5-year PD and, comparatively with Table 7, emerges that when circularity is represented by a comprehensive score (Model 1 and Model 2) its association with medium-term PD is again negative and statistically significant, but lower than the one on short-term PD. In fact, the coefficient of circularity score is -0.010 in Model 1, indicating that a 1 percentage point increase in the circularity score is associated with a 0.995% decrease in 5-year PD. Such an effect reduces to 0.896% when considering also control variables (Model 2). In this latter case ROE is no longer significant, confirming that a higher ROE may result from decisions aimed at increasing short-term profitability, which might not lead to a significant reduction in PD in the medium term. Further, when the 3R are considered, only Reduce has a statistically significant coefficient (-0.003 in Model 3 and Model 4), implying that a 1 percentage point increase in the Reduce dimension is associated with a 0.300% decrease in 5-year PD. As in Table 7, when circularity is represented by the 3R the role of Reduce remains quantitatively invariant when control variables are added. Again, in all models of Table 8 the constant term is quite large and negative even if its effect remains close to zero. For instance, the constant term is equal to -5.059 and statistically significant in Model 1, but the effect on PD is equal to 0.006 ($= e^{-5.059}$).

In both Table 7 and Table 8, an increase in Reduce variable (represented by a reduction in GHG emissions with respect to the previous year) has a negative association with PD, which is quantitatively lower (in absolute terms) than the one produced by an increase in the circularity score (represented by a reduction in GHG emission beside an increase in the share of renewable energy used and waste recycled or recovered). Thus, even if Reuse and Recycle alone are not able to explain PD, since their coefficients are not statistically significant, aggregated together with Reduce they have a crucial role to gauge companies' financial health. In addition, it emerges that the negative association of circularity issues, considered at the aggregate level or with individual dimensions, with PD is quantitatively higher for 1-year pd with respect to 5-year PD. This result, consistent with the one obtained by Zara and Ramkumar (2022), might the consequence of immediate benefits (e.g. tax benefits, easier access to credit, better reputation) that offset implementation costs, which instead can be amortized over years. Moreover, in the medium term these benefits might stabilize and be less pronounced once production processes are optimized.

Table 7. Regression results for log 1-year PD as dependent variable

	Model 1	**Model 2**	**Model 3**	**Model 4**
Dep. Var	log 1-year PD	log 1-year PD	log 1-year PD	log 1-year PD
C_score	-0.031 ** (-2.46)	-0.027 ** (-2.31)		
Reduce			-0.011 ** (-2.50)	-0.011 ** (-2.49)
Reuse			-0.014 (-1.13)	-0.011 (-0.98)
Recycle			-0.005 (-0.40)	-0.001 (-0.11)
ROE		0.013* (1.91)		0.013 * (1.86)
ROA		-0.107 *** (-3.61)		-0.105 *** (-3.58)
Interest cov. ratio		-0.002 (-0.60)		-0.002 (-0.62)
Current ratio		-0.093 (-1.18)		-0.095 (-1.23)
Net debt to EBITDA		0.071 ** (2.37)		0.073 ** (2.35)
Mkt cap to Tot. assets		-0.737 * (-1.75)		-0.744 * (-1.85)
Constant	-12.002 *** (-30.20)	-10.615 *** (-14.46)	-12.277 *** (-14.30)	-11.070 *** (-9.97)
Company fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Clustered standad errors	yes	yes	yes	yes
Adjusted R2	0.587	0.629	0.586	0.628
F	(5, 107) = 129.43***	(11,107) = 67.05***	(7, 107) = 97.78***	(13, 107) = 58.54***
Observations	540	540	540	540

Notes: t-values are reported in brackets, ***, ** and * represent significance at 1, 5, 10% levels. Fixed effects are not shown for the sake of brevity.

Table 8. Regression results for log 5-year PD as dependent variable

	Model 1	**Model 2**	**Model 3**	**Model 4**
Dep. Var	log 5-year PD	log 5-year PD	log 5-year PD	log 5-year PD
C_score	-0.010 ** (-2.56)	-0.009 ** (-2.43)		
Reduce			-0.003 ** (-2.48)	-0.003 ** (-2.59)
Reuse			-0.005 (-1.18)	-0.003 (-0.98)
Recycle			-0.002 (-0.57)	-0.001 (-0.20)
ROE		0.002 (0.91)		0.002 (0.87)
ROA		-0.030 *** (-3.20)		-0.030 *** (-3.20)
Interest cov. ratio		-0.001 (-0.55)		-0.001 (-0.56)
Current ratio		-0.015 (-0.67)		-0.016 (-0.72)
Net debt to EBITDA		0.022 ** (2.07)		0.023 ** (2.06)
Mkt cap to Tot. assets		-0.230 * (-1.81)		-0.232 * (-1.91)
Constant	-5.059 *** (-41.65)	-4.643 *** (-21.18)	-5.120 *** (-20.20)	-4.777 *** (-14.43)
Company fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Clustered standad errors	yes	Yes	yes	yes
Adjusted R2	0.592	0.634	0.590	0.634
F	(5, 107) = 143.98***	(11, 107) = 75.87***	(7, 107) = 107.74***	(13, 107) = 66.28***
Observations	540	540	540	540

