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Do Circular Economy Strategies Create Value? Evidence From the United States

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ABSTRACT

This study provides the first large-scale, longitudinal evidence on how capital markets interpret circular economy (CE) strategies for US firms. Using more than 7500 ESG reports of US firms (1998–2023), we map the disclosure of CE practices in the United States and examine their valuation effects. We show that references to CE terminology surged after the Paris Agreement, whereas detailed disclosures of concrete strategies declined, suggesting a rhetorical rather than substantive turn. We further show that CE communication is, on average, negatively associated with Tobin's Q. However, disaggregating the 10R framework uncovers substantial heterogeneity: Medium-loop strategies reduce firm value, whereas short- and long-loop strategies have no significant effect. We further identify four mechanisms, such as financial slack, greenwashing, stock liquidity, and information asymmetry, that condition these relationships. By integrating granular strategy-level evidence with theoretically grounded mechanisms, our study clarifies prior contradictory findings on the financial impact of CE on firm performance and advances understanding of when, why, and how CE strategies are valued by capital markets.

1 | Introduction

The increasing urgency of climate change has placed sustainability at the center of corporate strategy and policy debates. International agreements, most notably the 2015 Paris Agreement, have intensified pressure on firms to reduce their environmental footprints and adopt business models that decouple growth from resource consumption. Among the proposed alternatives, the circular economy (CE) has emerged as a central framework. CE seeks to close material loops through practices such as reuse, repair, and recycling, thereby extending product lifespans and minimizing waste. Although policymakers actively promote CE and firms increasingly highlight it in their sustainability agendas, the capital-market implications of CE remain insufficiently understood, and it is unclear whether investors differentiate across CE strategy types (short, medium, and long loops) or treat circularity as a homogeneous signal. This gap is especially salient in the United States, where circularity is less policy mandated and more market driven, increasing the importance of disclosure as a channel through which CE commitments are assessed by investors. Accordingly, in the market-driven US setting, critical questions therefore remain: Does CE create or erode value, under what conditions, and through which mechanisms?

Recent studies such as Palea et al. (2023) and Mazzucchelli et al. (2022) provide valuable early contributions by differentiating among CE practices and examining international samples. Yet findings across the literature remain fragmented and often contradictory. Some studies report positive associations between CE adoption and firm performance, whereas others document negligible or even negative effects. A key reason for this inconsistency lies in how CE is typically measured. Many studies aggregate diverse activities into broad categories, overlooking important differences in complexity, risk, and timing. Short-loop strategies, like refusing and reducing, often generate immediate efficiency gains; medium-loop strategies (e.g., repairing, remanufacturing, and repurposing) involve more complex processes with uncertain or delayed payoffs. Collapsing these into a single construct obscures heterogeneity and likely contributes to inconsistent findings. Moreover, the mechanisms through which CE may influence performance remain underexplored. CE initiatives can yield efficiency gains and signal environmental commitment, but they may also be perceived as symbolic or greenwashing, thereby undermining credibility with investors. These limitations point to the need for granular and systematic evidence on *whether*, *when*, and *how* CE strategies matter for firm value.

Conceptually, CE has been framed as a cornerstone of corporate sustainability (Blomsma and Brennan 2017). Its central aim is to decouple economic development from finite resource consumption by closing loops and extending product lifecycles (Korhonen et al. 2018). Initially encapsulated in the "3Rs" of reduce, reuse, and recycle, CE has since expanded into the 10R framework, which encompasses strategies such as rethinking, reducing, reusing, repairing, remanufacturing, recycling, and recovering (Potting et al. 2017; Reike et al. 2018). The objective is to preserve the value of products, materials, and resources for as long as possible, thereby reducing waste and limiting demand for virgin extraction (Stahel 1994; Rosa et al. 2019). Beyond environmental benefits, CE has been associated with improvements in product design (Bocken et al. 2016), supply chain management (Barros et al. 2021; Salvador et al. 2021), and production processes (Panchal et al. 2021), reinforcing its appeal as both an ecological and strategic business model.

CE strategies have gained prominence in part due to increasing regulatory stringency and environmental policy debates (Geissdoerfer et al. 2016; Maeder and Fröhling 2024). Environmental economics provides the theoretical foundations for understanding why and how such strategies emerge, offering insights into the valuation of natural capital, the pricing of externalities, and the design of market-based mechanisms that can incentivize firms to adopt circular practices (Calvo-Porral and Lévy-Mangin 2020; Geissdoerfer et al. 2018). In this sense, CE can be interpreted not merely as a voluntary corporate choice but also as an endogenous reaction to increasing policy stringency and regulatory pressures. Although these theoretical underpinnings highlight why firms may be increasingly driven toward circular models, the extent to which such adoption translates into tangible financial benefits remains debated. On the one hand, several studies show that CE strategies enhance firm performance through cost efficiency, innovation, and reputational benefits (Kristoffersen et al. 2021; Liu et al. 2023; Mazzucchelli et al. 2022; Y. Yu, Xu, et al. 2022; Z. Yu, Khan, and Umar 2022). On the other hand, others highlight more complex dynamics. D'Angelo et al. (2023) find curvilinear effects, with the performance improving at low adoption levels but deteriorating beyond a threshold. Van Loon et al. (2022) show that firms often need up to 7 years to make circular models profitable due to high upfront costs, reverse-logistics challenges, and uncertain returns. This conflicting evidence suggests that CE's value relevance is conditional on the specific strategies pursued, how they are implemented, and how investors interpret them.

Three gaps are particularly salient in the literature. First, we lack clarity on which CE strategies create or destroy value, under what conditions, and through which mechanisms. Second, prior research has largely relied on conceptual frameworks (e.g., Bocken et al. 2016; Lüdeke-Freund et al. 2019) or small-sample case studies (e.g., Ranta et al. 2018; Santa-Maria et al. 2022), leading to fragmented insights. Third, existing measures of CE adoption, such as survey indicators (Weisberg 2005) or keyword counts in ESG reports (Stewart and Niero 2018), struggle to capture the heterogeneity of CE practices. Collectively, these limitations highlight the need for a standardized and comprehensive approach to identifying firm-level CE strategies and assessing their financial impact. This need is pressing, given the growing attention of investors, regulators, and managers to how circularity defines firm performance.

To address these gaps, we draw on a novel dataset of more than 7500 ESG reports from US firms over 1998–2023. This 26-year period enables us to provide the first long-run evidence on the evolution of CE communication and its valuation by capital markets. Our descriptive analysis shows that references to "circular economy" and "circularity" remained marginal until the mid-2010s but surged 20-fold between 2015 and 2021, coinciding with the Paris Agreement. Yet, this surge is driven largely by generic references: Disclosures of specific 10R strategies such as repair, remanufacturing, or repurposing have declined, whereas recycling continues to dominate. These patterns suggest that firms increasingly invoke CE rhetorically while providing less detail on concrete practices, raising concerns about the substantive credibility of CE reporting.

We then examine the financial consequences of CE communication by linking disclosures to next year's Tobin's Q. On average, CE communication is significantly and negatively associated with firm value. This suggests that investors discount CE disclosures, likely due to doubts about credibility, specificity, or strategic relevance. Consistent with prior literature, such skepticism may also reflect long payback horizons, high upfront costs, and uncertain outcomes associated with circular investments (Sarja et al. 2021; Bressanelli et al. 2019; Govindan and Hasanagic 2018; Jaeger and Upadhyay 2020; Kirchherr et al. 2018; Urbinati et al. 2021). Disaggregating disclosures into short-, medium-, and long-loop categories reveals a more nuanced picture. Only medium-loop strategies are negatively associated with Tobin's Q, whereas short- and long-loop strategies show no significant effect. These differences likely reflect investors' risk perceptions. Recycling, for example, has long benefited from regulatory support (Ghisellini et al. 2016; Ranta et al. 2018) and widespread implementation (Eichner and Pethig 2001; Gaustad et al. 2010), lowering its perceived risk. By contrast, medium-loop strategies such as repair and remanufacturing require complex reverse logistics, involve quality uncertainties, and entail significant labor and technical costs (Guide 2000; Lüdeke-Freund et al. 2019; Kühl et al. 2022; Morseletto 2020), which likely explain investors' more negative assessments.

Leveraging the breadth of our dataset, we examine mechanisms that condition the association between CE strategies and firm value. The negative association is stronger when financial slack is higher, suggesting that investors view circularity spending as inefficient resource allocation (Zhang 2022;

Xia et al. 2023). It is also stronger when CE communication is more generic, proxied by higher textual similarity across firms, consistent with greenwashing concerns (He et al. 2025). In addition, the association intensifies for firms with higher stock liquidity, in line with a more risk-averse investor base discounting long-horizon projects. Finally, it is more negative when information asymmetry is higher, which constrains investors' ability to assess the credibility of CE commitments. Together, these patterns suggest that investor skepticism varies systematically with firms' financial flexibility, the specificity of disclosure, investor base, and the information environment.

These results contribute to the literature in four main ways. First, we rely on a large dataset of more than 7500 ESG reports from US firms spanning 1998–2023, a 26-year period that is substantially longer and broader than any prior study in this field. This unique sample enables us to provide one of the first large-scale, longitudinal analyses of the implementation of CE in corporations, moving beyond the limitations of earlier research that typically relied on surveys, small samples, or nonstandardized proxies (e.g., Khan et al. 2020; Kristoffersen et al. 2021; Ranta et al. 2018; Santa-Maria et al. 2022; Ünal et al. 2019). Recent large-sample work has begun to explore this question (e.g., Palea et al. 2023; Yin et al. 2023; Mocanu et al. 2021), but these studies cover shorter time frames, focus on a narrower set of CE practices, or examine different institutional contexts. We extend this emerging stream by analyzing a longer time horizon, a broader range of strategies through the 10R framework, and disclosures in the US market. With this approach, we offer a holistic descriptive analysis of how CE strategies are implemented and assess which strategies are value enhancing or value reducing.

Second, we employ the established 10R framework (Potting et al. 2017; Reike et al. 2018) to systematically identify and categorize 10 distinct CE strategies. Building on this framework, we developed a structured and comprehensive dictionary of over 43,000 CE-related terms that explicitly covers all dimensions of the 10R model. This unique dictionary allows us to capture the full spectrum of firm-level activities across short-, medium-, and long-loop strategies by detecting the presence of these terms in companies' ESG reports. By relying on this novel approach, our study moves beyond prior research that often relied on narrower constructs or smaller sets of keywords. Instead, we provide a detailed, strategy-level analysis of the financial consequences of CE adoption, offering a nuanced interpretation of why earlier findings on the financial impact of CE have been inconsistent. To the best of our knowledge, this is the first study to combine automated content analysis with such a large, systematically designed dictionary, thereby acknowledging the heterogeneity of CE strategies and enabling a more granular understanding of their financial implications.

Third, our study extends the literature by focusing on the United States, a context largely overlooked in CE research. Unlike Europe and Asia (e.g., China), where regulatory frameworks and policy incentives actively promote circularity (e.g., D'Angelo et al. 2023; Liu et al. 2023; Y. Yu, Xu, et al. 2022; Z. Yu, Khan, and Umar 2022), federal regulation and governmental support for CE are largely absent in the United States. This makes the United States a distinctive setting where CE adoption is shaped primarily by firm-level choice and market forces. By situating our analysis in this environment, we provide novel insights into how capital markets evaluate CE in the absence of strong institutional support.

Finally, we move beyond recent research that primarily asks whether CE affects firm value (e.g., Yin et al. 2023; Palea et al. 2023; Mocanu et al. 2021) by examining why these effects occur. Specifically, we test mechanisms related to financial slack, greenwashing perceptions, earnings volatility, and information asymmetry, which condition how markets interpret CE communication. By identifying these channels, we provide systematic evidence on the drivers of investor skepticism and show why circularity may be penalized in the US context. In this way, our study complements and extends recent work by offering new evidence on both the scope of CE practices and the mechanisms shaping their financial relevance.

The following section provides the theoretical background and specifies the research questions of this study. Section 3 describes the research design, our sample, and variables. Section 4 discusses the empirical findings of our models, alongside endogeneity and mechanism tests. Section 5 provides robustness checks. Lastly, Section 6 concludes the paper.

2 | Literature Review

2.1 | The CE as a Heterogeneous Construct

Prior research identifies a wide variety of drivers motivating companies to implement CE, ranging from regulatory requirements and environmental protection to efficiency gains and opportunities for economic growth (Govindan and Hasanagic 2018). These drivers can be both internal and external. Internal factors include improving operations, reducing supply chain dependence, avoiding price volatility, strengthening brand value, improving cost efficiency, and creating new business opportunities (Tura et al. 2019). Recent studies emphasize that CE adoption is jointly shaped by firm governance, financial strategies, and innovation capabilities, highlighting the systemic nature of sustainability transitions across different institutional contexts (Agyemang, Yusheng, and Osei 2025; Osei et al. 2025). CE adoption is also closely linked to corporate social responsibility, which can enhance a company's reputation and, in turn, improve financial performance (Fortunati et al. 2020). By lowering costs through efficiency or generating revenues through new offerings, some CE practices directly create financial benefits. In this sense, CE can complement traditional environmental-economics instruments by reducing compliance costs or serve as a substitute when such instruments are absent or weakly enforced. Because these choices are shaped by regulatory, market, and firm-specific conditions, CE adoption is inherently nonrandom, which has implications for how its effects can be studied.

The first challenge for research, however, is that this rapid diffusion has produced considerable conceptual heterogeneity. The emergence of the CE can be traced back to Boulding's (1966)

Spaceship Earth metaphor, depicting a closed-loop Earth where the economy and the environment coexist in perfect equilibrium. Since then, the notion of CE has evolved and developed through successive waves of interpretations (Reike et al. 2018). Early work emphasized the "3Rs" of reduce, reuse, and recycle, highlighting waste reduction and resource efficiency. Over time, the scope expanded to include related concepts such as eco-design, industrial ecology, cleaner production, cradle-to-cradle, product-service systems, and the 10R framework, each stressing different levers for circularity. This evolution generated a proliferation of definitions across academic, policy, and professional domains, underscoring both the richness and the contested nature of the concept. After reviewing 221 definitions, Kirchherr et al. (2023, 7) propose one of the most comprehensive formulations, describing CE as "a regenerative economic system which necessitates a paradigm shift to replace the 'end of life' concept with reducing, alternatively reusing, recycling, and recovering materials throughout the supply chain, with the aim to promote value maintenance and sustainable development, creating environmental quality, economic development, and social equity, to the benefit of current and future generations. It is enabled by an alliance of stakeholders (industry, consumers, policymakers, academia) and their technological innovations and capabilities." Furthermore, Korhonen et al. (2018) characterize CE as an essentially contested concept (Gallie 1956) consisting of multiple subconcepts, whereas Blomsma and Brennan (2017) similarly describe it as an umbrella construct that requires acknowledging the wide range of strategies it covers (see also Blomsma et al. 2023). This conceptual plurality highlights the need for a comprehensive framework to capture the breadth of practices that fall under the CE label.

At the same time, transitioning from a linear to a circular model introduces barriers that are cultural, regulatory, technological, and market based (Kirchherr et al. 2018). Among these, market barriers are especially pressing. They include the low cost of virgin materials, high upfront investment requirements, uncertain returns, long payback times, and the dominance of short-term financial metrics in decision-making (Bressanelli et al. 2019; Govindan and Hasanagic 2018; Jaeger and Upadhyay 2020; Kirchherr et al. 2018; Urbinati et al. 2021). Financial barriers are also significant, including lack of resources, costly investments in circular models, and unclear business cases (Vermunt et al. 2019). Sarja et al. (2021), in reviewing catalysts and obstacles, underscore the tension between the motivating effect of potential financial benefits and the inhibiting effect of outcome uncertainty on CE adoption. They identify ambivalent factors, such as regulation, which may either support or impede the transition depending on context.

