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CIRCULAR ECONOMY AND DEFAULT RISK

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By decoupling economic growth from the exploitation of virgin raw materials and environmental degradation, as well as by developing practices more resilient to the economic cycle, Circular Economy (CE) offers effective hedging of linear risks and shields from the risk of stranded values. We tested this hypothesis focusing on default risk of a sample of 222 European circular issuers focused on manufacturing, construction, energy, metal and oil and gas industries. The time period considered is 2013–2018. The main explanatory variable is the Circularity Score, a brand-new indicator based on material variables pertinent to CE. Default risk is measured on PD values, corresponding to external rating classes, provided by Bloomberg. We found that issuers with a higher level of circularity confirm de-risking hypothesis at both short and long terms. Moreover, the contribution offered by circularity on de-risking is more relevant in the long-term analysis, ranking as third in relation to fourth in the short-term model.

Keywords: Credit risk; de-risking effect; circular finance; sustainable finance; circular metrics.

JEL Classifications: G32, G21, G10, G39

1. Introduction

The Circular Economy (CE) paradigm has been gaining momentum in both academic and policymaking fields as a practical implementation of sustainability-related principles to the business environment. In fact, CE allows to couple economic growth with environmental limits related to virgin resources and natural capital exploitation

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as well as to keep the competitive advantage of an economic system (Bocconi University *et al.* 2021). Research on CE is still limited compared to that related to Corporate Social Responsibility (CSR) or the Green Economy, meaning that the topic is far from being saturated and has room for further conceptual development (Geissdoerfer *et al.* 2017). The gap is even higher if referred to the relationship between CE and finance, an almost virgin field of research. The goal of this paper is to present the results of a research on the relationship between the degree of circularity of corporate borrowers and their risk of default. For investigating this field, we started considering two strands of literature. The first refers to CE as an economic paradigm, in order to explain the main reasons that imply the possibility to drive a de-risking effect on circular investments and asset classes (e.g. Stahel 2010, 2014, Kama 2015, Lacy *et al.* 2019). Moreover, there is a gap in the literature concerning a lack of consensus and definition on how to outline an asset class as circular and how to measure the degree of circularity for financial assets at company level (Grewal *et al.* 2017, Pauliuk 2018). The second one analyzes the empirical research on the relationship between sustainability and risk-adjusted performance in financial markets. Most of the authors agree on the fact that sustainable asset classes generate an overall de-risking effect and, in some cases, also a superior risk-adjusted performance (e.g. Eccles & Serafeim 2013, Friede *et al.* 2015, Giudici & Bonaventura 2018, Giese *et al.* 2019). Unluckily, up to now, scholars have not yet considered CE as a peculiar field of analysis for sustainable finance as well as, when debt finance is considered, most of the empirical researches focus mainly on the relationship between Environmental, Social and Governance (ESG) adoption and bonds' performance (e.g. Bauer & Hann 2014, Stellner *et al.* 2015) and, when more focused on sustainability-linked issues, on green bonds (e.g. Reed *et al.* 2017, Zerbib 2019), without enlarging on issuers (Sun & Cui 2014, Lebelle *et al.* 2020).

This research tests the hypothesis on de-risking suggested by the pertaining literature, with a specific focus on debt finance. Instead of a generic sustainability concept linked to the usual ESG framework, the triggers for de-risking refer to the specific field of CE. We intend to pursue this goal by putting CE in direct relation with financial performance in a broad sense and more in detail: on the one hand, CE will be represented by a brand-new measure, the Circularity Score (CS), in order to scale the degree of circularity of corporates; on the other hand, we will focus on a specific feature of the financial performance, i.e. de-risking effect, focusing on debt capital and referring to probability of default (PD) as its measure.

The proposed analysis shows some peculiar features. First of all, it has been set an original sample of companies that have external credit ratings and are active in industries which could be highly affected by finite resource consumption and negative externalities. Moreover, the need to develop a financially material measure of circularity in order to connect it to the pertinent risk variables has been matched through the CS as a continuing random variable. Furthermore, we tested the relationship between credit risk, as a dependent variable, and the CS, as the main independent variable, designing and implementing a bunch of econometric models via OLS estimation. Finally, a dominance analysis has been carried out in order to rank the relevance of the contributions offered by the CS, in relation to the other control variables, in explaining the behavior of the dependent variable.

With regard to the main results, we found that CE, in terms of the CS measure, has a negative and statistically significant relationship with the risk of default, in terms of PD referred to both short-term (one year) and medium-term (five years) perspectives. Lagging by a year the CS in relation to the dependent variable, we found that the relationship is confirmed and we argue in favor of this result as evidence of the existence of a causal link, stating that a higher degree of circularity results as an effective de-risking strategy in the sample considered. Moreover, the dominance analysis proved that the contribution offered by the CS in relation to the control variables and fixed effects is pretty relevant, ranking as fourth when we consider PD 1YR and raising as third when we pass to PD 5YR. Finally, robustness checks confirm the stability and consistency of our findings.

The structure of the paper is as follows. In Sec. 2, we introduce the relevance of the research and define the hypothesis in detail. In Sec. 3, we define our sample and describe the variables considered, digging more in depth into the CS methodology. In Sec. 4, we define our models, then present and discuss the results and finally check for their robustness. Lastly, in Sec. 5 we conclude.