Notes: t-values are reported in brackets ***, ** and * represent significance at 1, 5, 10% levels. Fixed effects are not shown for the sake of brevity.

6. Conclusion

The academic literature has extensively examined the effects, in terms of financial performance and credit risk reduction, generated by sustainability and corporate social responsibility practices. However, although circularity practices (e.g. waste recycling, emission reduction, renewable energy use) have been increasing also spurred by regulation, few researches have explored the financial implications of circularity and only one study (Zara and Ramkumar, 2022) has investigated the effect of circularity on companies' probability of default.

The aim of this paper is to gauge the role of circularity and its main determinants in explaining firms' PD in the short-term (1 year) and in the medium-term (5 years). To this end, in order to compute a circularity measure, we combine the most commonly used CE classification system that relates to the 3R principle (Reduce, Reuse, Recycle) with a measurement approach as the one represented by the three environmental indicators of the Eco-Efficiency Indicator (Park & Behera, 2014). We identify three main dimensions of circularity whose mean represents what can be considered an overall circularity score. The first, Reduce, represents the degree of reduction in GHG emissions with respect to the previous year, the second, Reuse, measures the share of renewable energy used and the third, Recycle, represents the share of waste recycled or recovered. Our estimates of the relationship of the 3R with the PD are based on an OLS regression with company and year fixed effects, which is performed over a sample of 108 companies that were part of the STOXX Europe 600 Index, observed over the period 2017-2021. Both financials and circularity data are retrieved from Bloomberg database.

Three main results emerge from our analysis, which are qualitatively the same. First, circularity practices as measured by the overall circularity score are associated to a lower companies' PD both in the short and medium term, even after controlling for the main economic-financial indicators. Specifically, a 1 percentage point increase in the circularity score is associated with a 2.664% decrease in 1-year PD and a 0.896% decrease in 5-year PD. Second, when we focus on each of the 3 circularity dimensions, only Reduce has a significant negative association with PD, while Reuse and Recycle alone do not have a significant contribution in explaining the PD. By contrast, a 1 percentage point increase in the Reduce score is associated to a reduction in the 1-year PD and 5-year PD by 1.094% and 0.300% respectively. In sum, while the two individual components Reuse and Recycle do not have a significant relationship with the PD, Reduce is negatively and significantly associated with the risk of default, although such an association is quantitatively lower than the one captured by the overall circularity score. This suggests that a holistic consideration of all CE determinants and dimensions is preferable to gauge companies' financial health. Third, when comparing the effect of circularity in the short term versus the medium term, it emerges that the negative relationship is more pronounced in the short term, whether considering the overall Circular Economy score or its individual dimensions. This result is suggestive of short-term benefits of circularity in terms of default risk measurement, which can in principle offset implementation costs, which instead can be amortized over years. Further, circularity activities can improve access to sustainable financing and attract sustainability-conscious investors. Finally, efforts to reduce emissions and waste of resources can rapidly improve the company's reputation with customers, partners, and investors, reducing PD through increased trust and improved corporate image. On the other hand, in the medium term these benefits may stabilize and become less pronounced as production processes become optimized and the advantages of circularity become more standardized within industries.

In summary, CE practices can serve as an effective strategy for the sustainable development of companies (e.g. Chen & Dagestani, 2023) also in terms of measurement of the company probability of default and, according to our results, GHG emission reduction activities appear to be the most relevant.

Amidst growing interest in CE from both individual companies and supranational institutions, this study can offer a twofold implication. First, from the firms' viewpoint, the negative empirical association between the probability of default and circularity actions, particularly GHG emission reduction, can represent a useful information in their decision-making processes. Second, from the policymakers' viewpoint, regulation should actively promote circular economy practices among companies (e..g. via fiscal incentives) since the negative relation of circularity issues with probability of default could contribute to financial stability.

Future research work may focus on the differences between CE and ESG scores in explaining PD, in order to investigate two main issues: first, whether CE is able to capture further features with respect to the environmental pillar of ESG, second, what are the effect of the social and governance pillars (if any) in explaining PD.

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