2.2 | The Impact of the CE on Firm Performance

Against this backdrop, a central question is how CE affects firm performance. However, research in this area is still nascent (Kanzari et al. 2022) and provides no consensus on the financial implications of CE adoption. On the one hand, several studies document positive effects. Kristoffersen et al. (2021), surveying 125 European firms, find that CE adoption enhances environmental and financial performance as well as competitiveness and corporate reputation. Z. Yu, Khan, and Umar (2022), drawing on a survey of Chinese automobile firms, find that CE practices in purchasing and design are associated with improvements in both economic and operational performance. Liu et al. (2023), using data from 255 Chinese manufacturers, conclude that circular manufacturing practices positively influence both financial and environmental outcomes. Focusing specifically on financial performance, Y. Yu, Xu, et al. (2022) survey 308 Chinese manufacturing firms and find that CE adoption improves financial results. Similar findings emerge in Europe. Scarpellini et al. (2020) show that CE-related environmental capabilities enhance financial performance in 87 Spanish firms, whereas Mazzucchelli et al. (2022), studying 404 Italian firms, find that CE adoption boosts financial performance through reputational gains. Khan et al. (2020), surveying 220 Italian manufacturers, also report improvements, though they note that financial outcomes lag behind environmental performance, competitiveness, and reputation.

Recent studies have started to provide large-sample evidence on the financial consequences of CE adoption. Palea et al. (2023), for example, study a global sample of listed firms from 2010 to 2019 and examine the financial consequences of selected CE strategies, focusing on eco-design, take-back systems, and waste reduction. Their analysis shows that these practices can shape profitability, debt financing, and market valuation and distinguishes between pre– and post–Paris Agreement effects. Our study extends this line of work by covering a longer time period, examining a broader set of strategies through the 10R framework, and focusing on how CE disclosures are interpreted in the US capital market.

On the other hand, other studies highlight more nuanced or negative effects. D'Angelo et al. (2023), drawing on Eurostat data from 10,618 executives, show that CE adoption improves turnover at low levels but reduces it beyond a certain threshold. Blasi et al. (2021) find that CE adoption benefits low- and medium-performing SMEs but provides no financial gains for high performers. Van Loon et al. (2022), in a case study, show that it took 7 years before a circular model became profitable due to high upfront investments and underestimated operating costs. Existing evidence indicates that the effects of sustainability-related disclosure and CE practices vary with firm-level characteristics, including ownership structure and innovation capacity, and may follow nonlinear patterns (Zhou et al. 2025; Adam et al. 2025).

Taken together, these studies reveal no clear consensus on CE's financial impact. Importantly, most of the evidence is based on small-scale surveys or case studies, which identify correlations rather than causal effects. Such approaches rarely account for unobserved firm-level heterogeneity, raising concerns about omitted variable bias and limiting the reliability of conclusions. This methodological limitation highlights the need for large-scale, standardized approaches. Our study addresses this gap by focusing on the United States, leveraging more than 7500 ESG reports from 1998 to 2023, and systematically categorizing CE strategies through the 10R framework. The US setting is particularly relevant because, unlike Europe or China, CE adoption is driven primarily by firm-level choice and market forces rather than by regulatory mandates, offering new insights into how capital markets evaluate circular strategies in the absence of strong institutional support.

2.3 | The Need for a Standardized Framework

A key reason for inconsistent findings is that prior research often treats CE as a homogeneous construct, neglecting its inherent heterogeneity (Bocken et al. 2016; Lüdeke-Freund et al. 2019; Ranta et al. 2018; Santa-Maria et al. 2022; Ünal et al. 2019). As such, the financial consequences of CE adoption are expected to be highly strategy specific. Consistent with this observation, Table 1 illustrates the diversity of constructs used in prior research. Although some studies adopt broad definitions (Kristoffersen et al. 2021), others focus on specific practices such as waste treatment and recycling (Mazzucchelli et al. 2022), circular purchasing and design (Z. Yu, Khan, and Umar 2022), ecological design and investment recovery (Y. Yu, Xu, et al. 2022), or circular product design and cleaner production (Liu et al. 2023). Unsurprisingly, different strategies have been linked to different financial outcomes. Yet despite this diversity, the literature still lacks a standardized, replicable framework to capture CE practices in a systematic manner.

Prior attempts in the literature rely on narrow or indirect measures. Specifically, Stewart and Niero (2018), for example, use limited keyword counts in ESG reports, whereas survey-based approaches (e.g., Weisberg 2005) provide standardized responses but are subject to design biases and interpretation issues. To address this limitation, we adopt the 10R framework developed by Potting et al. (2017) and Reike et al. (2018), which distinguishes between short-, medium-, and long-loop strategies.[1] This framework has been widely used across case studies (Bjørnbet et al. 2021) and applied to research on topics ranging from digitalization (Kalogiannidis et al. 2022) and business model innovation (Izquierdo-Montfort and De Rongé 2025; Gamonal et al. 2025) to supply chains (Muller et al. 2022) and CE targets (Morseletto 2020).

Building on this foundation, we construct a holistic library of 43,233 terms covering the full set of CE strategies within the 10R framework. Applying this to US firms' ESG reports enables us to systematically identify which strategies firms adopt and to assess how these strategies influence future firm value. In doing so, our study is among the first to empirically recognize the heterogeneous impact of CE strategies on financial outcomes. This leads to the following research questions:

RQ1. What CE strategies are adopted by US companies?

RQ2. How do CE disclosures affect firm value?

RQ3. Which specific CE strategies (short, medium, or long loops) influence firm value?

2.4 | Mechanisms Linking CE and Firm Performance

Although prior studies examine whether CE adoption influences performance, much less attention has been paid to the mechanisms that may explain these effects. A few contributions suggest that CE practices can reduce costs through resource efficiency, stimulate innovation, or strengthen stakeholder relations by signaling environmental commitment (Kristoffersen et al. 2021; Liu et al. 2023). Others raise concerns that CE initiatives may be perceived as symbolic or as instances of greenwashing, eroding credibility and discouraging investor support (Blasi et al. 2021; Kirchherr et al. 2018).

Beyond such tentative arguments, systematic empirical evidence on mechanisms remains scarce. Most existing studies document correlations without exploring the conditions under which investors reward or penalize CE practices. Yet several plausible channels have been highlighted in the broader literature. Firms with greater financial slack may be scrutinized more heavily when allocating resources to uncertain circular projects, whereas high earnings volatility can amplify perceived risks. Similarly, the distinctiveness of CE communication may determine whether disclosures are viewed as credible or dismissed as greenwashing, and the degree of information asymmetry may condition investors' ability to evaluate the credibility of CE commitments. Related evidence suggests that governance and financial conditions shape how sustainability disclosures are interpreted by stakeholders, influencing their perceived credibility and signaling value (Agyemang, Osei, and Kongkuah 2025).

The lack of empirical research on these mechanisms is a critical gap. Addressing it is essential not only to reconcile inconsistent findings but also to build a deeper understanding of how capital markets interpret CE initiatives. Our study contributes by explicitly testing these channels, thereby advancing knowledge of why and under what conditions CE disclosures influence firm value. Accordingly, we pose a final research question:

RQ4. What mechanisms determine the extent to which CE disclosures affect firm value?

3 | Data, Variables, and Method

3.1 | Sample

Although prior research has centered predominantly on European and Chinese firms (D'Angelo et al. 2023; Kristoffersen et al. 2021; Farooque et al. 2022), this paper focuses on stand-alone ESG reports provided by firms listed on the NYSE and the NASDAQ between 1998 and 2023. We focus on stand-alone ESG reports due not only to their growing prevalence across the broader economy but also because, as highlighted by Cho et al. (2012) and Unerman and O'Dwyer (2007), such reports enhance organizational accountability and serve as a powerful means of assessing a firm's social and environmental impact.

To collect our sample of ESG reports, we proceed in two steps. At each step in the sample selection, any observation with missing data for the required control variables is discarded. In the first step, we hand-collect all the ESG reports from the firms listed on the NYSE and NASDAQ. We obtain 8185 ESG reports between 1998 and 2023. If a report is found on the company's website, we rename it using the company's ticker, with the fiscal year of the release separated by a hyphen (e.g., "INTC-2015"). If the report is not found on the company's website, we use Google and search for the report based on a list of keywords. We first mention the company name, the country of the company's headquarters, and the fiscal year, "+ESG

TABLE 1 | Prior literature on the impact of CE on firm's performance.

		Financial variables		CE variables		
Article	**Method**	**Concept used**	**What it includes**	**Concept used**	**What it includes**	**Link with 10R**
Mazzucchelli et al. (2022)	Survey (404) Italy Manufacturers	Financial performance	Not clearly defined	CE	Waste treatment	R8
					Reduction	R2
					Recycling	R8
Z. Yu, Khan, and Umar 2022	Survey (286) China Automobile	Economic performance	Profitability, market share	CE	Circular purchasing	R2, R6, R8
		Operational performance	Quality, new product		Circular design	R2, R5, R6, R8
Kristoffersen et al. (2021)	Survey (125) Europe Multiple industries	Firm performance	Environmental performance, financial performance, competitiveness, and corporate reputation. Not further defined	CE	CE	R2, R3, R4, R5, R8
Khan et al. (2020)	Survey (220) Italy Manufacturers	Environmental performance	Reduced energy consumption, reduced waste generation, reduced atmospheric pollution, decreased water consumption	CE implementation level	Design and production stage	R2, R4, R5, R8, R9
		Financial performance	Decreased manufacturing/operational costs, increased annual turnover, increased profit growth, increased market share		Consumption and collection stage	R4, R5
		Competitiveness	Increased capability to introduce innovative products/services, improved quality of products/services, improved brand value of products/services, increased accessibility to new markets			
		Corporate reputation	Improved corporate image among customers, improved relationship with suppliers/local community/regulatory organization, increased satisfaction and support from investors/partners, increased satisfaction and loyalty of employees		Recycling and resourcing stage	R8

(Continues)

TABLE 1 | (Continued)

Article	Method	Financial variables: Concept used	Financial variables: What it includes	CE variables: Concept used	CE variables: What it includes	CE variables: Link with 10R
Y. Yu, Xu, et al. 2022	Survey (308) China Manufacturers	Financial performance	Growth in sales, return on sales, growth in return on sales, growth in profit, growth in market share, return on investment, growth in return on investment	CE	Ecological (environmental) design	R0, R2, R3, R6, R8
					Investment recovery	R3, R8
Liu et al. (2023)	Survey (255) China Manufacturers	Financial performance	Growth in sales revenue, return on sales, growth in profit, net profit margin, return on investment, growth in market share	Circular manufacturing	Circular product design	R4, R5, R6, R7, R8
		Environmental performance	Emissions of greenhouse gases, wastewater, other wastes, total amount of hazardous and toxic waste, consumption of hazardous/harmful/toxic materials		Cleaner production	R0, R2
D'Angelo et al. (2023)	Survey (10,618 from Eurostat) Europe SMEs	Economic performance	Variation of total turnover	Breadth of CE activities	Breadth of CE activities	R2, R3, R8
Blasi et al. (2021)	Regression model (168 from AIDA Bureau Van Dijk) Italy Manufacturers SMEs	Firm performance	Return on assets	CE	CE	R0, R1, R2, R3, R4, R5, R6, R8, R9
Van Loon et al. (2022)	Case study Slovenia White goods	Profitability	Profits minus costs	Circular business model	Leasing	R1
Scarpellini et al. (2020)	Survey (87) Spain	Financial performance	Return on equity, return on sales, return on assets	Environmental capabilities for the CE	Environmental management systems	n.a.
					Environmental capabilities and accounting	n.a.
					CSR	n.a.

(Continues)

TABLE 1 | (Continued)

Article	Method	Financial variables: Concept used	Financial variables: What it includes	CE variables: Concept used	CE variables: What it includes	CE variables: Link with 10R
Agan et al. (2013)	Survey (500) Türkiye Manufacturers SMEs	Firm performance	Short-term profits, long-term profits, market share, firm's image, competitive advantages	Environmental processes	Waste treatment	R9
					Reduction	R2
					Recycling within the firm	R8
					Design	n.a.
					EMS	n.a.
Palea et al. (2023)	Regression model Worldwide Mining, manufacturing, utilities, and construction industries	Financial performance	Profitability; operational efficiency; financing and market value	CE	Eco-design products Waste reduction initiatives E-waste reduction initiatives Renewable energy use Policy on water efficiency Policy on energy efficiency Resource reduction/ improvement objectives Take-back and recycling initiatives	R1 R2 R8

Note: R0: refuse; R1: rethink; R2: reduce; R3: reuse; R4: repair; R5: refurbish; R6: remanufacture; R7: repurpose; R8: recycle; R9: recover.

CSR report," enclosed by inverted commas, for instance, "Intel-USA-2015 + ESG CSR REPORTS." In addition to the company's website, we rely on external sources to identify the ESG report, such as CSRwire.com, CorporateRegister.com, GlobalReporting.org, SocialFunds.com, or BusinessWire.com. Such websites allow us to obtain the ESG reports from firms that are delisted, bankrupt, or merged, which therefore minimizes the survivorship bias in our sample.

To obtain accounting-based data, we merge the hand-collected sample with the US COMPUSTAT Annual Industrial database, which results in 7983 observations. Next, we merge our sample with the stock market CRSP data and the Thomson Financial Spectrum Database to obtain institutional investment data. Our sample is then reduced to 7783 observations. After merging with the IBES database to obtain analysts' forecast variables, our final sample is composed of 7557 firm-year observations between 1998 and 2023 for 1714 firms, of which 610 firms are listed on the NASDAQ and 1104 on the NYSE.

3.1.1 | Preprocessing of the ESG Reports

The raw files in our sample are typically in a PDF format. Therefore, to analyze the text contained in the reports, we use the Tesseract Optical Character Recognition (OCR) engine in R to convert the PDF files to TXT format. Based on these documents, various preprocessing steps on the text are implemented, namely, non-English characters (punctuation and numbers), non-alphanumeric symbols, numbers, repeated space characters, one-letter words, letters attached to special characters (taking care not to delete words such as o2 and co2), and lemmatizing the words into their root forms. We then remove stopwords, which are frequent words with little information value, such as "the," "is," "have," "of," "a," and "thus." Finally, we follow Huang et al. (2018) and remove company names, websites, and tickers to prevent the bag-of-words method from identifying firms as a CE word. All these steps increase the interpretability of the topics identified and the quality of the output.

3.2 | Variable Definition

To determine the implementation of the CE by firms and its financial impact, we identify CE-related content related to the 10R framework in firms' corporate reports through a CE dictionary. This section describes the variables used in the analyses, which are summarized in Appendix B.