2. Relevance and Scope of the Research

The literature on CSR/ESG and credit risk (Bauer & Hann 2014, Stellner *et al.* 2015, Rizwan *et al.* 2017) to some extent argues in favor of a de-risking effect, mainly driven by the G factor. On the one hand, from a theoretical point of view, this effect could be justified by the fact that a high score in the G pillar signals good managerial practices which could cause an increase of reputational capital and a sound management of the company; moreover, paying attention to E and S items implies a proper respect of both rules on externalities and duties concerning private contracts that could generate a superior internal hedging against negative events. On the other hand, considering sustainability in terms of CSR/ESG frameworks does not imply a change in the economic paradigm. In fact, our current economy has been applying a linear model, which takes resources, makes products, consumes them and disposes as a waste, since the second half of the 18th century. The convenience to investigate sustainability in terms of CE relies on the possibility to better focus the field of consideration upon the "economic engine" of sustainability, referring to the sphere that is definitively linked to the conduct and the performance of the economic actors. As stated by Ellen MacArthur Foundation (EMF)[a]: "The circular economy is based on three principles, driven by design: (i) eliminate waste and pollution; (ii) circulate products and materials at their highest value; (iii) regenerate nature. It is

[a] Ellen MacArthur Foundation is the most important private organization which promotes the adoption of CE principles in the economy. For delving deeper, readers can refer to: https://ellenmacarthurfoundation.org/.

underpinned by a transition to renewable energy and materials. A circular economy decouples economic activity from the consumption of finite resources. It is a resilient system that is good for business, people and the environment." In light of these features, CE can generate direct benefits by reducing the risk profile of the assets and their financial claims, leveraging on some strong theoretical arguments, such as (Zara 2020): (i) the reduction of the exposure to price increase and volatility affecting procurement of virgin raw materials and energy from fossils; (ii) a better management of the natural capital that implies a lower exposure to climate risks, such as drought, flood, etc.; (iii) the reduction of negative externalities, such as carbon emissions, which increases the compliance and reduces their legal risks; and (iv) an orientation towards new circular revenue and business models, which implies higher efficiency by keeping the resources more in the economic circles and increases their level of resilience, in particular during crises, such as the case of COVID-19 pandemic (Zara *et al.* 2021). Starting from this theoretical framework, the relevance of the research lies in the fact that, for the first time, the de-risking hypothesis in the sustainability case is tested on a sample of circular assets, namely debt borrowers that are circular to a certain extent. Moreover, we wish to test our hypothesis by referring to not only bonds but also private debt. The scope of the research is introduced through the following generic question:

> "Does a company, which has a higher degree of circularity, show a lower credit risk?"

This is better designed distinguishing between short-term and long-term perspectives as stated in the following.

Hypothesis 1. *CE can drive a de-risking effect on debt of a* "circular borrower" *referring to PD* 1 *YR* (*short-term risk*).

Hypothesis 2. *CE can drive a de-risking effect on debt of a* "circular borrower" *referring to PD* 5 *YR* (*medium-term risk*).

Testing empirically if the CE can generate a de-risking effect is in the interest of both debt issuers, given the effects on capital provision and its cost, and debt-holders, who can bear a lower level of risk according to their lending decisions. Default risk of the borrower is the kind of financial risk that lenders suffer. We measured default risk in terms of PD for the borrower, distinguishing between PD short-term (one year) and PD medium-term (five years).

3. Data and Methodology

3.1. *The sample selection and definition*

We chose to focus on the European market — sampling companies listed in Europe 15 plus Switzerland — and on the manufacturing sector, even though with some relevant additions. The focus on the manufacturing sector was due to the fact that the CE has the greatest value creation within operations and production, where closed loops, efficiency and systemic approach untap value. Proving the lower riskiness of circular manufacturing companies constitutes a powerful incentive for the sector to seek resilience and risk hedging through circular strategies.

Following the Standard Industrial Classification (US SIC), the Manufacturing Section (Division D) comprises 20 industries (two-digit codes) and we considered 15 of them, excluding five (21: Tobacco, 27: Printing & Publishing, 29: Petroleum Refining, 32: Stone and Concrete and 34: Primary Metal Industries) which were not relevant for our analysis. We made an addition to the Manufacturing Section including two industries from Division B (Basic Metals and Oil & Gas Extraction), three from Construction (the whole Division C) and one from Division E (Utilities), so, at the end, we considered 21 industries (double-digit). Moreover, considering that we split sector 37 (Transport) into three sub-sectors and sector 39 (Other Industries) into two, we reached an overall amount of 24. Starting from the selected SIC codes, we used the Amadeus database to sample firms based on the industries of interest. In columns I and II of Table A.1 in Appendix A, all the industries selected are reported. The initial universe of 5,148,790 companies was filtered to 2,326,304 referring to relevant geographies within Europe; we found that 1,448 of these are public companies with info disclosure. The final sample comprised 1,052 companies with securities having data available for the time period of 2013–2018. When not already selected, we included European manufacturing companies in the pertinent industries belonging to the Ellen MacArthur Foundation CE100, reaching a total of 1,130 firms.[b]

3.2. *The measure of circularity*

Considering the given sample of 1,130, we needed to develop a specific metric for measuring their level of circularity in a way useful to build a continuous random variable which could be suitable for the intended analysis. In fact, measures of circularity are still lacking and largely under debate when they must be referred to at the meso-level (industry) and micro-level (company) as well as featured as financially material (Zara & Zanni 2019). This variable has been called the Circularity Score and it is consistent with expectations on the sustainability measures suggested by financial investors as well as adopted by scholars in the research field of sustainable asset classes (e.g. Khan 2016, Giudici & Bonaventura 2018). The computation of the score relied on the Refinitiv ESG Dataset [formerly Thomson Reuters Eikon (TR-E) ASSET4]. The score has been figured out in terms of the degree of circularity of the company in relation to that inside its industry. To further strengthen the predictive capacity of the CS for financial performance, the notion of materiality (i.e. Chong 2015) is introduced in the computation. The materiality factor refines the score by assigning higher circular performance to those companies focusing on issues particularly relevant to their industries. Throughout the analysis, we applied the

[b]CE100 is the name of the network of companies that have reached the EMF community in order to establish a network to promote and adopt circular practices in their operations and business models.

materiality framework proposed by the Sustainability Accounting Standards Board (SASB) that, together with the Global Reporting Initiative (GRI), is the most commonly used reporting tool for sustainability. Contrary to GRI which is seen as principle-based, SASB uses a rule-based approach that follows the SEC definition of materiality as interpreted by the United States Supreme Court and leaves less room for managerial maneuvering in the process of reporting (Murninghan 2013). In Appendix B, we describe more in depth the main features regarding the methodology for the calculation of the CS.

At the end of the process, a measure of circularity, that is relative to the industry level and is adjusted for materiality, is obtained. According to the presence of non-financial information disclosure provided by companies in the starting group of 1,130, it was possible to figure out the CS for a total of 222 companies for the time period of 2013–2017, which allowed us to set the panel dataset.

3.3. *Economic and financial variables*

With the sample list of 222, we gathered panel data from Bloomberg Dataset for various control variables, which are financial measures and risk-related ratios, for the same time period. These included: *Market Capitalization* to control for the equity size of the company and its market dimension; *Number of Employees* to control for the company's size; *Cash Flow* to control for the company's repayment capacity; *Return on Assets* (ROA) to control for the income performance of the company's assets, still capacity; *Net Debt to EBITDA* to control for the company's solvency and its level of risk; *Current Ratio* to control for the company's short-term financial obligations; and *Interest Coverage Ratio* still to control for the company's liquidity risk. For some companies we had missing data, mainly referring to the control variables Net Debt to EBITDA, Interest Coverage Ratio and ROA and for specific years in the time period considered.

3.4. *Risk of default variables*

As we stated in Sec. 1, we measure the risk of default in terms of the company's PD, in both short (1YR) and medium (5YR) time horizons. Data was gathered from Bloomberg Database. PD 1YR and PD 5YR are, alternatively, dependent variables in our analysis to understand the effect of circularity, in terms of SASB_CS, on the default risk measure.

In Table A.4 of Appendix A, the main descriptive statistics are reported referring to the following:

ID: Companies in the sample;
Year: Time period;
PD 1YR: Dependent variable, both absolute and log-transformed;
PD 5YR: Dependent variable, both absolute and log-transformed;

Circularity variables: We figured out both plain CS (CS) and CS with Materiality (SASB_CS);
CE100: A dummy which indicates companies in the EMF network;
Market Cap (€ml.): Control variable (size);
Number of Employees: Control variable (size; log-transformed);
Cash Flow (€ml.): Control variable (capacity);
Return on Assets: Control variable (capacity);
Net Debt on EBITDA: Control variable (solvency);
Current Ratio: Control variable (liquidity; log-transformed);
Interest Coverage Ratio: Control variable (liquidity).

In Table A.5 of Appendix A, we report the correlation matrix between the main circularity variable (SASB_CS) and the control variables in order to assess the degree of independence amongst them.

4. Analysis and Results

Using panel data for the time frame of 2013–2017 for the sample list of firms, a series of regression analyses were conducted. In order to reduce the skewness of the distribution of the data for statistical analysis, the dependent variables, PD 1YR and PD 5YR, and the control variables, Number of Employees and Current Ratio, were transformed by taking the natural logarithm.

We employed an OLS regression method with LOG PD 1YR and LOG PD 5YR as the dependent variables, according to the following regression model:

$$\begin{aligned}\log\mathrm{PD}_{i,t} = {}& \beta_1 * \text{SASB Circularity Score}_{i,t} + \beta_2 * \text{control variables}_{i,t} + \text{industry}_{\text{dummy}} \\ & + \text{time}_{\text{dummy}} + \varepsilon, \end{aligned} \tag{4.1}$$

where i refers to ID, $t = (2013; 2017)$, $\text{industry}_{\text{dummy}}$ is a vector of industry dummies for control and $\text{time}_{\text{dummy}}$ is a vector of year dummies for control.

4.1. *Short-term probability of default*

The results of the regression for SASB_CS on LOG PD 1YR are displayed in Table 1. An interpretation of the coefficients is provided since a log transformation of the dependent variable requires also a transformation of the coefficient. With a log-transformed dependent variable, a change in the independent variable is interpreted as a percentage change in the dependent variable.

The results of the model show that, *ceteris paribus*, CS, corresponding to the SASB_CS variable, has a statistically significant negative relationship with PD within one year. Since SASB_CS takes on a value between 0 and 1, the results showed that a 0.1-point increase in the SASB_CS variable will result in a 8.63% decrease in the one-year PD. This evidence confirms Hypothesis 1 for the given sample. In fact, a higher level of circularity, measured through SASB_CS, corresponds to a lower likelihood of default in the short term, in terms of one-year PD.

Table 1. Results of PD 1YR regression analysis.(+)

	PD 1YR	Interpretation of coefficient
SASB Circularity Score	**−1.98****	**−8.63%** change per 0.1-point increase
	(0.95)	
Market Cap	6.64E−06*	0.7% change per unit increase
	(3.97E−06)	
Net Debt to EBITDA	0	
	(0)	
Cash Flow	−6.54E−05*	−6.5% change per EUR 1,000 increase
	(3.80E−05)	
Log Number of Employees	0.45	
	(0.08)	
Interest Coverage Ratio	−1.19E−03***	−0.12% change per unit increase
	(−3.97E−04)	
Log Current Ratio	−0.04	−0.31% change per 1% increase
	(0.16)	
Return on Assets	−0.10***	−9% change per unit increase
	(0.02)	
Constant	−10.08***	
	(0.46)	
Observations	1,014	
Companies	207(++)	
R^2	0.26	
F(26,894)	24.97***	
	(0)	
RMSE	2.85	

Notes: ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. (+)Fixed effects are not shown for the sake of brevity. (++)We excluded 15 companies from the original 222 having missing data for the control variables. RMSE: Root-mean-square error.

Moreover, the regression results also showed that there are significant relationships between LOG PD 1YR and some of the control variables. However, since they are all in different units, it is not possible to compare the coefficients and understand the relative importance of each of the independent variables. In order to overcome this limitation, we conducted a dominance analysis, which determines the dominance of one independent variable over another and creates a ranking of the importance of each of the independent variables in estimating the dependent one. From the results of the dominance analysis, we determined that while SASB_CS has a statistically significant negative impact on PD 1YR, its relative importance is ranked as fourth in the cluster of all independent variables and fixed effects included in the model, after ROA, ranked as first, Industry Fixed Effects, ranked as second, and Interest Coverage Ratio, ranked as third.