3.2.1 | Independent Variables

To operationalize firms' CE strategic orientation as communicated in public disclosure, we create an independent variable called *CIRCULAR_STRATEGIES* using content analysis of ESG reports. Content analysis is a "research technique for making replicable and valid inferences from texts (or other meaningful matter) to the contexts of their use" (Krippendorff 1980, 18). Despite some potential disadvantages such as the difficulties in identifying the ambiguity of words' meanings, content analysis has several advantages such as being unobtrusive, easily replicable, context sensitive, and applicable to a wide range of organizational-related phenomena (Duriau et al. 2007; Kim and Kuljis 2010; Krippendorff 1980; Woodrum 1984; Arslan-Ayaydin et al. 2016, 2020, 2021; Boudt and Thewissen 2019; Boudt et al. 2018; Xia et al. 2023). Moreover, it can handle large amounts of unstructured and diverse data, both internal and external to the firm (Jauch et al. 1980), which allows the use of longitudinal research design due to the existing and available data, easily comparable through time in documents such as annual corporate reports (Jauch et al. 1980; Kabanoff 1996; Weber 1990).[2]

This disclosure-based approach is appropriate for our objective of assessing the informational content of CE communication for capital markets. We use a dictionary-based approach, which is the most common in computer-assisted text analysis (Landmann and Zuell 2008; Thewissen, Shrestha, et al. 2022; Thewissen et al. 2026; Thewissen, Thewissen, et al. 2022; Yan et al. 2021; Xia, Thewissen, Herrezuelo, et al. 2024; Xia, Thewissen, Huang, and Yan 2024; Xia, Thewissen, Shrestha, and Yan 2024). Dictionaries for text analysis consist of a list of entries—words, word stems, and/or phrases—with shared meanings (Landmann and Zuell 2008; Weber 1990). Due to the lack of CE dictionaries in academic research, we start our dictionary with an initial word list (IWL) consisting of the 10 CE strategies included in the 10R framework of Potting et al. (2017) and Reike et al. (2018). Academic research and firms do not always use the same terms, and there is a lack of appropriate language and tools, especially in the context of circular business model innovation (Blomsma and Brennan 2017). Thus, to develop the entries of the dictionary, we employ different techniques (see Figure 1). The initial list of 10 keywords is expanded with synonyms (see Table 2), and although the stemming technique, which consists of truncating words, is used for those verbs always used within the context of the CE, such as recycle, contextualization by adding direct objects is used in all other cases, including reduce and recover. After two reviewers individually review each term, a total of 10,800 contextualized terms and 15 verbs not requiring contextualization are included. Additionally, to account for inflections, or different forms of the same word, we inflect the root word to capture the different forms in which they can appear in a report (Loughran and McDonald 2011). After a last review and discussion between the authors, 18 new keywords are added, resulting in a total amount of 43,233 keywords categorized into the 10R strategies. Lastly, we conduct keywords-in-context (KWIC) technique (Fielding and Lee 1998), a data analysis method that compares the words preceding and following a key term, uncovering their usage within a given context (Leech and Onwuegbuzie 2007), which ensures the accuracy and relevance of the dictionary's terms. We manually apply the KWIC approach to the reports with the highest frequency of occurrences, as well as a subset of randomly selected reports. This validation technique confirms the alignment between our keywords and the CE and their proper classification within the 10R framework. For a more detailed description of the dictionary creation process, see Appendix C.[3]

The variable *CIRCULAR_STRATEGIES* is a composite score reflecting a report's emphasis on the 10 CE strategies included in the 10R framework, calculated by averaging the number of

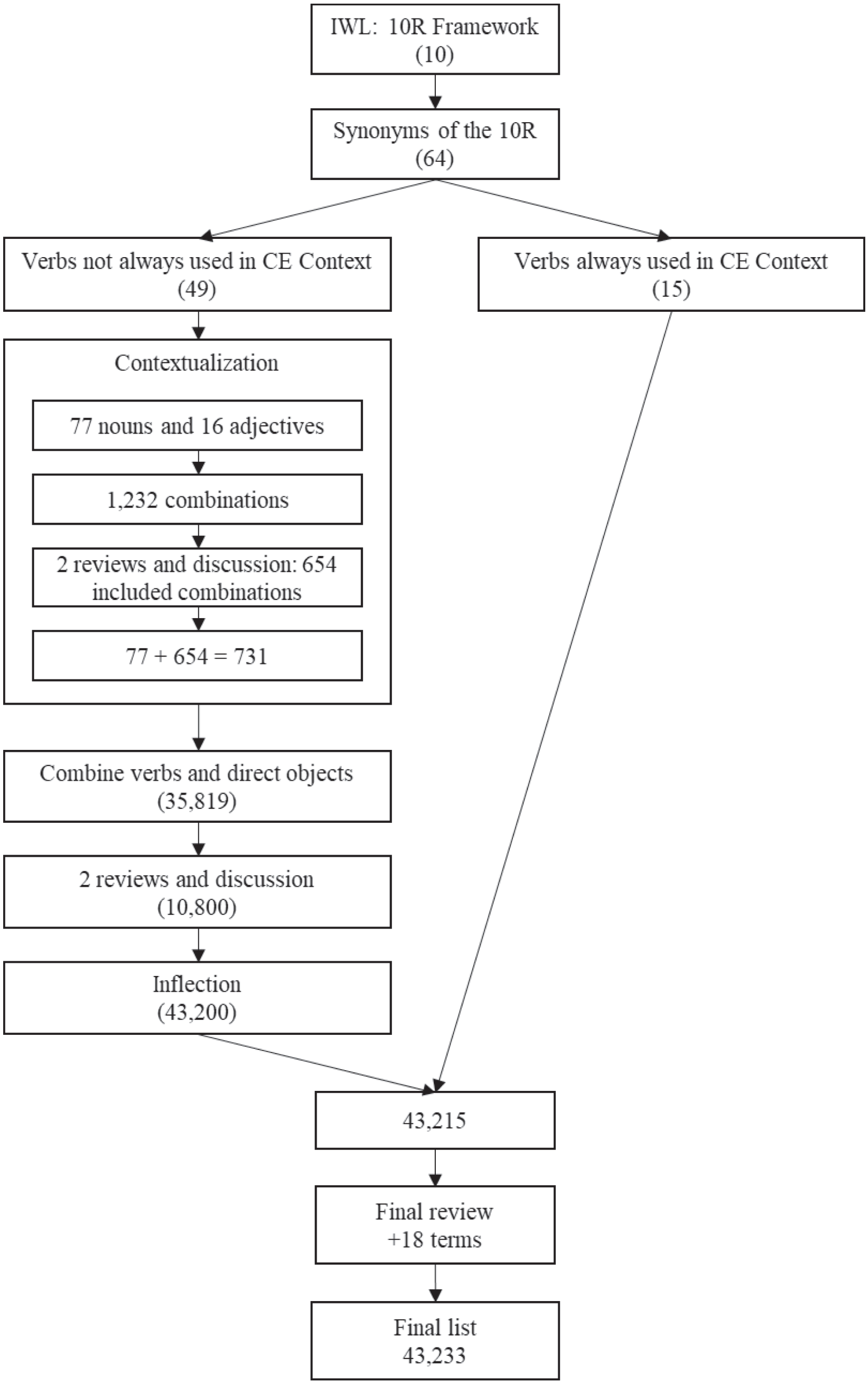

FIGURE 1 | Creation process of the CE keyword list. Visual representation of the creation process of the CE keyword list.

times the keywords of the dictionary appears in the reports. In addition, we decompose the *CIRCULAR_STRATEGIES* variable into three resource loops: the short loop, including the most circular strategies of refuse, rethink, and reduce; the medium loop, including reuse, repair, refurbish, remanufacture, and repurpose; and the long loop, including recycle and recover. This disaggregation enables us to analyze not only the overall impact of CE but also the specific effects of each resource loop. Moreover, to assess the robustness of our findings, we include two additional independent variables: *TOTAL_SCORE*, which extends the original measure by incorporating broader references to circularity, and *ESG_REFINITIV*, a commonly used ESG rating. Both are further described and tested in Section 5.

TABLE 2 | List of terms used in the dictionary creation including verbs, nouns, adjectives, and final additions.

Verbs	Refuse, prevent, eliminate, avoid, reject, stop, rethink, re-think, share, rent, lease, reduce, minimize, decrease, diminish, lower, lessen, reuse, re-use, resell, re-sell, repair, fix, maintain, mend, refurbish, upgrade, update, overhaul, modernize, remanufacture, recondition, renew, restore, repurpose, recycle, upcycle, downcycle, process, reprocess, compost, remine, re-mine, recover, incinerate, use, develop, design, create, purchase, buy, source, procure, sell, increase, enlarge, expand, extend, maximize, prioritize, broaden, raise, double, triple
Nouns	Product, good, device, equipment, object, component, part, element, piece, packaging, pack, box, bag, package, bottle, container, waste, byproduct, by-product, scrap, chemical, pollution, pollutant, contaminant, platform, model, service, system, nutrients, biomass, biogas, material, fabric, substance, resource, input, plastic, bioplastic, PET, rPET, wood, lumber, timber, mineral, alloy, ore, textile, cloth, fiber, yarn, glass, ceramic, paper, cardboard, leather, composite, stone, rock, gravel, concrete, energy, energy efficiency, energy consumption, water, wastewater, Product-service-system, PSS, Product-as-a-service, PAAS, Access model, Performance model, Function model, Result model, market, shop, emission, CO2
Adjectives	Virgin, non-virgin, renewable, non-renewable, secondary, toxic, hazardous, harmful, polluting, end-of-life, second-hand, second-hand, electrical, electronic, raw, critical
Final additions	Access model, anaerobic digestion, cleaner production, energy from waste, function model, Functional economy, PAAS, pay-per-use, performance model, product-as-a-service, product-service-system, PSS, result model, servitization, waste to energy, waste-to-energy, WTE, W-T-E

3.2.2 | Dependent Variables

We measure financial performance as a firm's value using Tobin's Q ratio, widely used in management and financial research to evaluate corporate market responses to different phenomena such as CEO duality (Yang and Zhao 2014), ESG disclosure (Chen and Xie 2022), corporate culture in family firms (Huang et al. 2015), and the use of Data Envelopment Analysis for environmental assessment (Sueyoshi and Wang 2014), among others. Tobin's Q is the most used investment prediction variable (Blanchard et al. 1993), and it equals the market value of a firm divided by the replacement value of its assets:

$$Tobin's\ Q = \frac{Total\ Market\ Value\ of\ Firm}{Total\ Asset\ Value\ of\ Firm}$$

Tobin's Q (*TOBIN'S Q*) is used as a proxy of a firm's growth opportunities, and it measures whether a firm is either overvalued or undervalued. Hence, the greater Tobin's Q ratio, the greater the investment opportunities, which means that investors have confidence in the future income potential of the firm (Yang et al. 2015). Tobin's Q has the advantage of considering intangible assets and incorporates a forward-looking approach while also accounting for risk (Sarkissian and Schill 2012). In addition, Tobin's Q can be used to compare firms across industries as it does not consider accounting conventions (Chakravarthy 1986).

3.2.3 | Control Variables

A large set of control variables from prior literature is defined in this study (Bushman and Smith 2003; Choi and Richardson 2016; Du and Yu 2021; Jones 2007; Schoenfeld 2017). We use two types of control variables: firm specific and report specific.

Regarding firm-specific variables, we control for firm size (*SIZE*), the natural logarithm of total assets at the end of the current year, as well as year (*YEAR*) and industry fixed effects (*INDUSTRY*). We also include four control variables linked to a firm's performance, such as the firm's return on assets (*ROA*), measured as the income before extraordinary items divided by the total assets at the end of the preceding year, and earnings surprise (*SURPRISE*), denoting the variance between the consensus EPS forecast by analysts, defined as the average of the most recent analyst predictions for the company in the current year, and the actual EPS, divided by the stock price at the conclusion of the previous year. Additionally, we introduce the dummy variable *EPS_DECLINE*, which takes a value of 1 if the EPS decreases in the current year and 0 otherwise, and the momentum variable (*MOMENTUM*), the cumulative abnormal return over 1 year from the [−375, −10] trading day interval, with the ESG reporting date as the event.

To control for factors such as financing needs, stock price liquidity, R&D investment, and firm information environment that might influence the adoption of CE strategies, we include eight additional control variables: financing activities (*FINANCING*), stock liquidity (*LIQUIDITY*), intensity of research and development (*RD*), analyst coverage (*NOA*), financial leverage (*LEVERAGE*), earnings uncertainty (*VOLATILITY*), and operational complexity formed by the variables geographical segment (*GEO_SEGMENT*) and business segment (*BUS_SEGMENT*).

Financing activities (*FINANCING*) is calculated as the net debt amount and raised equity capital during the year, scaled by total assets at year-end. Stock liquidity (*LIQUIDITY*) represents the volume of shares traded divided by the total number of shares outstanding for the same year. Research and development expenses are adjusted by sales during the year to capture R&D intensity (*RD*). The number of analyst coverage (*NOA*) is defined as the natural logarithm of 1 plus the number of financial analysts at the end of the same year. Following Huang et al. (2014), we control for operational complexity by including the logarithm of the number of geographical (*GEO_SEGMENT*) and business segments (*BUS_SEGMENT*). Lastly, we control for information uncertainty with the variables financial leverage (*LEVERAGE*), computed as the total debt divided by the total assets at year-end, and earnings uncertainty (*VOLATILITY*), calculated as the standard deviation on return on assets over a 5-year period.

Regarding report-specific variables, we control for their length using the logarithm of the total amount of words in the report (*WORDCOUNT*). Additionally, following Du and Yu (2021), we control for the report's readability (*FOG*) through Strong's (1986) Gunning's FOX index, which estimates the years of education required for an average reader to comprehend the text fully. It is measured by combining the average words per sentence with the percentage of complex words per sentence. Furthermore, we include the report's tone (*TONE*), defined as the ratio of positive to negative words scaled by the total amount of words in the report. Following Du and Yu (2021), we use the list developed by Loughran and McDonald (2011) to identify positive and negative words. As this list is tailored for analyzing 10-K documents, we also incorporate the variable ESG emphasis (*ESG_EMPHASIS*), calculated as the ratio of ESG-specific words defined by Baier et al. (2020) to the total amount of words in the report.

In line with Loughran and McDonald (2014) and Hope et al. (2016), we also integrate measures of specificity (*SPECIFICITY*) and uncertainty (*UNCERTAINTY*) from the text. Specificity is determined using a Named Entity Recognition (NER) automated tool (Apache NER) to identify terms related to named entities like persons, organizations, locations, percentages, monetary values, and dates. The text's specificity represents the total count of unique named entities detected by NER. We use Loughran and McDonald's (2014) list of uncertain terms to identify the proportion of uncertain words in the text (*UNCERTAINTY*). Finally, following Bozanic et al. (2018), who link disclosures rich in forward-looking information to stronger market reactions, we add the proportion of forward-looking sentences (*FORWARDLOOK*), based on the method of Henry (2008), Henry et al. (2023), and Athanasakou and Hussainey (2014).

3.2.4 | Additional Variables

To explore the mechanisms that may shape the relationship between CE communication and firm value, we introduce a set of additional variables, which are discussed in more detail in Section 4.4. These capture four moderating channels: financial slack, greenwashing risk, risk perception, and information asymmetry. These variables are interacted with *CIRCULAR_STRATEGIES* to assess whether the valuation effects of CE disclosures vary across different financial, reputational, and informational contexts.

NET_DEBT proxies financial slack and is calculated as total debt minus cash and cash equivalents, scaled by total assets (Arslan-Ayaydin et al. 2014). Greenwashing risk is assessed using two measures of textual similarity: *GREENWASHING_FIRM*, the cosine similarity between a firm's consecutive ESG reports, and *GREENWASHING_SECTOR*, the median cosine similarity between a firm's ESG report and those of its industry peers (He et al. 2025; Hahn and Lülfs 2014). To capture information asymmetry, we include *DISP*, the dispersion in analyst earnings forecasts, and *ESG_DISAGREEMENT*, the standard deviation of percentile-ranked ESG scores across MSCI, LSEG, and Bloomberg, reflecting disagreement among rating agencies (Gibson Brandon et al. 2021).