4.2. *Long-term probability of default*

To test our second hypothesis that Circularity Score affects the long-term likelihood of default, we replicated the earlier regression analyses using the five-year PD as the

Table 2. Results of PD 5YR regression analysis.(+)

	PD 5YR	Interpretation of coefficient
SASB Circularity Score	**−0.68*****	**−4.93%** change per 0.1-point increase
	(0.27)	
Market Cap	1.71E−06	
	(1.07E−06)	
Net Debt to EBITDA	0	
	(0)	
Cash Flow	−2.50E−05**	−2.5% change per EUR 1,000 increase
	(1.18E−05)	
Log Number of Employees	4.57E−07	
	(4.28E−07)	
Interest Coverage Ratio	−2.59E−04***	−0.03% change per unit increase
	(8.42E−05)	
Log Current Ratio	0.01	
	(0.05)	
Return on Assets	−0.03***	−3% change per unit increase
	(0.01)	
Constant	−4.78***	
	(0.12)	
Observations	1,014	
Companies	207(++)	
R^2	0.27	
$F(26{,}894)$	27.14***	
	(0)	
RMSE	0.82	

Notes: ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. (+)Fixed effects are not shown for the sake of brevity. (++)We excluded 15 companies from the original 222 having missing data for the control variables.

dependent variable. The results of the regression of SASB_CS on LOG PD 5YR are reported in Table 2. Also, this analysis showed that, *ceteris paribus*, SASB_CS variable has a statistically significant negative relationship with the PD within five years. A 0.1-point increase in the SASB_CS will result in a 4.93% decrease in the five-year PD. Hypothesis 2 is confirmed too. In fact, a higher level of circularity reduces the likelihood of default in the long term, shown as the five-year PD. Moreover, the magnitude of risk reduction is not as strong as that found for the one-year PD.

As for the short-term analysis, we conducted a dominance analysis, to determine the relative importance and the ranking of each of the independent variables in estimating the dependent variable. From the results of the dominance analysis, the SASB_CS variable is found to have increased importance compared to control variables and fixed effects for determining PD 5YR. In fact, the rankings show that circularity moved up from fourth in terms of impact on PD 1YR to third in terms of impact on PD 5YR, replacing Interest Coverage Ratio which dropped to the fourth position. Thus, circularity has a slightly stronger relative importance for the long-term probability of default.

4.3. *Effect of time lag on the short-term and long-term probabilities of default*

We also conducted additional analyses to test for causal links in the relationship between circularity and likelihood of default by introducing a time lag. In the results so far, we were unable to distinguish the direction of the effect between circularity and likelihood of default. As previous regression results show a correlation and not a causation, we cannot say that higher circularity causes lower default rates.

If we were to lag the SASB_CS variable by one year, we would be able to determine whether the previous year's Circularity Score would have an effect on the next likelihood of default. Since the relationship is time-dependent, we would be certain that circularity would have a causal effect on the likelihood of default. Thus, 2014–2018 data on LOG PD and the control variables were used with the 2013–2017 data on SASB_CS. The new OLS model is stated as follows:

$$\begin{aligned}\log\mathrm{PD}_{i,t} &= \beta_1 * \text{SASB Circularity Score}_{i,(t-1)} + \beta_2 * \text{control variables}_{i,t} \\ &\quad + \text{industry}_{\text{dummy}} + \text{time}_{\text{dummy}} + \varepsilon. \qquad (4.2)\end{aligned}$$

By doing so, we were able to determine to what extent the previous year's SASB_CS causes the one-year PD and five-year PD to vary. The results of the analysis are introduced in Tables 3 and 4. They show that the lagged SASB_CS retains its statistically significant negative relationship with both the one-year PD as well as the five-year PD. In fact, a 0.1-point increase in the SASB_CS will result in a 9.01% decrease in the one-year PD and a 5.37% decrease in the five-year PD. This highlighted that there also exists a causal negative relationship between circularity and likelihood of default in both the short and long terms. So, we can argue that circularity causes a reduction of risk of default after issuers have increased their SASB_CS value. Even though the size of our sample is quite limited, we observe that in the lagged model, in comparison to the contemporaneous one, the coefficients for the main explanatory variable are higher for both PDs as dependent variables, thus reflecting a stronger risk reduction for the same CS variation; moreover, a slight increase of the R^2 is present for both analyses.

4.4. *Robustness analysis*

In this sub-section, we verify if our main results are robust to a series of alternative specifications for our main variable. Even though we tested several hypotheses and possible criticisms, for the sake of brevity we focus on two peculiar analyses that could affect the quality of our results: (a) different levels of information disclosure on circularity and (b) CS distribution.

(a) **Levels of information disclosure about circularity.** We observed the presence of a dual level of disclosure across the sample. In fact, five out of 14 sectors cover all the 140 indicators considered relevant for evaluating the degree of circularity, while the remaining sectors cover nearly 48 circular indicators.

Table 3. Results of PD 1YR time-lag regression analysis.(+)

	PD 1YR	Interpretation of coefficient
Lag SASB Circularity Score	−**2.31****	−**9.01%** change per 0.1-point increase
	(0.93)	
Market Cap	3.93E−06	
	(4.27E−06)	
Net Debt to EBITDA	0.01**	0.9% change per unit increase
	(0)	
Cash Flow	−5.95E−05	
	(3.67E−05)	
Number of Employees	2.61E−06*	0.3% change per 1,000 employees increase
	(1.51E−06)	
Interest Coverage Ratio	−1.02E−03***	−0.1% change per unit increase
	(3.45E−04)	
Log Current Ratio	0.02	
	(0.16)	
Return on Assets	−0.11***	−10% change per unit increase
	(0.02)	
Constant	−9.98***	
	(0.45)	
Observations	1,015	
Companies	207(++)	
R^2	0.28	
F(24,990)	18.55***	
	(0)	
RMSE	2.81	

Notes: ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. (+)Fixed effects are not shown for the sake of brevity. (++)We excluded 15 companies from the original 222 having missing data for the control variables.