3.3 | Method

3.3.1 | The Impact of the CE on Firm Value

To address our first research question (RQ1), we begin by conducting a content analysis of firms' ESG reports using the CE dictionary described in Section 3.2. This procedure allows us to systematically identify which CE strategies firms adopt and the frequency of their disclosure. Building on this, we turn to our second research question (RQ2) by testing whether CE disclosure affects firm value and, if so, in which direction.

We estimate the following baseline model, regressing firm value (Tobin's Q) on the firm's emphasis on CE:

$$Tobin's\ Q_{it} = \beta_0 + \beta_1 CE_{it} + \sum_{i=1}^{17} \beta_i Control_{it} + \varepsilon_{it} \tag{1}$$

where $Control_{it}$ is the set control variable defined in Section 3.2.3. The significance of the coefficients is tested using Newey–West standard errors. If the impact of the firm's emphasis on CE has a positive (negative) impact on firm value, we expect β_1 to be positive (negative). To address our third research question (RQ3), we follow the same approach as in RQ2, but instead of overall CE disclosure, we distinguish between short-, medium-, and long-loop disclosures. If these types of CE strategies create (reduce) firm value, we expect the corresponding coefficients to be positive (negative).

Finally, for our fourth research question (RQ4), we extend the baseline model by interacting CE disclosure variables with different mechanism factors, regressing firm value on both the main effects and their interaction:

$$Tobin's\ Q_{it} = \beta_0 + \beta_1 CE_{it} + \beta_2 Factor_{it} + \beta_3 CE_{it} Factor_{it} + \sum_{i=1}^{17} \beta_i Control_{it} + \varepsilon_{it} \tag{2}$$

In this case, if the moderating factor strengthens (weakens) the effect of CE disclosure on firm value, we expect β_3 to be positive (negative).

3.3.2 | Endogeneity Tests

CE adoption is not random but reflects firms' responses to regulatory pressure, cost structures, and market opportunities. Other examples include organizational culture, managerial attitudes, government regulations and funding, market conditions, and access to resources (Assmann et al. 2023). If such unobserved factors are correlated with both CE adoption and performance, estimates may be biased by omitted variables or reflect spurious associations rather than causal effects. To mitigate these concerns, we follow prior studies (e.g., Colombo and Grilli 2010; Fisch and Momtaz 2020; Thewissen, Thewissen, et al. 2022; Tong et al. 2026) and employ three complementary approaches. We begin with propensity score matching (PSM), which compares firms that adopt CE strategies with observationally similar firms that do not, thereby reducing bias from observable differences. We then implement entropy balancing (EB), which reweights control observations to match the mean and variance of covariates in the treatment group, ensuring stronger covariate balance than conventional matching methods. Finally, we apply a restricted control function (rCF) approach, introducing control functions based on potential instruments to account for unobserved heterogeneity that may simultaneously influence CE adoption and performance.

Using these three approaches in combination allows us to triangulate the robustness of our findings. Although matching and reweighting techniques address bias from observable firm characteristics, the control function approach provides a means of accounting for unobserved factors. We present the results of these robustness analyses in Section 4.3, following our baseline regressions. Although these methods provide a more comprehensive assessment of whether the relationship between CE disclosure and firm value reflects a causal link rather than confounding influences, the CE adoption reflects strategic firm responses to regulation and market conditions. As such, our estimates should be interpreted as associations rather than definitive causal effects.

3.3.2.1 | PSM. We first apply the PSM method to construct a new sample to assess the causal impact of CE strategies on firm performance. Unlike OLS regression, which assumes a linear relationship between the dependent variable and the covariates, PSM is a nonparametric method that does not impose any functional form assumptions. However, following best practices outlined in prior literature (see, e.g., Marino et al. 2016), we match firms based solely on pretreatment characteristics, that is, variables that are not influenced by the potential outcome variable ($TOBIN'S\ Q$) or the treatment assignment ($CIRCULAR\_STRATEGIES$). This design helps address the concern that treatment assignment could influence the covariates used in matching.

To assess the causal effect of the environmental context on firms' behavior and outcomes, we adopt a design inspired by Tchorzewska et al. (2022), who use regional variation in environmental taxation across Spanish regions as a quasi-exogenous source of treatment assignment. Similarly, we exploit geographic variation in environmental stringency at the US state level, proxied by a standardized environmental score published annually by SmileHub, an independent nonprofit that ranks states based on multiple dimensions of environmental performance and regulatory enforcement.

A key identification challenge in estimating the impact of environmental factors on firm-level outcomes is that firms may self-select into environmentally friendly behavior or states may adjust policies in response to local economic conditions. To mitigate this endogeneity concern, we use the exogenous cross-state variation in environmental scores as a natural experiment: Firms are "treated" with higher environmental pressure simply by operating in a state with stricter environmental policies, rather than through firm-specific decisions. This aligns with the approach in Tchorzewska et al. (2022), who treat regional tax heterogeneity as an external source of variation. Concretely, we construct a binary treatment indicator: Firms located in states with an environmental score above the national median are assigned to the treatment group, and those below the median to the control group. This median split ensures a balanced design and maximizes comparability between groups.

By relying on this exogenous geographic criterion rather than firm-level self-selection, we reduce the risk that unobserved firm characteristics drive both the environmental context and performance outcomes. To further strengthen identification, we ensure that PSM is implemented using only firm-level pretreatment covariates, such as size, industry, and prior financial performance, mirroring the approach described in Marino et al. (2016) and Tchorzewska et al. (2022). This matching balances observable characteristics between treated and control firms and helps isolate the effect of the environmental context.

To estimate propensity scores, we run a Probit regression using a subset of pretreatment firm characteristics, drawn in part from the control variables defined in Equation (1). In line with Marino et al. (2016), we only include covariates that are determined prior to treatment assignment and are therefore unaffected by a firm's subsequent decision to adopt CE strategies. This ensures that the matching procedure balances firms on relevant observable characteristics while avoiding posttreatment bias. Each firm in the treatment group is matched with up to four control firms using nearest-neighbor matching of propensity scores, yielding a balanced sample that supports more credible causal inference.

3.3.2.2 | EB. Although PSM has been widely applied in prior research (Shipman et al. 2017), more recent work highlights important limitations. King and Nielsen (2019) argue that PSM may fail to achieve covariate balance and, in some cases, can even increase imbalance. Moreover, nearest-neighbor matching discards a subset of control observations, leading to information loss and reduced statistical power (Hainmueller 2012).

To address these limitations, we complement our PSM analyses with EB. Unlike matching, EB is a reweighting procedure that guarantees covariate balance by assigning observation-specific weights to the control group. Through an optimization process, EB ensures that the first, second, and third moments of the reweighted control group match those of the treatment group, thereby achieving exact balance without discarding observations. Consistent with our PSM design, we define treatment and control groups using the state-level environmental stringency median split and employ the same set of pretreatment covariates. After computing the balancing weights, we estimate weighted ordinary least squares regressions, where each control observation contributes proportionally to its entropy weight. This approach allows us to retain the full sample while achieving a higher degree of covariate balance than is feasible with conventional matching methods.

3.3.2.3 | rCF. As a third robustness approach, we follow Mansouri and Momtaz (2022) and implement an rCF design to address unobserved heterogeneity. The rCF framework proceeds in two stages. A selection equation is first estimated to obtain generalized residuals (GRs), which are then included in the outcome equation as additional regressors. This procedure helps correct for potential endogeneity arising from omitted variables or spurious correlations (Gourieroux et al. 1987; Heckman and Navarro-Lozano 2004). Unlike matching methods, which adjust only for observed firm characteristics, rCF explicitly accounts for latent factors that may jointly drive CE adoption and performance.

We employ two complementary implementations of this approach. First, we apply the Inverse Mills Ratio (IMR) correction (Heckman 1979). In the first stage, we estimate a Probit model predicting the likelihood that a firm has a high $CIRCULAR\_STRATEGIES$ score based on exogenous firm characteristics. The IMR derived from the predicted values is then included in the main regression to capture selection bias arising from unobserved variables correlated with both CE adoption and firm performance. Second, we implement a GR-based instrumental variables procedure, in line with Mansouri and Momtaz (2022). Using the same Probit specification, we compute GRs and employ them as instruments for CE strategies in a two-stage least squares (2SLS) framework. This design isolates exogenous variation in CE strategies, correcting for both observed and unobserved confounding (Gourieroux et al. 1987; Heckman and Navarro-Lozano 2004).

By presenting both the IMR-adjusted model and the GR-IV model, we provide complementary perspectives on the relationship between CE strategies and firm value. This approach enhances the robustness and credibility of our empirical findings.

4 | Empirical Results

The subsequent section reports the empirical results, with particular attention to the prevalence of CE strategies among US firms, their association with firm value, and the implementation of endogeneity tests designed to assess the robustness and validity of our findings.

4.1 | RQ1—The Emphasis on CE in US Firms' ESG Reports

To address RQ1, our findings document a marked increase in the explicit use of the term circular economy in the ESG reports of US firms. As illustrated in Figure 2, references to CE have expanded exponentially over time. Between 2007 and 2017, the average number of occurrences remained below 0.5 per report; this average rose notably by 2019 and spiked to 1.87 in 2021, indicating a substantial escalation in the use of the CE terminology. Although a decline is observed after 2021, usage remains at comparatively elevated levels. However, despite this surge in explicit references to CE, disclosures of concrete CE strategies show a declining trajectory, both in aggregate and across each resource loop (see Table 3). This divergence suggests that although CE has gained prominence as a rhetorical construct, firms increasingly emphasize the generic label rather than specific practices such as recycling or repairing, which may be perceived as less novel or strategically compelling (Olczak et al. 2023).

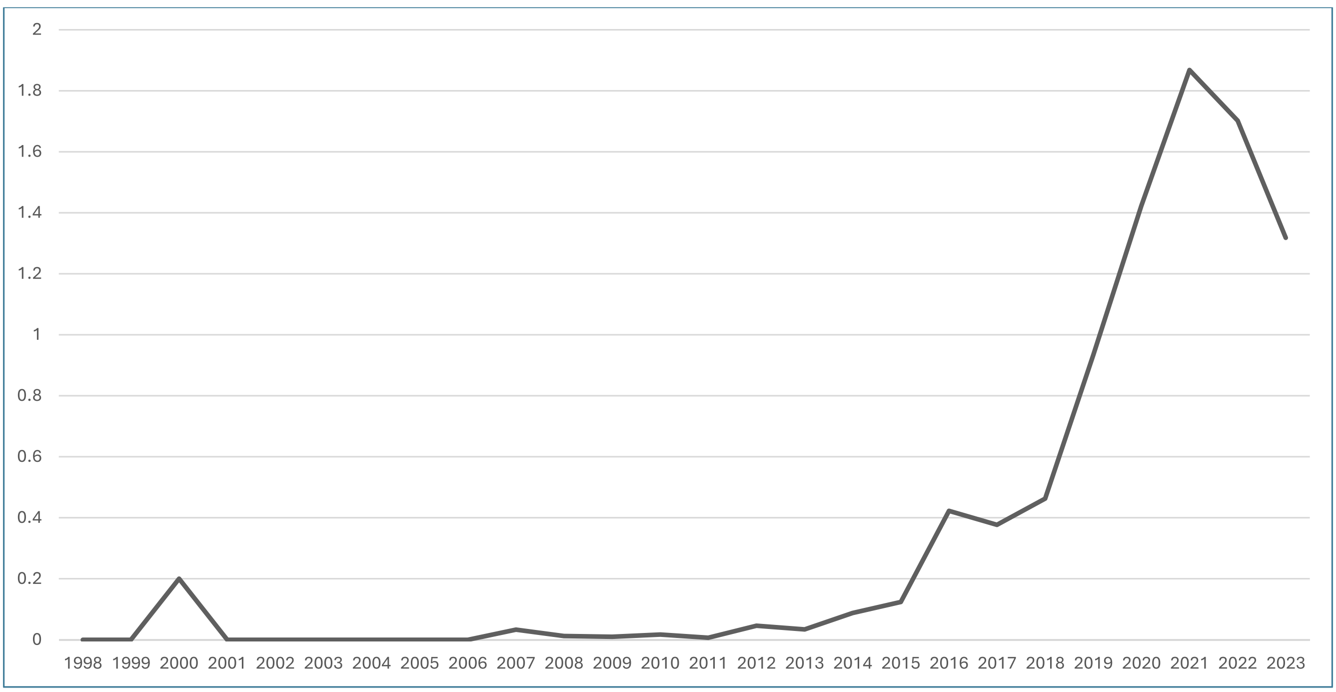

FIGURE 2 | Use of the CE terms in ESG reports of US firms, by year. Line graph with the yearly evolution of the terms "circular economy," "circularity," and "circular" during the period 1998–2023. The figure includes the following note: It includes the use of "circular economy," "circularity," and "circular."

TABLE 3 | Emphasis on CE strategies and breakdown by resource loop and 10R, by year (1998–2010).

Year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Mean
Reports	2	2	5	6	11	20	24	33	45	60	81	102	115	146	174	205	251	283	348	451	624	869	1098	1334	1224	44	291
Average words	7066.5	12,782.5	10,159	18,356.17	16,064.82	17,137.35	24,084.16	19,893.69	20,935.51	19,490.51	20,145.25	19,746.25	19,114.86	19,221.85	19,243.05	18,665.07	18,113.93	17,203.84	16,521.74	15,441.09	14,300.99	14,378.88	16,199.96	17,487.5	18,317.49	14,808.25	16,888.6
CIRCULAR_ STRATEGIES	**67.5**	**53.5**	**38.8**	**47.67**	**41.55**	**41.75**	**53.62**	**39.48**	**40.51**	**45.75**	**44.89**	**44.57**	**42.5**	**40.72**	**37.57**	**38.45**	**36.39**	**33.69**	**30.88**	**28.5**	**27.85**	**28.91**	**30.69**	**32.34**	**35.53**	**32.7**	**32.97**
SHORT_LOOP	11	14.5	8.2	7	10.64	7.65	9.5	8.06	9.31	10.08	10.16	9.72	10.25	10.52	9.46	9	8.8	8	7.82	6.98	6.61	6.55	7.22	7.4	8.25	6.93	7.72
R0: REFUSE	1	0.5	1	1.17	1.18	0.35	1.29	0.58	0.69	0.43	0.56	0.6	0.57	0.65	0.6	0.72	0.66	0.55	0.56	0.56	0.54	0.52	0.59	0.59	0.64	0.82	0.59
R1: RETHINK	0.5	1	0.4	0.67	2.82	2.45	2.21	1.97	1.91	1.6	0.96	0.97	0.95	1.1	0.98	0.6	0.82	0.79	0.89	0.71	0.72	0.69	0.77	0.82	0.96	0.57	0.84
R2: REDUCE	9.5	13	6.8	5.17	6.64	4.85	6	5.52	6.71	8.05	8.64	8.15	8.73	8.77	7.88	7.67	7.32	6.67	6.36	5.72	5.34	5.34	5.86	5.99	6.65	5.55	6.28
MEDIUM_LOOP	16.5	11	9.2	7.17	8.55	7.5	9.79	8.24	9.58	8.17	7.96	8.44	7.68	7.87	7.43	7.75	7.69	7.14	6.68	5.86	5.55	6.03	6.31	6.83	7.62	6.59	6.82
R3: REUSE	15	11	7.8	5.67	6.36	5.65	6.88	5.15	5.93	5.62	5.62	5.91	5.41	5.28	4.94	4.86	4.87	4.5	4.18	3.72	3.44	3.83	3.89	4.12	4.35	3.93	4.22
R4: REPAIR	0.5	0	0.4	0.67	1	0.95	1.38	1.7	1.58	1.32	1.23	1.69	1.08	1.32	1.32	1.44	1.37	1.16	1.28	1.07	1.24	1.26	1.26	1.46	1.78	1.18	1.38
R5: REFURBISH	1	0	1	0.67	1.09	0.7	1.12	1	1.53	0.73	0.64	0.5	0.52	0.53	0.66	0.69	0.68	0.65	0.5	0.47	0.39	0.39	0.45	0.5	0.63	0.61	0.53
R6: REMANUFACTURE	0	0	0	0.17	0.09	0.2	0.42	0.39	0.53	0.42	0.36	0.23	0.53	0.51	0.33	0.49	0.55	0.62	0.42	0.25	0.18	0.21	0.32	0.3	0.39	0.11	0.33
R7: REPURPOSE	0	0	0	0	0	0	0	0	0	0.08	0.11	0.12	0.14	0.22	0.17	0.26	0.22	0.22	0.3	0.35	0.3	0.34	0.39	0.45	0.49	0.75	0.36
LONG_LOOP	40	28	21.4	33.5	22.36	26.6	34.33	23.18	21.56	27.4	26.77	26.34	24.53	22.25	20.59	21.62	19.82	18.33	16.01	15.17	14.84	15.29	15.65	16.4	17.33	16.16	17.27
R8: RECYCLE	40	28	21.4	33.5	22.27	26.55	34.29	23.09	21.49	27.25	26.64	25.92	24.29	21.9	20.3	21.19	19.51	18	15.73	14.91	14.52	15.05	15.48	16.22	17.13	16.07	17.03
R9: RECOVER	0	0	0	0	0.09	0.05	0.04	0.09	0.07	0.15	0.12	0.42	0.24	0.36	0.29	0.44	0.31	0.33	0.28	0.25	0.32	0.24	0.17	0.18	0.2	0.09	0.23

Note: The definitions of the variables are provided in Appendix A. Statistics shown in bold correspond to the main variable of interest in this study.

Our results further highlight the considerable heterogeneity in CE strategies disclosed by US firms when classified according to the 10R framework and grouped into the three resource loops. As reported in Panel A of Table 4, the long loop emerges as the most emphasized, with a mean occurrence of 17.27, whereas the medium loop registers the lowest average of 6.82. A closer inspection shows that recycling dominates disclosures, with the highest mean frequency (17.03), reflecting a pronounced emphasis on this strategy. In contrast, reducing (6.28) and reusing (4.22) appear far less frequently, and strategies such as recovering, remanufacturing, and repurposing are rarely mentioned, with mean values ranging only from 0.23 to 0.36. The large standard deviations observed across several variables point to significant variation among firms. Although some companies place strong emphasis on specific CE strategies, others provide little to no disclosure, emphasizing the uneven integration of circular practices across the sample.

We further analyze the disclosure of CE strategies across industries and identify pronounced differences. As shown in Table 5, manufacturing, retail, and transportation exhibit the highest emphasis on CE strategies, with mean values of 44.90, 44.35, and 33.95, respectively. In contrast, the finance and services sectors disclose the least, with means of 14.36 and 17.51, respectively. Across all industries, long-loop strategies, particularly recycling, remain the most frequently reported, whereas medium-loop strategies receive limited emphasis, with the exception of transportation, mining, and manufacturing, where they appear more prominently.

Table 6 further reports Pearson correlation matrix between the variables used in the main regression analysis. We find a positive and significant association at 99% confidence level between our independent variable *CIRCULAR_STRATEGIES* and several control variables, particularly *SIZE*, *ROA*, *EPS_DECLINE*, *GEO_SEGMENT*, *VOLATILITY*, *RD*, *NOA*, *WORDCOUNT*, *SPECIFICITY*, and *ESG_EMPHASIS*. On the contrary, we find a negative association at a 99% confidence level with the variables *FINANCING*, *TONE*, *UNCERTAINTY*, and *FORWARDLOOK*.

Our dependent variable (*Tobin's Q*) is positively correlated at a 90% confidence level with our independent variables and at the 99% confidence level for the control variables *SIZE*, *ROA*, *GEO_SEGMENT*, *VOLATILITY*, *RD*, *NOA*, and *TONE* and negatively correlated to *MOMENTUM*, *LEVERAGE*, *SURPRISE*, *BUS_SEGMENT*, *FINANCING*, *LIQUIDITY*, *WORDCOUNT*, *FOG*, *UNCERTAINTY*, *SPECIFICITY*, *FORWARDLOOK*, and *ESG_EMPHASIS*. Overall, the correlation matrix shows that all values are well below the critical threshold of ±0.8 (Farrar and Glauber 1967), suggesting that there are no severe multicollinearity problems in interpreting our findings.

4.2 | RQ2—The Impact of the CE on Firm Value

We further test RQ2, which examines the impact of disclosing information about CE strategies on firm value. Table 7 Model 1 provides the results of Equation (1). Contrary to prior findings (Kristoffersen et al. 2021; Liu et al. 2023; Mazzucchelli et al. 2022; Y. Yu, Xu, et al. 2022; Z. Yu, Khan, and Umar 2022), we find that, on average, disclosing information about CE strategies decreases a firm's value at a 99% confidence level. The negative impact on firm value suggests that investors in the United States are weary of the risks of implementing CE strategies, leading to a lower valuation of the firm's stock. The higher perceived risk can be due to several factors such as the uncertain outcome of circular investments (Sarja et al. 2021), longer payback times, and the use of short-term indicators in decision-making (Bressanelli et al. 2019; Govindan and Hasanagic 2018; Jaeger and Upadhyay 2020; Kirchherr et al. 2018; Urbinati et al. 2021).

4.3 | RQ3—The Impact of Specific CE Strategies on Firm Value

To answer RQ3, we next explore the contrasting results and portray the heterogeneity of CE strategies. To do this, we decompose the umbrella concept of the CE into its different strategies. As shown in Table 7 Model 2, we find that not all CE strategies have the same relevance. Specifically, we observe significant and negative effects for the medium loop, whereas the other two show no meaningful impact.[4] These results show how investors perceive varying levels of risk associated with different CE strategies.

The analysis of short loop shows a nonsignificant impact on firm value, which can be attributed to the balancing effects of two contrasting strategies within this loop: rethinking and reducing. Rethinking strategies, characterized by their complexity and the lengthy processes involved (van Loon et al. 2022), are associated with high uncertainty and a higher risk perception among investors. Conversely, reducing strategies aim at enhancing resource efficiency in both product and production processes, a goal that is already well integrated into linear business models and thus carries lower risk (Bocken et al. 2016). Reduce strategies often result in cost reductions and are supported by established targets and metrics, making their benefits more predictable and measurable (Morseletto 2020). As the short loop includes both types of CE strategies, the risk-reducing nature of resource efficiency improvements may be counterbalanced by the uncertainty of rethinking strategies, resulting in an overall nonsignificant effect on firm value when both are aggregated in the short-loop category.

Regarding the medium loop, we observe a significant negative impact on firm value. Previous literature highlights several factors that may explain why the medium loop is perceived as riskier. Guide (2000) identifies various characteristics of medium-loop strategies, particularly remanufacturing and repairing, that contribute to their perception as risky. These include uncertainties in the timing and quantity of returns, the condition of the product and materials, the required processes and processing time, as well as challenges in managing the disassembly process, balancing product returns with demand, and establishing a reverse-logistics program. In this line, Lüdeke-Freund et al. (2019) highlight technical expertise and the importance of reverse logistics in business models based on middle-loop strategies. Moreover, there are very few targets and indicators regarding middle-loop strategies (Morseletto 2020), making their measurement and communication complicated. In addition, the prioritization of new products over repaired or

TABLE 4 | Summary statistics.

Statistic	Mean	St. dev.	Pctl(25)	Median	Pctl(75)
Dependent variable					
TOBIN'S Q.W	1.787	1.537	0.874	1.288	2.137
Independent variables					
CIRCULAR_STRATEGIES	32.970	41.436	9.000	21.000	41.000
Control variables					
Firm-specific features					
MOMENTUM	0.011	0.401	−0.256	0.011	0.276
SIZE	31,618.360	83,100.050	3,353.047	9,652.527	27,773.590
ROA	4.240	10.152	1.064	3.992	8.295
LEVERAGE	67.365	24.879	51.679	65.854	82.049
EPS_DECLINE	0.354	0.478	0.000	0.000	1.000
SURPRISE	7.076	615.369	−0.0004	0.0005	0.002
BUS_SEGMENT	2.621	1.819	1.000	2.000	4.000
GEO_SEGMENT	3.329	2.897	1.000	3.000	4.000
VOTALITY	3.478	6.313	0.712	1.802	3.966
FINANCING	−0.385	10.260	−4.397	−0.595	1.751
LIQUIDITY	2.051	2.042	1.054	1.655	2.527
RD	24.503	1,239.356	0.000	0.000	2.772
NOA	15.681	9.888	8.000	14.000	22.000
ESG report characteristics					
WORDCOUNT.W	16,888.600	13,837.970	7,375.000	13,060.000	22,122.000
FOG.W	20.468	1.623	19.449	20.495	21.464
TONE.W	0.887	0.601	0.505	0.890	1.272
UNCERTAINTY.W	0.986	1.427	0.346	0.569	0.959
SPECIFIC.W	286.903	212.898	136.000	231.000	373.000
FORWARDLOOK.W	7.937	2.940	5.921	7.556	9.524
ESG_EMPHASIS.W	1,085.569	864.026	468.000	854.000	1,439.000
Panel A—Breakdown by circular economy strategies					
SHORT_LOOP	7.716	8.565	2.000	5.000	10.000
R0: REFUSE	0.594	1.280	0.000	0.000	1.000
R1: RETHINK	0.843	2.273	0.000	0.000	1.000
R2: REDUCE	6.280	7.095	2.000	4.000	9.000
MEDIUM_LOOP	6.818	9.563	1.000	4.000	9.000
R3: REUSE	4.223	6.281	0.000	2.000	6.000
R4: REPAIR	1.378	2.972	0.000	0.000	2.000
R5: REFURBISH	0.527	1.315	0.000	0.000	1.000
R6: REMANUFACTURE	0.335	2.348	0.000	0.000	0.000
R7: REPURPOSE	0.355	1.215	0.000	0.000	0.000

(Continues)

TABLE 4 | (Continued)

Statistic	Mean	St. dev.	Pctl(25)	Median	Pctl(75)
LONG_LOOP	17.266	25.851	4.000	9.000	20.000
R8: RECYCLE	17.033	25.619	4.000	9.000	20.000
R9: RECOVER	0.234	1.084	0.000	0.000	0.000

Note: The definitions of the variables are provided in Appendices A and B. *W* indicates that the variables have been winsorized.

refurbished ones is still common among both customers and salespeople (Kühl et al. 2022). From an economic perspective, repair involves higher labor costs and value-added taxes (Kühl et al. 2022), and the revenue models for repair business models remain uncertain (Lüdeke-Freund et al. 2019).

Our results show no significant impact of the long loop on firm value. The long loop includes recycling, the most common strategy, which has already been implemented long before the concept of the CE became mainstream (Blomsma and Brennan 2017). Moreover, in the early stages of the CE promotion by governments, the focus was mainly on recycling (Ghisellini et al. 2016), and the institutional environment supports recycling above other CE strategies (Ranta et al. 2018). Thus, designing for recycling has been put in place for many years (Eichner and Pethig 2001; Gaustad et al. 2010), and several recycling targets exist (Morseletto 2020). Consequently, recycling is no longer perceived as a novel approach but rather as a standard practice, which diminishes its attractiveness for investors.

We further explore the robustness of our main findings regarding endogeneity concerns as discussed in Section 3.3.2. Model 3 of Table 7 reports the results using a PSM-matched sample, employing one-to-four nearest-neighbor matching. The threshold for distinguishing the treatment and control groups is set at the median value of *CIRCULAR_STRATEGIES*. The PSM regression sample includes 5449 observations. The coefficient of our main variable of interest remains negative and statistically significant at a 99% confidence level. Models 4 and 5 of Table 7 present the second stage of the rCF approach, where the coefficient of *CIRCULAR_STRATEGIES* is consistent with the main findings at a 95% confidence level. In Model 6 of Table 7, we re-estimate our model with third-order moments entropy-balanced sample, and the coefficient of *CIRCULAR_STRATEGIES* remains similar in both magnitude and significance at a 90% confidence level, which suggests that our results are robust to potential selection bias between the treatment group (high CE strategies adoption) and the control group (low CE strategies adoption). Overall, these tests suggest that our findings are robust to potential endogeneity biases between firms with high and low CE adoption. In conclusion, although endogeneity can rarely be fully ruled out, the evidence continues to support the conclusion that the adoption and disclosure of CE strategies are associated with lower firm value.

4.4 | RQ4—What Drives This Negative Relationship? A Mechanism Analysis

The persistent negative association between circularity communication and Tobin's Q highlights the need to identify the mechanisms behind investor reactions, which we address in RQ4. We focus on four theoretically grounded channels that may condition this relationship.

First, investors may interpret CE initiatives as an inefficient allocation of financial slack, penalizing firms with greater financial flexibility. Second, when circularity disclosures are highly similar across firms, investors may question their distinctiveness and interpret them as symbolic or imitative rather than substantive, thereby associating CE communication with greenwashing. Third, higher stock liquidity may indicate a more risk-averse investor base, leading such investors to discount CE initiatives more strongly, given their uncertain and long-term payoffs. Finally, greater information asymmetry restricts investors' ability to evaluate the credibility of CE commitments, intensifying skepticism toward circularity discourse.

4.4.1 | Financial Slack

Agency theory suggests that when firms possess excess resources, managers are more likely to allocate capital to projects with weak or uncertain returns (Jensen 1986). In this setting, CE initiatives may be interpreted as managerial overinvestment. To test this mechanism, we interact *CIRCULAR_STRATEGIES* with net debt. Net debt (*NET_DEBT*), defined as total debt minus cash and cash equivalents, scaled by total assets at year-end, serves as our proxy for financial slack, with lower values indicating greater flexibility (Arslan-Ayaydin et al. 2014). Model 1 of Panel A in Table 8 shows that the negative coefficient on CE communication is stronger in firms with lower net debt. This finding supports the agency-based view that financial slack amplifies investor skepticism toward CE initiatives. When firms appear to have ample discretionary resources, markets may suspect overinvestment in projects with uncertain payoffs, interpreting circularity disclosures less as value-creating commitments and more as potential signs of managerial opportunism.

4.4.2 | Greenwashing Risk

Legitimacy theory posits that firms disclose sustainability initiatives to maintain social approval, but symbolic or imitative reporting erodes credibility (Hahn and Lülfs 2014). In the CE context, generic or highly similar disclosures may be perceived as greenwashing, or "window dressing," rather than substantive commitment. Following He et al. (2025), we proxy greenwashing risk with the textual similarity of ESG reports and distinguish two dimensions. The first is firm-level similarity (*GREENWASHING_FIRM*), measured as the cosine similarity between a firm's consecutive ESG reports, with higher

TABLE 5 | Emphasis on CE strategies and breakdown by resource loop and 10R, by industry.