Table 4. Results of PD 5YR time-lag regression analysis.(+)

	PD 5YR	Interpretation of coefficient
Lag SASB Circularity Score	−**0.77*****	−**5.37%** change per 0.1-point increase
	(0.26)	
Market Cap	1.24E−06	
	(1.14E−06)	
Net Debt to EBITDA	0**	0.3% change per unit increase
	(0)	
Cash Flow	−2.62E−05**	−2.6% change per EUR 1,000 increase
	(1.12E−05)	
Number of Employees	5.33E−07	
	(4.10E−07)	
Interest Coverage Ratio	−2.33E−04***	−0.02% change per unit increase
	(7.79E−05)	
Log Current Ratio	0.03	
	(0.05)	
Return on Assets	−0.03***	−3% change per unit increase
	(0)	

Table 4. (*Continued*)

	PD 5YR	Interpretation of coefficient
Constant	−4.75***	
	(0.12)	
Observations	1,015	
Companies	207$^{(++)}$	
R^2	0.30	
$F(24.990)$	16.8***	
	(0)	
RMSE	0.80	

Notes: *** $p < 0.01$, ** $p < 0.05$ and * $p < 0.1$. $^{(+)}$Fixed effects are not shown for the sake of brevity. $^{(++)}$We excluded 15 companies from the original 222 having missing data for the control variables.

In Table A.6 of Appendix A, we report the scope of disclosure according to all the industries which are considered in the sample. Moreover, different arrangements are taken depending on the legal category of the single name: for example, in the Construction Materials sector, firms with primary code indicating holdings of companies normally follow partial disclosure (48 indicators), while companies registered as general contractors usually follow full disclosure. Generally speaking, full disclosure is adopted by industries whose externalities have long been under the scrutiny of public opinions, such as Apparel & Textile, Food & Beverages, Construction and Energy. In order to investigate whether the persistence of the relations could be affected by different levels of information disclosure, we built the dummy variable Disclosure for each company in the sample, taking a value of 1 if adopting full disclosure, namely all the 140 indicators that we considered, and a value of 0 if adopting partial disclosure, namely only 48 indicators are present. We consequently run our model for each subsample and considering first PD 1YR and then PD 5YR as the dependent

Table 5. Robustness check related to information disclosure: Main results.

	PD 1YR (Full disclosure)	PD 1YR (Partial disclosure)	PD 5YR (Full disclosure)	PD 5YR (Partial disclosure)
SASB Circularity Score$^{(*)}$	−2.15***	−4.39**	−0.55**	−1.38**
	(0.81)	(1.91)	(0.23)	(0.53)
Observations	305	709	305	709
Companies	62	145	62	145
R^2	0.56	0.33	0.52	0.34
$F(16.274)$ (full disclosure)	30.21***	24.57***	28.88***	25.66***
F (22,607) (partial disclosure)	(0)	(0)	(0)	(0)
RMSE	1.83	2.86	0.51	0.81

Notes: * $p < 0.05$, ** $p < 0.01$ and *** $p < 0.001$. $^{(*)}$Control variables are included in the models but we do not report them for the sake of brevity.

Table 6. Robustness check related to SASB_CS distribution: Main results.

	PD 1YR (High SASB score)	PD 1YR (Low SASB score)	PD 5YR (High SASB score)	PD 5YR (Low SASB score)
SASB Circularity Score$^{(*)}$	−17.24***	−9.11**	−4.86***	−3.10***
	(2.39)	(3.80)	(0.66)	(1.03)
Observations	381	633	381	633
Companies$^{(+)}$	86	156	86	156
R^2	0.37	0.29	0.35	0.31
$F(24{,}608)$ (low SASB score)	14.68***	16.07***	15.02***	13.11***
F (16.364) (high SASB score)	(0)	(0)	(0)	(0)
RMSE	2.38	2.96	0.67	0.85

Notes: *$p < 0.05$, **$p < 0.01$ and ***$p < 0.001$. $^{(*)}$Control variables are included in the models but we do not report them for the sake of brevity. $^{(+)}$A number of companies higher than 207 implies that some of them moved from a cluster to another one during the period of observation.

variable. Table 5 shows a summary of results. We found that our main explanatory variable, SASB_CS, retains its statistical significance and negative sign for both sub-samples and for both default risk measures, stating that the level of information disclosure on circularity does not affect the persistence of our findings.

(b) **CS distribution.** In Appendix A, Fig. A.1 shows the distribution of SASB_CS values for the whole sample. We realized that companies have values that tend to be grouped into two main clusters, so we wondered whether having two clusters could affect the stability of our results. We fixed the threshold of SASB_CS at a value of 0.2 and created two sub-samples, the Low CS sub-sample, below the threshold, and the High CS one, above the threshold. We run our models in order to check the persistence of results across the two sub-samples and considering alternatively the two dependent variables of risk. Table 6 shows the main results. We found that the CS–risk relations are always significant and with negative sign, nonetheless the risk of default variable assumed. Differences in SASB_CS values, referring to high- and low-score clusters, do not affect the soundness of the relation, either in the short or in the long period.