Industry	Mining	Construction	Manufacturing	Transportation	Wholesale	Retail	Finance	Services	Other
Reports	407	112	3081	987	183	371	1403	993	20
Average words	22,098.98	13,441.50	17,456.18	19,778.30	11,087.00	15,863.36	15,123.40	13,936.00	42,645.57
CIRCULAR_ STRATEGIES	**33.69**	**19.92**	**44.90**	**33.95**	**28.23**	**44.35**	**14.36**	**17.51**	**111.10**
SHORT_LOOP	7.77	6.06	10.03	8.38	5.75	8.55	4.27	4.68	21.15
R0: REFUSE	0.48	0.38	0.83	0.67	0.44	0.83	0.24	0.26	3.20
R1: RETHINK	0.72	0.37	0.97	1.46	0.51	0.53	0.52	0.56	1.25
R2: REDUCE	6.58	5.31	8.23	6.26	4.80	7.19	3.52	3.86	16.70
MEDIUM_LOOP	10.48	3.41	9.10	7.69	6.63	7.03	2.41	3.59	24.55
R3: REUSE	7.04	1.86	5.97	3.97	3.48	4.56	1.09	2.34	16.90
R4: REPAIR	2.75	0.98	1.41	2.42	1.68	1.50	0.72	0.52	2.85
R5: REFURBISH	0.41	0.36	0.61	0.71	0.60	0.47	0.34	0.38	2.25
R6: REMANUFACTURE	0.04	0.03	0.68	0.18	0.56	0.13	0.04	0.04	0.05
R7: REPURPOSE	0.25	0.19	0.42	0.41	0.31	0.37	0.23	0.30	2.50
LONG_LOOP	14.89	10.14	23.77	17.42	15.23	26.85	7.36	8.96	44.45
R8: RECYCLE	14.66	10.04	23.52	16.89	15.10	26.52	7.28	8.87	44.25
R9: RECOVER	0.23	0.10	0.26	0.53	0.13	0.33	0.07	0.09	0.20

Note: The definitions of the variables are provided in Appendix A. Transportation also includes communications, electric, gas, and sanitary services; Finance also includes insurance and real estate. Statistics shown in bold correspond to the main variable of interest in this study.

TABLE 6 | Correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1. CIRCULAR_ STRATEGIES	1	0.801***	0.832***	0.924***	0.027*	−0.01	0.228***	0.140***	−0.003	0.047***	−0.006	0.019	0.162***	0.048***	−0.069***	−0.018	0.098***	0.155***	0.673***	−0.029*	−0.135***	−0.240***	0.658***	−0.089***	0.682***
2. SHORT_LOOP	0.801***	1	0.620***	0.609***	0.028*	0.001	0.233***	0.104***	−0.009	0.030*	−0.004	0.060***	0.177***	0.011	−0.040**	−0.042**	0.131***	0.148***	0.639***	0.050***	−0.086***	−0.208***	0.611***	−0.043**	0.652***
3. MEDIUM_LOOP	0.832***	0.620***	1	0.681***	−0.015	−0.017	0.214***	0.097***	−0.032*	0.066***	−0.002	0.042**	0.154***	0.058***	−0.043**	−0.028*	0.106***	0.127***	0.621***	0.012	−0.162***	−0.216***	0.606***	−0.097***	0.623***
4. LONG_LOOP	0.924***	0.609***	0.681***	1	0.041**	−0.011	0.186***	0.148***	−0.005	0.033*	−0.002	−0.009	0.125***	0.048***	−0.078***	0.007	0.073***	0.143***	0.563***	−0.078***	−0.120***	−0.213***	0.560***	−0.092***	0.572***
5. TOBIN'S Q	0.027*	0.028*	−0.015	0.041**	1	−0.038**	0.319***	0.536***	−0.170***	−0.025	−0.059***	−0.105***	0.156***	0.169***	−0.201***	−0.028*	0.399***	0.239***	−0.068***	−0.131***	0.087***	−0.040**	−0.082***	−0.045***	−0.045***
6. MOMENTUM	−0.01	0.001	−0.017	−0.011	−0.038**	1	−0.057***	0.008	0.044**	−0.115***	0.087***	0.015	−0.014	0.042**	−0.033*	0.019	−0.039**	−0.065***	0.002	0.037**	−0.035**	0.017	0.002	0.024	0.01
7. SIZE	0.228***	0.233***	0.214***	0.186***	0.319***	−0.057***	1	0.331***	0.050***	−0.062***	−0.050***	0.113***	0.116***	−0.120***	−0.082***	−0.262***	0.183***	0.633***	0.366***	−0.105***	0.009	−0.158***	0.411***	−0.199***	0.349***
8. ROA	0.140***	0.104***	0.097***	0.148***	0.536***	0.008	0.331***	1	−0.218***	−0.288***	0.034*	0.011	0.125***	0.032*	−0.364***	−0.100***	0.178***	0.179***	0.059***	−0.150***	0.071***	−0.068***	0.074***	−0.099***	0.067***
9. LEVERAGE	−0.003	−0.009	−0.032*	−0.005	−0.170***	0.044**	0.050***	−0.218***	1	−0.01	−0.018	0.015	−0.137***	−0.124***	0.079***	0.028*	−0.206***	0.058***	0.039**	−0.033*	0.028*	−0.016	0.076***	−0.044**	0.024
10. EPS_DECLINE	0.047***	0.030*	0.066***	0.033*	−0.025	−0.115***	−0.062***	−0.288***	−0.01	1	−0.073***	0.001	0.050***	0.158***	0.121***	0.122***	0.076***	0.006	0.031*	−0.017	−0.060***	−0.02	0.024	0.002	0.031*
11. SURPRISE	−0.006	−0.004	−0.002	−0.002	−0.059***	0.087***	−0.050***	0.034*	−0.018	−0.073***	1	0.001	0.005	0.030*	−0.030*	0.061***	0.02	−0.023	−0.008	0.027*	0.005	0.031*	−0.014	0.002	0.001
12. BUS_SEGMENT	0.019	0.060***	0.042**	−0.009	−0.105***	0.015	0.113***	0.011	0.015	0.001	0.001	1	0.125***	−0.101***	0.013	−0.124***	0.089***	0.009	0.075***	0.031*	0.053***	−0.011	0.092***	−0.053***	0.077***
13. GEO_SEGMENT	0.162***	0.177***	0.154***	0.125***	0.156***	−0.014	0.116***	0.125***	−0.137***	0.050***	0.005	0.125***	1	0.177***	−0.111***	0.019	0.459***	0.081***	0.123***	−0.007	−0.038**	−0.061***	0.099***	−0.038**	0.162***
14. VOTALITY	0.048***	0.011	0.058***	0.048***	0.169***	0.042**	−0.120***	0.032*	−0.124***	0.158***	0.030*	−0.101***	0.177***	1	−0.130***	0.333***	0.217***	0.059***	−0.029*	0.009	−0.097***	0.006	−0.057***	0.048***	0.004
15. FINANCING	−0.069***	−0.040**	−0.043**	−0.078***	−0.201***	−0.033*	−0.082***	−0.364***	0.079***	0.121***	−0.030*	0.013	−0.111***	−0.130***	1	−0.088***	−0.116***	−0.140***	−0.006	0.101***	−0.038**	0.035*	−0.006	0.043**	−0.021
16. LIQUIDITY	−0.018	−0.042**	−0.028*	0.007	−0.028*	0.019	−0.262***	−0.100***	0.028*	0.122***	0.061***	−0.124***	0.019	0.333***	−0.088***	1	0.054***	0.222***	−0.153***	−0.078***	−0.012	0.071***	−0.154***	0.072***	−0.129***
17. RD	0.098***	0.131***	0.106***	0.073***	0.399***	−0.039**	0.183***	0.178***	−0.206***	0.076***	0.02	0.089***	0.459***	0.217***	−0.116***	0.054***	1	0.157***	0.029*	−0.021	0.046***	−0.037**	0.01	−0.044**	0.056***
18. NOA	0.155***	0.148***	0.127***	0.143***	0.239***	−0.065***	0.633***	0.179***	0.058***	0.006	−0.023	0.009	0.081***	0.059***	−0.140***	0.222***	0.157***	1	0.174***	−0.231***	0.061***	−0.104***	0.214***	−0.136***	0.173***
19. WORDCOUNT.W	0.673***	0.639***	0.621***	0.563***	−0.068***	0.002	0.366***	0.059***	0.039**	0.031*	−0.008	0.075***	0.123***	−0.029*	−0.006	−0.153***	0.029*	0.174***	1	0.109***	−0.294***	−0.321***	0.957***	−0.077***	0.976***
20. FOG.W	−0.029*	0.050***	0.012	−0.078***	−0.131***	0.037**	−0.105***	−0.150***	−0.033*	−0.017	0.027*	0.031*	−0.007	0.009	0.101***	−0.078***	−0.021	−0.231***	0.109***	1	−0.111***	0.046***	0.036**	0.280***	0.171***
21. TONE.W	−0.135***	−0.086***	−0.162***	−0.120***	0.087***	−0.035**	0.009	0.071***	0.028*	−0.060***	0.005	0.053***	−0.038**	−0.097***	−0.038**	−0.012	0.046***	0.061***	−0.294***	−0.111***	1	0.012	−0.284***	0.078***	−0.304***
22. UNCERTAINTY.W	−0.240***	−0.208***	−0.216***	−0.213***	−0.040**	0.017	−0.158***	−0.068***	−0.016	−0.02	0.031*	−0.011	−0.061***	0.006	0.035*	0.071***	−0.037**	−0.104***	−0.321***	0.046***	0.012	1	−0.320***	0.105***	−0.305***
23. SPECIFICITY.W	0.658***	0.611***	0.606***	0.560***	−0.082***	0.002	0.411***	0.074***	0.076***	0.024	−0.014	0.092***	0.099***	−0.057***	−0.006	−0.154***	0.01	0.214***	0.957***	0.036**	−0.284***	−0.320***	1	−0.154***	0.926***
24. FORWARDLOOK.W	−0.089***	−0.043**	−0.097***	−0.092***	−0.045***	0.024	−0.199***	−0.099***	−0.044**	0.002	0.002	−0.053***	−0.038**	0.048***	0.043**	0.072***	−0.044**	−0.136***	−0.077***	0.280***	0.078***	0.105***	−0.154***	1	−0.061***
25. ESG_EMPHASIS.W	0.682***	0.652***	0.623***	0.572***	−0.045***	0.01	0.349***	0.067***	0.024	0.031*	0.001	0.077***	0.162***	0.004	−0.021	−0.129***	0.056***	0.173***	0.976***	0.171***	−0.304***	−0.305***	0.926***	−0.061***	1

Note: The definitions of the variables are provided in Appendices A and B. *W* indicates that the variables have been winsorized. We use logarithmic values for the variables *SIZE*, *LEVERAGE*, *BUS_SEGMENT*, *GEO_SEGMENT*, *NOA*, *ESG_SCORE*, *WORDCOUNT.W*, *FOG.W*, *UNCERTAINTY.W*, *SPECIFICITY.W*, *FORWARDLOOK.W*, and *ESG_EMPHASIS.W*. However, for presentation purposes, they are expressed in their regular form.

*$p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

TABLE 7 | The economic value of the CE.

	TOBIN'S Q					
	Panel A—Baseline models		Panel B—Endogeneity tests			
	(1) Aggregated variable	(2) Disaggregated variables	(3) PSM	(4) IMR	(5) IV	(6) Entropy balancing
CIRCULAR_ STRATEGIES	−0.019***		−0.019***	−0.016**	−0.048**	−0.015*
	(0.006)		(0.006)	(0.006)	(0.021)	(0.009)
SHORT_LOOP		−0.010				
		(0.007)				
MEDIUM_LOOP		−0.016**				
		(0.006)				
LONG_LOOP		−0.001				
		(0.006)				
Control variables						
Firm-specific features						
MOMENTUM	−0.002	−0.002	−0.002	0.001	−0.002	−0.003
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
SIZE	0.076***	0.077***	0.076***	0.080***	0.076***	0.073***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ROA	0.012***	0.012***	0.012***	0.013***	0.012***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LEVERAGE	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
EPS_DECLINE	0.004	0.004	0.004	0.006	0.003	0.021***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
SURPRISE	−0.001	−0.001	−0.001	−0.001	−0.002	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
BUS_SEGMENT	−0.096***	−0.096***	−0.096***	−0.093***	−0.097***	−0.077***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)

(Continues)

TABLE 7 | (Continued)

	TOBIN'S Q					
	Panel A—Baseline models		**Panel B—Endogeneity tests**			
	(1) Aggregated variable	**(2) Disaggregated variables**	**(3) PSM**	**(4) IMR**	**(5) IV**	**(6) Entropy balancing**
GEO_SEGMENT	0.005	0.005	0.005	0.008	0.004	−0.018**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
VOTALITY	0.007***	0.007***	0.007***	0.007***	0.007***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FINANCING	0.0004	0.0004	0.0004	0.001	0.0004	0.001
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
LIQUIDITY	−0.003	−0.003	−0.003	−0.003	−0.003	0.005**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
RD	0.0005***	0.0005***	0.0005***	0.002***	0.0005***	0.012***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.001)
NOA	0.026***	0.025***	0.026***	0.015	0.026***	0.001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
ESG report characteristics						
WORDCOUNT.W	0.133***	0.138***	0.132***	0.145***	0.135***	0.049
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.032)
FOG.W	−0.071	−0.067	−0.070	−0.066	−0.069	0.006
	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.067)
TONE.W	−0.019**	−0.019**	−0.019**	−0.027***	−0.017**	−0.029***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
UNCERTAINTY.W	−0.037***	−0.037***	−0.037***	−0.032***	−0.037***	−0.036***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)
SPECIFICITY.W	−0.121***	−0.122***	−0.122***	−0.144***	−0.115***	−0.149***
	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.022)

(Continues)

TABLE 7 | (Continued)

	TOBIN'S Q					
	Panel A—Baseline models		Panel B—Endogeneity tests			
	(1) Aggregated variable	(2) Disaggregated variables	(3) PSM	(4) IMR	(5) IV	(6) Entropy balancing
FORWARDLOOK.W	0.024*	0.023	0.024*	0.032**	0.020	0.011
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
ESG_EMPHASIS.W	−0.092***	−0.094***	−0.091***	−0.149***	−0.073**	−0.011
	(0.027)	(0.027)	(0.027)	(0.030)	(0.030)	(0.027)
IMR				−0.059***		
				(0.014)		
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.048***	0.998***	1.051***	1.333***	1.000***	0.000
	(0.313)	(0.315)	(0.313)	(0.318)	(0.316)	(0.003)
Observations	5452	5452	5449	5451	5448	5452
R^2	0.616	0.616	0.616	0.619	0.614	0.906
Adjusted R^2	0.597	0.597	0.597	0.600	0.595	0.902
Residual std. error	0.275 (df = 5197)	0.275 (df = 5195)	0.275 (df = 5194)	0.274 (df = 5195)	0.275 (df = 5193)	0.172 (df = 5227)
F statistic	32.832*** (df = 254; 5197)	32.607*** (df = 256; 5195)	32.796*** (df = 254; 5194)	33.052*** (df = 255; 5195)		225.536*** (df = 224; 5227)

Note: The definitions of the variables are provided in Appendices A and B. *W* indicates that the variables have been winsorized. We use logarithmic values for the variables *TOBIN'S Q*, *SIZE*, *BUS_SEGMENT*, *GEO_SEGMENT*, *NOA*, *WORDCOUNT.W*, *FOG.W*, *UNCERTAINTY.W*, *SPECIFICITY.W*, *FORWARDLOOK.W*, and *ESG_EMPHASIS.W*. However, for presentation purposes, they are expressed in their regular form.

*$p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

TABLE 8 | Mechanisms: Moderation tests.

	TOBIN'S Q					
	Panel A—Financial slack	**Panel B—Greenwashing risk**		**Panel C—Risk perceptions**	**Panel D—Information asymmetry**	
	(1) *NET_DEBT*	**(2) *GREENWASHING_FIRM***	**(3) *GREENWASHING_SECTOR***	**(4) *LIQUIDITY***	**(5) *ESG_DISAGREEMENT***	**(6) *DISP***
CIRCULAR_STRATEGIES	0.077*	0.115***	0.047	0.009	0.018	−0.004
	(0.041)	(0.042)	(0.035)	(0.008)	(0.015)	(0.007)
FACTOR	−0.203***	0.909***	0.541**	0.017**	0.003	−0.0001
	(0.035)	(0.205)	(0.228)	(0.008)	(0.003)	(0.041)
CIRCULAR_STRATEGIES:FACTOR	−0.023**	−0.220***	−0.141**	−0.008***	−0.001*	−0.023*
	(0.010)	(0.065)	(0.071)	(0.003)	(0.001)	(0.013)
Control variables						
Firm-specific features						
MOMENTUM	0.001	−0.006	−0.006	−0.018	−0.006	−0.019*
	(0.010)	(0.010)	(0.011)	(0.011)	(0.014)	(0.011)
SIZE	0.086***	0.076***	0.076***	0.080***	0.071***	0.083***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.007)	(0.004)
ROA	0.010***	0.014***	0.014***	0.017***	0.017***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LEVERAGE	0.005***	0.001***	0.001***	−0.0001	0.002***	−0.0001
	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
EPS_DECLINE	−0.006	0.007	0.008	0.019*	0.007	0.022**
		(0.009)	(0.009)	(0.010)	(0.013)	(0.010)
SURPRISE	−0.001	−0.001	−0.00001	0.006	−0.004	−0.003
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
BUS_SEGMENT	−0.096***	−0.088***	−0.089***	−0.118***	−0.071***	−0.117***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.014)	(0.010)
GEO_SEGMENT	−0.0001	0.013	0.012	0.006	0.010	0.008

(Continues)

TABLE 8 | (Continued)

	TOBIN'S Q					
	Panel A—Financial slack	**Panel B—Greenwashing risk**		**Panel C—Risk perceptions**	**Panel D—Information asymmetry**	
	(1) *NET_DEBT*	**(2) *GREENWASHING_FIRM***	**(3) *GREENWASHING_SECTOR***	**(4) *LIQUIDITY***	**(5) *ESG_DISAGREEMENT***	**(6) *DISP***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.016)	(0.010)
VOTALITY	0.005***	0.008***	0.008***	0.011***	0.004***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
FINANCING	0.0003	−0.0004	−0.0005	0.001**	−0.001	0.001**
	(0.0005)	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)
LIQUIDITY	−0.003	−0.002	−0.002		0.002	−0.005
	(0.003)	(0.003)	(0.003)		(0.004)	(0.003)
RD	0.0004***	0.001***	0.001***	0.001***	0.011***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.0001)
NOA	0.019**	0.017*	0.016	0.018*	−0.037**	0.015
	(0.010)	(0.010)	(0.010)	(0.010)	(0.019)	(0.010)
ESG report characteristics						
WORDCOUNT.W	0.120***	0.107***	0.122***	0.131***	0.019	0.027
	(0.032)	(0.035)	(0.035)	(0.031)	(0.047)	(0.034)
FOG.W	−0.109	−0.065	−0.061	−0.072	−0.216**	−0.341***
	(0.069)	(0.072)	(0.073)	(0.066)	(0.101)	(0.072)
TONE.W	−0.021***	−0.016*	−0.016*	−0.020***	−0.026**	−0.003
	(0.008)	(0.009)	(0.009)	(0.008)	(0.011)	(0.008)
UNCERTAINTY.W	−0.045***	−0.034***	−0.036***	−0.036***	−0.033**	−0.029**
	(0.010)	(0.011)	(0.011)	(0.010)	(0.015)	(0.011)
SPECIFICITY.W	−0.120***	−0.103***	−0.107***	−0.121***	−0.074**	−0.153***
	(0.021)	(0.023)	(0.024)	(0.020)	(0.030)	(0.022)
FORWARDLOOK.W	0.027*	0.022	0.018	0.022	0.025	0.036**

(Continues)

TABLE 8 | (Continued)

	TOBIN'S Q					
	Panel A—Financial slack	**Panel B—Greenwashing risk**		**Panel C—Risk perceptions**	**Panel D—Information asymmetry**	
	(1) *NET_DEBT*	**(2) *GREENWASHING_FIRM***	**(3) *GREENWASHING_SECTOR***	**(4) *LIQUIDITY***	**(5) *ESG_DISAGREEMENT***	**(6) *DISP***
	(0.014)	(0.015)	(0.015)	(0.014)	(0.021)	(0.015)
ESG_EMPHASIS.W	−0.084***	−0.085***	−0.094***	−0.091***	−0.003	0.028
	(0.028)	(0.030)	(0.031)	(0.027)	(0.041)	(0.029)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.023**	−0.074	0.172	1.039***	0.933**	2.163***
	(0.010)	(0.345)	(0.341)	(0.313)	(0.377)	(0.349)
Observations	5.063	4.327	4.305	5.452	2.495	5.452
R^2	0.596	0.644	0.642	0.433	0.695	0.435
Adjusted R^2	0.575	0.622	0.620	0.427	0.668	0.430
Residual std. error	0.276 (df = 4810)	0.263 (df = 4081)	0.263 (df = 4059)	0.328 (df = 5397)	0.261 (df = 2286)	0.327 (df = 5396)
F statistic	28.137*** (df = 252; 4810)	30.099*** (df = 245; 4081)	29.681*** (df = 245; 4059)	76.303*** (df = 54; 5397)	25.088*** (df = 208; 2286)	75.681*** (df = 55; 5396)

Note: The definitions of the variables are provided in Appendices A and B. *W* indicates that the variables have been winsorized. We use logarithmic values for the variables *TOBIN'S Q*, *TOTAL_SCORE*, *SIZE*, *BUS_SEGMENT*, *GEO_SEGMENT*, *NOA*, *WORDCOUNT.W*, *FOG.W*, *UNCERTAINTY.W*, *SPECIFICITY.W*, *FORWARDLOOK.W*, and *ESG_EMPHASIS.W*. However, for presentation purposes, they are expressed in their regular form.

*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

values indicating repetitive disclosure over time. The second is sector-level similarity (*GREENWASHING_SECTOR*), measured as the median cosine similarity of a firm's report with those of its industry peers in the same year, with higher values indicating convergence toward sectoral templates. Interacting *CIRCULAR_STRATEGIES* with these measures, Models 2 and 3 of Panel B in Table 8 show that the negative association with firm value strengthens when similarity increases, suggesting that investors discount circularity claims when they lack distinctiveness. Taken together, these findings indicate that when CE disclosures resemble boilerplate or mimic sectoral templates, markets interpret them as symbolic or as a potential greenwashing tool, thereby reinforcing skepticism about their credibility and financial value.

4.4.3 | Risk Perception

Risk–return theory (Markowitz 1952) and behavioral perspectives (Kahneman and Tversky 1979) suggest that investors are particularly cautious toward projects with uncertain or delayed payoffs. CE initiatives, which often involve high upfront costs and long horizons, are therefore likely to be penalized more strongly by risk-averse investors. Following this reasoning, we use stock liquidity as a proxy for the risk tolerance of a firm's investor base, with higher liquidity (*LIQUIDITY*) indicating a more risk-averse clientele. Interacting *CIRCULAR_STRATEGIES* with *LIQUIDITY*, Model 4 of Panel C in Table 8 shows that the negative coefficient becomes more pronounced in highly liquid firms, which is consistent with the notion that investors with lower risk tolerance are especially skeptical of circularity disclosures.

4.4.4 | Information Asymmetry

To further investigate the role of information asymmetry, we build on signaling theory, which holds that investors discount disclosures more heavily when their credibility cannot be easily verified (Spence 1973; Healy and Palepu 2001). We therefore test whether the negative relationship between CE communication and firm value is amplified in environments of heightened informational uncertainty. As a first proxy, we use analyst forecast dispersion (*DISP*), which reflects the degree of disagreement among analysts regarding firms' future earnings. Higher dispersion indicates weaker consensus on financial prospects; as such, consistent with our expectations, the interaction result in Model 6 of Panel D in Table 8 shows that CE disclosures are penalized more strongly when forecast dispersion is high. As a second proxy, we employ *ESG_DISAGREEMENT*, constructed following Gibson Brandon et al. (2021). This measure measures the dispersion in third-party assessments of firms' ESG performance, which prior work associates with higher capital market uncertainty. Specifically, ESG disagreement is defined as the standard deviation of year-specific percentile-ranked ESG scores across MSCI, LSEG, and Bloomberg. Because constructing this measure requires coverage from all three agencies, the sample is reduced to 2495 firm-years. Results of Panel D, Model 5, in Table 8 indicate that greater ESG rating disagreement further intensifies the negative association between CE disclosures and Tobin's Q, suggesting that markets are particularly skeptical of circularity claims when both financial and sustainability-related information environments are characterized by uncertainty. Taken together, these findings suggest that the negative valuation effect of CE disclosures is particularly pronounced when firms operate under higher information asymmetry. In such settings, investors are more likely to discount CE-related claims, perceiving them as less credible and potentially more costly when their verification is difficult.

5 | Robustness Checks

In this section, we conduct three robustness checks by (i) redefining our main variable through an extended circularity score (*TOTAL_SCORE*), (ii) comparing it against ESG ratings as an alternative proxy, and (iii) applying a sector-year demeaning approach to approximate firm fixed effects.

We begin by testing whether our findings hold when we employ an alternative independent variable, *TOTAL_SCORE*. This measure aggregates our original variable (*CIRCULAR_STRATEGIES*) with explicit mentions of the term "circular economy" as well as its commonly used synonyms in sustainability discourse, including "regenerative economy," "cradle-to-cradle," and "eco-design." In doing so, *TOTAL_SCORE* captures both concrete strategy disclosures and broader, more rhetorical references to circularity. The results in Table 9, Model 1, closely mirror those obtained with the original variable, providing further validation of our findings.

As no official ratings or indicators exist for CE, prior studies have sometimes used ESG ratings as a proxy. For example, Morea et al. (2022) employ Refinitiv's ESG score, which evaluates a firm's performance across 10 themes grouped into the three ESG pillars. Following this approach, we conduct a second robustness check using the Refinitiv ESG score (*ESG_REFINITIV*) as a proxy for circularity. We first confirm that *CIRCULAR_STRATEGIES* and *ESG_REFINITIV* are highly correlated, suggesting some conceptual overlap. Table 9, Model 2, shows that *ESG_REFINITIV* itself has a significant effect on firm value. Model 3, which includes both variables in the regression, reveals that *CIRCULAR_STRATEGIES* remains negative and statistically significant at the 1% level, whereas *ESG_REFINITIV* remains significant at the same level. These results suggest that CE strategies capture information not fully reflected in broader ESG ratings and serve as an independent and relevant predictor of financial outcomes.

Finally, to control for firm-level heterogeneity while avoiding overparameterization from firm-specific dummy variables, we adopt in Table 9, Model 4, a demeaning approach based on sector-year groupings. Specifically, firms are classified into broad industry categories, and within each sector-year cell, we compute median values of both the dependent and independent variables. These group-level medians are then subtracted from the original firm-level observations, producing demeaned variables that filter out variation attributable to sectoral or temporal commonalities. This approach provides a computationally efficient alternative to firm fixed effects in large, unbalanced panels. Conceptually, it aligns with the estimator proposed by Bramati

TABLE 9 | Robustness check.

	TOBIN'S Q			*d_TOBIN'S Q*	
	Panel A—Alternative measures			**Panel B—Firm fixed effects**	
	Model 1	**Model 2**	**Model 3**	**Model 4**	
TOTAL_SCORE	−0.020***				
	(0.006)				
ESG_REFINITIV		−0.276***	−0.274***		
		(0.040)	(0.040)		
CIRCULAR_STRATEGIES			−0.021***		
			(0.007)		
				d_CIRCULAR_STRATEGIES	−0.017***
					(0.006)
Control variables					
Firm-specific features					
MOMENTUM	−0.002	0.004	0.005	*d_MOMENTUM*	−0.015
	(0.010)	(0.011)	(0.011)		(0.011)
SIZE	0.076***	0.082***	0.082***	*d_SIZE*	0.077***
	(0.004)	(0.006)	(0.006)		(0.004)
ROA	0.012***	0.012***	0.012***	*d_ROA*	0.015***
	(0.001)	(0.001)	(0.001)		(0.001)
LEVERAGE	0.001***	0.001***	0.001***	*d_LEVERAGE*	0.001***
	(0.0002)	(0.0002)	(0.0002)		(0.0002)
EPS_DECLINE	0.004	−0.001	−0.001	*d_EPS_DECLINE*	−0.004
	(0.009)	(0.010)	(0.010)		(0.008)
SURPRISE	−0.001	−0.005	−0.006	*d_SURPRISE*	−0.001
	(0.005)	(0.007)	(0.007)		(0.005)
BUS_SEGMENT	−0.096***	−0.105***	−0.106***	*d_BUS_SEGMENT*	−0.084***
	(0.009)	(0.011)	(0.011)		(0.009)

(Continues)

TABLE 9 | (Continued)

	TOBIN'S Q			*d_TOBIN'S Q*	
	Panel A—Alternative measures			Panel B—Firm fixed effects	
	Model 1	Model 2	Model 3	Model 4	
GEO_SEGMENT	0.005	0.015	0.013	*d_GEO_SEGMENT*	−0.012
	(0.010)	(0.012)	(0.012)		(0.009)
VOTALITY	0.007***	0.005***	0.005***	*d_VOTALITY*	0.008***
	(0.001)	(0.001)	(0.001)		(0.001)
FINANCING	0.0004	0.0005	0.0005	*d_FINANCING*	0.001
	(0.0004)	(0.001)	(0.001)		(0.0005)
LIQUIDITY	−0.003	−0.004	−0.004	*d_LIQUIDITY*	−0.007**
	(0.003)	(0.003)	(0.003)		(0.003)
RD	0.0005***	0.0004***	0.0004***	*d_RD*	0.001***
	(0.0001)	(0.0001)	(0.0001)		(0.0001)
NOA	0.026***	0.030**	0.029**	*d_NOA*	0.031***
	(0.009)	(0.014)	(0.014)		(0.009)
ESG report characteristics					
WORDCOUNT.W	0.133***	0.041	0.049	*d_WORDCOUNT.W*	0.041
	(0.031)	(0.038)	(0.038)		(0.029)
FOG.W	−0.071	−0.011	−0.002	*d_FOG.W*	−0.208***
	(0.066)	(0.080)	(0.080)		(0.067)
TONE.W	−0.019**	−0.028***	−0.027***	*d_TONE.W*	−0.020**
	(0.008)	(0.009)	(0.009)		(0.008)
UNCERTAINTY.W	−0.037***	−0.030***	−0.031***	*d_UNCERTAINTY.W*	−0.042***
	(0.010)	(0.011)	(0.011)		(0.011)
SPECIFICITY.W	−0.121***	−0.058**	−0.055**	*d_SPECIFICITY.W*	−0.103***
	(0.020)	(0.024)	(0.024)		(0.020)

(Continues)

TABLE 9 | (Continued)

	TOBIN'S Q			*d_TOBIN'S Q*	
	Panel A—Alternative measures			**Panel B—Firm fixed effects**	
	Model 1	**Model 2**	**Model 3**	**Model 4**	
FORWARDLOOK.W	0.024*	0.012	0.008	*d_FORWARDLOOK.W*	0.018
	(0.014)	(0.016)	(0.016)		(0.014)
ESG_EMPHASIS.W	−0.092***	−0.044	−0.035	*d_ESG_EMPHASIS.W*	−0.022
	(0.027)	(0.033)	(0.033)		(0.025)
Year fixed effects	Yes	Yes	Yes	Year fixed effects	Yes
Industry fixed effects	Yes	Yes	Yes	Industry fixed effects	No
Constant	1.045***	0.203	0.099		
	(0.313)	(0.316)	(0.318)		
Observations	5452	3955	3955	Observations	5452
R^2	0.616	0.647	0.648	R^2	0.295
Adjusted R^2	0.597	0.625	0.625	Adjusted R^2	0.289
Residual std. error	0.275 (df = 5197)	0.269 (df = 3714)	0.269 (df = 3713)	Residual std. error	0.290 (df = 5406)
F statistic	32.836*** (df = 254; 5197)	28.405*** (df = 240; 3714)	28.380*** (df = 241; 3713)	*F* statistic	49.100*** (df = 46; 5406)

Note: The definitions of the variables are provided in Appendices A and B. *W* indicates that the variables have been winsorized. We use logarithmic values for the variables *TOBIN'S Q*, *TOTAL_SCORE*, *SIZE*, *BUS_SEGMENT*, *GEO_SEGMENT*, *NOA*, *WORDCOUNT.W*, *FOG.W*, *UNCERTAINTY.W*, *SPECIFICITY.W*, *FORWARDLOOK.W*, and *ESG_EMPHASIS.W*. However, for presentation purposes, they are expressed in their regular form. Variables prefixed with "*d_*" are sector-year demeaned values, obtained by subtracting the sector-year median from each observation to filter out structural and temporal heterogeneity.