5. Conclusions

We found that there is a significant and negative relation between circularity, measured through the CS, and the risk of default in terms of PD, both in the short and long terms. In fact, an increase in the CS value causes a corresponding decrease in the PD value. Both Hypotheses 1 and 2 in Sec. 2 are confirmed for a sample of European companies operating in industries that are strictly linked to resources — materials and energy — handling and consumption. In terms of size of risk reduction, coefficients featuring circularity variables are higher when the dependent variable is one-year PD in comparison with five-year PD. Moreover, through a time-lag regression, we positively tested the causal relation between circularity and default risk. This is an important evidence in favor of CE as a de-risking strategy for circular asset classes in debt markets. We also did a dominance analysis in order to understand the contribution of circularity in relation to that offered by a bunch of financial control variables that are normally considered as relevant to understand the default risk. We found that CS matters in terms of relevance, ranking as fourth when we considered PD 1YR and as third when we assumed PD 5YR. Moreover, we observed that dominance ranking is better in the medium term, when the dependent variable is five-year PD. This evidence argues in favor of the thesis that operating with a medium-term perspective helps circular practices to span their positive effects from the asset side to the capital structure of the company. The research also offered a contribution to the topic of circularity metrics that feature financial materiality at the meso-level (industry) and micro-level (company) through the design and first application of a brand-new metric that we called CS. In fact, the CS variable allowed including the degree of circularity in our quantitative analysis through a continuous variable which is material. Consistent with the industry focus of our sample, also the CS was particularly based on indicators pertaining to resource consumption and recovery.

Our findings have implication for both policymakers and businesses. Financial system regulators find evidence that sustainability field, especially with CE as its economic engine, can contribute to develop a more stable financial system through its de-risking effect. At the same time, circular asset classes can better match investors with a lower risk appetite, such as commercial banks and long-term institutional investors. Further research is necessary to better expand and confirm our findings. First, possible developments can be the extension of the analysis to a sample of companies that operate in service-based industries where CE principles refer mostly to resilience of business models and optimal usage of products in the economic circle. From the investor side, an important progress will be to link the de-risking effect to the financial performance, in terms of risk-adjusted return, in order to check if circularization of company's asset side can also generate asset classes with superior risk-adjusted performance.

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Appendix A. Tables and Figures

Table A.1. Sample composition.

I. Sector (SIC)	II. Group (SIC)	III. Industry (SICS)	IV. # N companies	V. ESG disclosing companies	VI. Companies with CS
20: Food Products & Beverages	20: 201–207; 208; 209	Food & Beverages	105	22 (20.9%)	22
22: Textile Mill Products;	22: 221–229;	Apparel & Textile	48	8 (16.7%)	8
23: Wearing Apparel;	23: 231–239;				
31: Leather Products;	31: 311–319;				
391: Other Manufacturing (Jewelry)	391				
24: Wood Products;	24: 242–244;	Containers & Packaging	35	7 (20%)	7
26: Paper Products	26: 261–267				
28: Chemical Products;	28: 281–289;	Chemicals	160	52 (32.5%)	48
30: Rubber and Plastics	30: 301–308				
34: Fabricated Metal Products	34: 341–349	Iron & Steel	51	9 (17.7%)	8
10: Basic Metals	10: 101–109	Metals & Mining	56	16 (29.1%)	12
36: Electrical & Electronic Equipment	36: 361–369	Electrical & Electronic Equipment	104	13 (12.5%)	13
35: Industrial Machinery and Computer Equipment	35: 351–359	Industrial Machinery	105	19 (18.1%)	6
37: Motor Vehicles and Trailers	371; 375	Motor Vehicles (Automobiles)	28	5 (17.9%)	3
37: Transport Equipment (Marine & Rail Transportation)	373; 374	Transportation Equipment	3	0 (0%)	
372: Transport Equipment	372	Air Freight & Logistic	12	11 (91.7%)	11
25: Furniture	251–254; 259	Furniture	9	0 (0%)	
39: Other Manufacturing	393–399	Toys & Sporting Goods	24	1 (4.2%)	1
38: Other Manufacturing	381–387	Medical Equipment	68	7 (10.3%)	7
49: Electricity, Gas and Steam	493	Utilities	79	25 (31.6%)	25
13: Oil & Gas Extraction	13	Oil & Gas	72	16 (22.2%)	16

Table A.1. (*Continued*)

I. Sector (SIC)	II. Group (SIC)	III. Industry (SICS)	IV. # N companies	V. ESG disclosing companies	VI. Companies with CS
C: Building Construction, General Contractors and Operative Builders; Heavy Construction	15; 16; 17	Construction Materials	171	39 (22.8%)	35
			1.130	250 (22.1%)	222

Notes: Columns I and II report the SIC industries selected and their corresponding codes; column III indicates the corresponding industry in the SICS classification; and columns IV–VI report figures about the sample composition.

Table A.2. Circularity Score: Indicators distribution and category weights.

Pillar	Category	#N indicators	Category weight	Pillar weight	New category weight	Pillar score
Environmental	Emissions	48	25%	80%	31%	Pillar Score = $\sum$ (New category weight × Category Score)
	Innovation	29	34%		43%	
	Resource Use	35	21%		26%	
Social	Community	6	4%	14%	32%	
	Product Responsibility	8	4%		26%	
	Workforce	5	6%		42%	
Governance	CSR Strategy	9	6%	6%	100%	

Table A.3. IWG score: Electric Utilities & Power industry.

Electric Utilities & Power			
ESG category	SASB disclosure topic	IWG score	Weight
Resource Use	— Water Management	4	0.43
	— Coal Ash Management	6	
Emissions	— Greenhouse Gas Emissions and Energy Resource Planning	1	0.13
	— Air Quality	2	
Innovation	— End-use Efficiency and Demand	7	0.43
	— Grid Resiliency	3	
Workforce			
Community			
Product Responsibility			
CSR Strategy			
Total		23	1

Notes: The example in this table represents the Utilities & Power sector, where categories belonging to the social and governance pillars are not assigned any score as they are not deemed to represent a material risk-opportunity for the industry: the indicators belonging to these categories will not be adjusted for materiality and their values reported by Refinitiv will be used as inputs for the CS. Instead, the clusters belonging to Resource Use, Emissions and Innovation will increase by 43%, 13% and 43%, respectively.

Table A.4. Descriptive statistics of the variables in the panel dataset.