*$p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

and Croux (2007) and Boudt et al. (2014), who advocate median-centering to mitigate the influence of outliers. Combined with year fixed effects, this procedure provides a tractable way to absorb structural heterogeneity without overfitting. Our results remain robust under this specification, lending further support to the validity of our findings.

6 | Conclusions

This study investigates the CE strategies disclosed by US firms and their implications for firm value. Analyzing more than 7500 ESG reports between 1998 and 2023, we document a sharp rise in explicit references to CE, yet a simultaneous decline in the disclosure of concrete CE practices. Recycling emerges as the most frequently cited strategy, whereas repurposing, remanufacturing, and recovering are rarely highlighted. Our results show that CE communication is, on average, negatively associated with firm value, but this effect is heterogeneous: Medium loop reduces firm value, whereas short- and long loops display no significant impact.

To explain why circularity disclosures tend to be penalized, we examine four theoretically grounded mechanisms. Investors react more negatively when firms possess greater financial slack, consistent with agency theory, and when disclosures converge in form and content, consistent with legitimacy theory and greenwashing concerns. Firms with more risk-averse investor bases also face stronger penalties, in line with risk–return perspectives. Finally, signaling theory suggests that credibility concerns intensify under high information asymmetry, a pattern confirmed using analyst forecast dispersion and ESG rating disagreement. Taken together, these findings demonstrate that investor responses to CE depend not only on the type of strategies disclosed but also on the financial, reputational, and informational conditions under which they are communicated, helping reconcile inconsistent results in prior literature.

By focusing on the United States, an environment in which CE adoption is largely market driven rather than policy mandated, this paper contributes to the environmental-economics literature by clarifying how capital markets interpret circularity in the absence of strong institutional support. The results also inform how firms communicate CE initiatives to investors. First, disclosures benefit from strategy specificity. Rather than presenting circularity as a generic commitment, firms can clarify which CE approach is pursued (short, medium, or long loops) and the anticipated economic channels. Second, firms can improve the informativeness of CE disclosure by providing decision-useful detail, such as investment commitments or capability development, implementation timelines, and measurable circularity indicators (e.g., recycled content, remanufacturing rates, and product return rates), together with consistent progress updates across reporting periods. Third, beyond content, firms can strengthen the verifiability of these claims by standardizing definitions and measurement, ensuring reconciliation over time, and, where feasible, seeking external assurance. Overall, the findings suggest that the valuation of CE is shaped not only by whether firms "talk circularity" but also by how clearly and credibly they communicate the underlying strategic pathway.

As such, several avenues for future research emerge. First, comparative studies across institutional contexts, such as Europe or China where regulatory support for CE is stronger, could further illuminate the role of policy in shaping financial outcomes. Second, more work is needed on the boundary between substantive and symbolic CE communications, examining how textual distinctiveness, third-party verification, or assurance mechanisms influence investor perceptions. Finally, further research may explore the interactions between CE strategies, as circular business models are rarely implemented in isolation (DiVito et al. 2022), and assess how bundles of practices shape firm performance over different horizons. Pursuing these directions will deepen our understanding of how capital markets interpret circularity and the conditions under which CE disclosures may create, rather than erode, firm value.

Author Contributions

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. The authors confirm their contribution to the paper as follows:

- Study conception and design: J.O. Izquierdo-Montfort, Y. De Rongé, J.O.G. Thewissen, and S. Wilmet.
- Acquisition of data: J.O.G. Thewissen and Ö. Arslan-Ayaydin.
- Analysis and interpretation of results: S. Wilmet, J.O. Izquierdo-Montfort, Y. De Rongé, and J.O.G. Thewissen.
- Draft manuscript preparation: J.O. Izquierdo-Montfort, Y. De Rongé, J.O.G. Thewissen, S. Wilmet, and Ö. Arslan-Ayaydin.

All authors reviewed the results and approved the final version of the manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Endnotes

[1] Appendix A details the 10R framework and its corresponding CE strategies, providing definitions organized into short, medium, and long loops.

[2] As stated by Krippendorff (1980, 43), the increasing available material, especially in electronic texts and other data available online, "have [sic] had the effect of bringing content analysis closer to large population surveys, but without such surveys' undesirable qualities (i.e., without being obtrusive, meaning obliterating, and context insensitive)."

[3] As our measures are derived from ESG-report narratives, they capture the salience and framing of CE strategies in corporate disclosure. Consequently, *CIRCULAR_STRATEGIES* is best interpreted as a proxy for disclosed strategic emphasis, rather than as a direct measure of independently verified operational implementation.

[4] When estimated separately, short- and long-loop strategies also exhibit significant associations with firm value. These associations vanish once medium-loop strategies are jointly included, suggesting that investors place greater weight on medium-loop strategies when assessing firms' CE engagement.

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Appendix A

The 10R framework, with the specific ce strategies (10r) and their definitions, grouped into short, medium, and long loops.

Resource loop	Circular strategy	Definitions
Short loops	R0—Refuse	Make a product redundant by abandoning its function or offering the same function with a radically different product.
	R1—Rethink	Make the use of a product more intensive, for instance, by implementing product-service systems; the virtualization or dematerialization of a product; the implementation of a hybrid or gap exploiter business model, based on selling a long-lasting product combined with consumables that are often disposables; or the implementation of a platform allowing for product or asset sharing.
	R2—Reduce	Increase efficiency in the production process by using fewer natural resources and materials.
Medium loops	R3—Reuse	Use a product multiple times, retaining both its identity and its function.
	R4—Repair	Make a defective or broken product operational so it can be used for its original function.
	R5—Refurbish	Upgrade or modernize a product to perform the same function, by using newer and advanced components.
	R6—Remanufacture	Use discarded products or parts in a new product with the same function to give the product the same quality as when it was brand new.
	R7—Repurpose	Use end-of-life products or their parts to create new products with different functions.
Long loops	R8—Recycle	Processing materials of waste or end-of-life products to obtain a material (called secondary material) of either the same or lower quality. It includes both secondary recycling, when the waste comes from discarded end-of-life postconsumer products, and primary recycling, when the waste comes from manufacturers.
	R9—Recover	Processing materials of waste or end-of-life products to capture the energy, typically through waste incineration.

Note: Based on Potting et al. (2017) and Reike et al. (2018).

Appendix B

Summary of variables.

Variables	Definition
Independent variables	
CE strategies (*CIRCULAR_STRATEGIES*)	Indicates the level of adoption of CE strategies of the firm.
Short loop (*SHORT_LOOP*)	Indicates the level of adoption of CE strategies of the short loop of the firm. It includes the strategies refuse, rethink, and reduce.
Medium loop (*MEDIUM_LOOP*)	Indicates the level of adoption of CE strategies of the medium loop of the firm. It includes the strategies reuse, repair, refurbish, remanufacture, and repurpose.
Long loop (*LONG_LOOP*)	Indicates the level of adoption of CE strategies of the long loop of the firm. It includes the strategies recycle and recover.
Total score (*TOTAL_SCORE*)	Variable that includes the use of terms linked to the CE, CE strategies, and potential synonyms of the CE in the ESG reports.
ESG rating of Refinitiv (*ESG_REFINITIV*)	Variable created by Refinitiv (LSEG) measuring a company's ESG performance across 10 main themes forming the three pillars of ESG, based on verifiable reported data in the public domain.
Dependent variable	
Tobin's Q (*TOBIN′S Q*)	Market value of a firm divided by the replacement value of its assets.
Control variables	
Firm-specific variables	
Size (*SIZE*)	The natural logarithm of total assets at the end of the current year.
Year (*YEAR*)	Dummy variable for each year in the sample.
Industry fixed effects (*INDUSTRY*)	Dummy variable for each industry of the MSCI classification system.
Return on assets (*ROA*)	The income before extraordinary items divided by total assets at the end of the previous year.
Earnings surprise (*SURPRISE*)	The spread in the analysts' consensus EPS forecast and the actual EPS, divided by the stock price at the end of the previous year. The consensus analyst forecast is defined as the average of the most recent analyst forecasts for the firm in the current year.
EPS decline (*EPS_DECLINE*)	A dummy variable that equals 1 if the EPS declined in the current year and 0 otherwise.
Momentum (*MOMENTUM*)	The 1-year cumulative abnormal return from the [−375, −10] trading day window, where the event is the ESG reporting date.
Financing activities (*FINANCING*)	Firm's net debt amount and raised equity capital (i.e., the sum of net sale of common and preferred shares and net long-term debt issuance) during the year scaled by total assets at the year-end.
Stock liquidity (*LIQUIDITY*)	The number of shares traded divided by the total number of shares outstanding for the same year.
Research and development intensity (*RD*)	The research and development expenses deflated by sales during the year.
Analyst following (*NOA*)	The natural logarithm of 1 plus the number of financial analysts at the end of the same year.
Geographical segments (*GEO_SEGMENT*)	The logarithm of the number of geographical segments.
Business segments (*BUS_SEGMENT*)	The logarithm of the number of business segments.
Financial leverage (*LEVERAGE*)	Total debt (short-term plus long-term debt) divided by total assets at the year-end.
Earnings uncertainty (*VOLATILITY*)	The standard deviation on ROA for a period of 5 years.
ESG score (*ESG_SCORE*)	The firm's environmental, social, and governance rating calculated by MSCI.
ESG report variables	
Word count (*WORDCOUNT*)	The logarithm of the total number of words in the document.
ESG report's readability (*FOG*)	The average number of words per sentence added to the percentage of words per sentence. The FOG index estimates the years of schooling that a reader of average intelligence would need to read and understand the text.

Variables	Definition
ESG report's tone (*TONE*)	Which is defined as the spread in the number of positive and negative words, scaled by the total number of words in the ESG report.
ESG emphasis (*ESG_EMPHASIS*)	The sum of the ESG-specific words from the Baier et al. (2020) list, divided by the total number of words in the ESG report.
ESG report's specificity (*SPECIFICITY*)	The total number of unique named entities detected by Named Entity Recognition (NER).
ESG report's uncertainty (*UNCERTAINTY*)	The percentage of uncertain words in the text based on Loughran and McDonald's (2014) lists of uncertain words.
ESG report's forward-looking information (*FORWARDLOOK*)	The proportion of forward-looking sentences based on the method adopted by Henry (2008), Henry et al. (2024), and Athanasakou and Hussainey (2014).
Additional variables	
Net debt (*NET_DEBT*)	Total debt minus cash and cash equivalents, scaled by total assets at year-end.
Firm-level textual similarity (*GREENWASHING_FIRM*)	Cosine similarity between a firm's consecutive ESG reports; higher values indicate repetitive disclosure over time.
Sector-level textual similarity (*GREENWASHING_SECTOR*)	Median cosine similarity of a firm's ESG report with those of its industry peers in the same year; higher values indicate convergence toward sectoral templates.
Earnings forecast dispersion (*DISP*)	Analyst forecast dispersion, capturing disagreement among analysts on firms' future earnings; higher values indicate greater informational uncertainty (He et al. 2025).
ESG rating disagreement (*ESG_DISAGREEMENT*)	Standard deviation of percentile-ranked ESG scores across MSCI, LSEG, and Bloomberg; higher values indicate greater disagreement among rating agencies and higher capital market uncertainty (He et al. 2025).

Appendix C

Dictionary Creation Process

We start the dictionary creation with an initial word list (IWL) consisting of the 10 CE strategies included in the 10R framework of Potting et al. (2017) and Reike et al. (2018): refuse, rethink, reduce, reuse, repair, refurbish, remanufacture, repurpose, recycle, and recover.

Due to the use of different terms between academic research and firms and the lack of appropriate language and tools, especially in the context of circular business model innovation (Blomsma and Brennan 2017), we used different techniques to develop the entries of the dictionary. First, we used extension by synonyms using an English thesaurus, which increased the number of keywords up to 64. As the dictionary was to be applied in reports of American companies, American English was used. Then we divided these keywords into two groups: those always used within the context of the CE, such as recycle, and those that can be used in nonrelated contexts, such as reduce and recover. Although the stemming technique consisting of truncating words was used for the 15 keywords of the first group, a contextualization technique by adding direct objects was used for 49 keywords of the second group. We used academic articles and companies' reports to identify 77 nouns and 16 adjectives to contextualize the verbs. We combined them and created 1232-bigram combinations containing one of the 16 adjectives and one of the 77 nouns. Each bigram was individually reviewed by two of the authors to make sure they were related to the CE and to exclude those that either did not make sense or, even if they made sense, would not contribute to the contextualization. Out of the 1232 bigrams, only in one case was there a disagreement between the two reviewers, which indicates almost total intercoder reliability, the agreement of data units on which the two coders agree (Feng 2014). An internal discussion was conducted to reach an agreement for the disagreed bigram. Finally, 654 bigrams were included. Together with the 77 nouns, a total of 731 direct objects to contextualize the verbs were selected.

A combination between the 49 verbs requiring contextualization and the 731 direct objects was created, resulting in a total of 35,819 combinations containing bigrams and trigrams. The same methodology as before was conducted. Two authors individually reviewed the combinations to exclude those combinations unrelated to the CE. Disagreements between the reviewers accounted for 303 combinations. An intercoder reliability of 99% was observed, and an internal discussion was conducted to reach an agreement, leading to the inclusion of 10,800 combinations.

To account for inflections, or different forms of the same words, we inflected the root word to capture the different forms in which they can appear in a report (Loughran and McDonald 2011). After inflection, the 10,800 combinations became a total of 43,200.

The resulting 43,200 combinations were added to the list of 15 verbs not requiring contextualization, and after a last review of two authors, 18 new keywords were added, resulting in a total of 43,233 keywords. Following this, two authors categorized the keywords into the 10R framework with almost total intercoder reliability.

Finally, we utilized the keywords-in-context (KWIC) technique (Fielding and Lee 1998), a method that analyzes the words surrounding a key term to understand its contextual usage (Leech and Onwuegbuzie 2007). This technique helps verify the accuracy and relevance of the terms in our dictionary. We manually implemented the KWIC approach on reports with the highest keyword frequency, as well as on a randomly selected sample of reports. Through this validation process, we confirmed that our keywords were appropriately linked to the CE and accurately classified within the 10R framework.