Variable	Obs.	Mean	Std. dev.	Min.	Max.
ID*	1,110	112	64	1	222
Year	1,110	2015	1.41	2013	2018
Risk of default variables					
PD 1YR	1,110	0	0.01	0	0.10
LOG PD 1YR	1,110	−9.59	3.30	−20.81	−2.26
PD 5YR	1,110	0.02	0.03	0	0.19
LOG PD 5YR	1,110	−4.66	0.96	−7.19	−1.64

Table A.4. (*Continued*)

Variable	Obs.	Mean	Std. dev.	Min.	Max.
Circularity variables					
Circularity Score	1,110	0.16	0.16	0	0.47
SASB Circularity Score	1,045	0.19	0.19	0	0.56
CE100	1,110	0.07	0.25	0	1
Control variables					
Market Cap (€ ml.)	1,110	13,772	34,374	21	475,595
Log Number of Employees	1,110	28,806	59,946	0	616,505
Cash Flow (€ ml.)	1,109	1,456	3,432	−2,656	36,194
Return on Assets	1,110	4.44	8.83	−68.95	52.58
Net Debt To EBITDA	1,102	2.12	22.14	−295.47	625
Log Current Ratio	1,107	0.41	0.64	−3.12	3.21
Interest Coverage Ratio	1,089	50	320	−1,241	6,557

Table A.5. Correlation matrix among independent variables (SASB_CS and control variables).

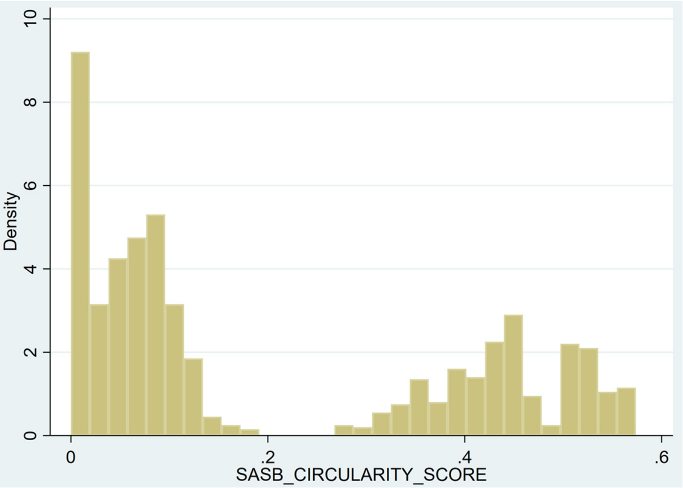
	SASB Circularity Score	Market Cap	Net Debt to EBITDA	Cash Flow	Number of Employees	Interest Coverage Ratio	Log Current Ratio	Return on Assets
SASB Circularity Score	1							
Market Cap	0.01	1						
Net Debt to EBITDA	−0.09	−0.02	1					
Cash Flow	−0.10	−0.67	−0.004	1				
Number of Employees	0.21	−0.01	0.02	−0.26	1			
Interest Coverage Ratio	0.08	−0.32	−0.02	0.10	0.03	1		
Log Current Ratio	−0.01	0.05	−0.01	0.02	0.12	−0.07	1	
Return on Assets	−0.19	−0.11	0.15	0.04	0.06	−0.19	−0.02	1

Table A.6. Scope of disclosure: Industry breakdown.

	Environmental			Social				Governance			
	EM	IN	RU	CO	PR	WO	HR	CS	SH	MN	Total
Circular Indicators	48	29	35	6	8	5	—	9	—	—	140

	Environmental			Social			Governance	
Industry	EM	IN	RU	CO	PR	WO	CS	Total
Air Freight	26	5	16	—	—	—	1	48
Apparel & Textile	48	29	35	6	8	5	9	140
Automobiles	26	5	16	—	—	—	1	48
Chemicals	26	5	16	—	—	—	1	48
Construction Materials(*)	48	29	35	6	8	5	9	140
Construction Materials(*)	26	5	16	—	—	—	1	48
Containers & Packaging	48	29	35	6	8	5	9	140
Electrical Equipment	26	5	16	—	—	—	1	48
Food & Beverages	48	29	35	6	8	5	9	140
Industrial Machinery	26	5	16	—	—	—	1	48
Iron & Steel	26	5	16	—	—	—	1	48
Medical Equipment	26	5	16	—	—	—	1	48
Metals & Mining	26	5	16	—	—	—	1	48
Oil & Gas	26	5	16	—	—	—	1	48
Utilities	48	29	35	6	8	5	9	140

Notes: EM: Emissions, IN: Innovation, RU: Resource Use, CO: Community, PR: Product Responsibility, WO: Workforce, HR: Human Rights, CS: CSR Strategy, SH: Shareholders and MN: Management. (*)Construction industry is split into two groups to properly show different levels of disclosure according to their primary status, either general contractors (140) or holdings of companies (48).



Notes: It refers to the distribution of the whole sample of 222 companies.

Fig. A.1. SASB_CS distribution in the sample.

Appendix B. CS Methodology

Starting from the methodology used by Thomson Reuters for evaluating the companies' ESG performance, the calculation of the Circularity Score is based on a bottom–up approach that requires multiple steps. Each score must be calculated for the single company for a specific year and adjusted for values reported by industry peers.

Preliminarily, it is necessary to check whether companies in our investable universe disclose their ESG performance through Thomson Reuters: for each disclosing company, it was possible to calculate the Circularity Score. Starting from our original sample of 1,130 companies, 222 disclosed the needed data for figuring out their CS. The disclosing rate of industries in the sample is summarized in column V of Table A.1 in Appendix A.

First of all, it was necessary to aggregate ESG data by industry. Data were retrieved from Datastream and aggregated by industry through a routine in Excel Visual Basic (VBA). The resulting dataset records for each array have the following fields: Company name, Category, Indicator and raw values reported in the six years (2013–2018) that were put into matrix in a format consistent with that shown in Fig. B.1.

Having the dataset of indicators ready, the process was featured with the following steps:

- **Exclude indicators non-relevant to the Circular Economy.** A total of 140 indicators are considered as relevant for the Circular Economy throughout the analysis. These indicators are used to calculate the weights applied to categories and pillars regardless of those actually reported by the companies, resulting in a lower final score for firms adopting partial disclosure. For example, firms focusing their ESG efforts on governance will obtain a relatively low score due to only 6% weight of indicators selecting that origin from the G-pillar.

Company	**Category**	**Indicator**	**2018**	**2017**	**2016**	**2015**	**2014**	**2013**
Company1	Cat1 : Cat7	Ind1 : Ind140	(1)C-c1-I1 : (1)C-c7-I140	. . .	. . .	. . .	. . .	(6)C-c1-I1 : (6)C-c7-I140
:								
Company*n*								

Fig. B.1. Example of structure of the dataset.

- **Calculate the Percentile Score for the company for each indicator.** The Percentile Score formula counts the number of companies in the industry performing worse and equal for a given indicator. It returns a number in the [0,1] range and represents a normalization of the values according to the peer group. The Percentile Score allows for eliminating the trouble of non-reported values. Non-reported values return a score equal to 0 by default, while indicators that report a value equal to 0 are factored in the Percentile Score formula and return a score higher than 0 depending on the performance of the peer group. In this way, companies with more comprehensive scope of disclosing obtain a higher score. The Percentile Score formula for a company in its industry for a given year is formulated as

$$\text{Score}_n = \frac{\text{No. of companies with worse value} + \frac{\text{No. of companies with same value}}{2}}{\text{No. of companies with a value}}.$$

- **Calculate the Category Score as arithmetic mean of indicators pertaining to the category.** Indicators are assigned a polarity according to their state being either positively or negatively related to their performance over the given category; values having negative polarity (e.g. NO_x emissions) are translated in their reverse (1-score). For each category, the average Category Score is computed as the mean of indicators as follows:

$$\text{Category Score} = \frac{\sum \text{Scores of indicators in the category}}{\text{No. of indicators in the category}}.$$

- **Calculate the Pillar Score.** The Pillar Score is the weighted sum of Category Scores, where weights are defined as new category weight and calculated as the ratio between category and pillar weights. The formula for calculating the Pillar Score is as follows:

$$\text{Pillar Score} = \sum \text{New category weight} * \text{Category Score},$$

  where the input new category weight is formulated as

$$\text{New category weight} = \frac{\text{Category weight}}{\text{Pillar weight}_1},$$

  and the two inputs, category weight and pillar weight$_1$, are formulated as

$$\text{Category weight} = \frac{\text{No. of indicators in the category}}{\text{Total no. of indicators}}$$

$$\text{Pillar weight}_1 = \sum \text{Category weights in the pillar.}$$

  Table A.2 in Appendix A reports the distribution of the 140 selected indicators amongst the seven categories and their corresponding weights for the Pillar Score calculation.

- **Calculate the Circularity Score.** Finally, the plain Circularity Score is computed as the weighted sum of the three pillars, where the weight is defined as the number of indicators belonging to the pillar through categories in the pillar over the total number of indicators through all the categories considered. We indicate the pillar weight with the notation Pillar weight$_2$ and it is formulated as

$$\text{Pillar weight}_2 = \frac{\text{No. of indicators in the pillar}}{\text{Total no. of indicators}}$$

Moreover, CS takes into consideration financial materiality, being calculated applying the Materiality Map developed by the US SASB. The SASB Materiality Framework is based on a Materiality Map which is a matrix that outlines 26 sustainability-related business issues. According to each industry, every issue is ranked as: highly material, material or non-material. The taxonomy of industries is formalized in the Sustainable Industry Classification System® (SICS®), created by SASB in order to cluster companies on the basis of their sustainability-related risks and opportunities. The SICS is composed of 11 business areas (e.g. consumer goods, healthcare, infrastructure and renewable & alternative energy) and divided into 77 industries (e.g. consumer goods comprise apparel, appliances, e-commerce, etc.). For each industry, SASB appointed an Industry Working Group (IWG) which is in charge for assessing the level of materiality for each of the 26 business issues.[c] The final output of Industry Working Groups is a matrix where few topics (in a range of 2–11) are identified as material for the given industry and assigned a score from 1 to 10.

Applying the Materiality Map to the purpose of CS calculation requires some adaptations, namely the following:

- **Reconcile the sample firms' SIC codes with SICS sectors utilized by SASB in the Materiality Map.** For most industries, there is a straightforward correspondence between the two classifications; nonetheless, the SICS Look-up Tool allows to determine the primary SICS industry for nearly all companies globally that are listed on the US exchanges searching by the name or ticker. Comparable one can be used whenever a firm in the sample is not comprised in the database. After having reconciled the SIC and SICS industries, we assumed that material topics for the SICS industry are also material for the corresponding SIC industry. Columns I–III of Table A.1 in Appendix A summarize the reconciliation between the two taxonomies.
- **Assign material issues to categories.** By doing so, it is possible to overweight material categories. The methodological choice to assign material topics to categories rather than establishing a direct linkage between indicators and material issue could be recognized as least discretionary. In fact, there is more conformity between the fields covered by issues and categories, while working at the indicator

[c] The IWG score is the fundamental input used to determine the level of materiality of a given issue: it measures the percentage of industry experts that consider a given variable material for the reference industry. Working groups are representative of corporations, market participants and public interest intermediaries; their feedback is collected via an online survey, and further investigated by SASB's research team through one-to-one interviews.

level would have resulted in a more cumbersome process and a higher hazard of errors.

- **Increase category scores through IWG scores reported by SASB.** The percentage is calculated as the ratio between the IWG score assigned to one category and the total IWG scores for that industry. An example regarding Electric Utilities & Power sector is reported in Table A.3 of Appendix A.

The outcome of the adjustment is to have a measure which allows to recognize if companies in the sample are engaging in efforts that positively impact on the resilience of the ecosystem or, on the contrary, they rely more on elements that are only marginal and may be classified as green washing. The process results in the SASB_CS for a given company in a specific year, which is based on plain CS and adjusted by the SASB Materiality Map pertaining its industry.

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