

Research article

Secondary raw materials use and impacts on Italian firms' performance: Survey-based evidence

Edoardo Quattromini^{a,*}, Elisa Chioatto^b, Alessio D'Amato^c, Emy Zecca^d

^a *Istituto di Management - Sant'Anna School of Advanced Studies, Italy*

^b *Dipartimento di Economia e Management, Università Degli Studi di Ferrara and Sustainability, Environmental Economics and Dynamics Studies (SEEDS), Italy*

^c *Dipartimento di Studi Economici e Giuridici, Università Degli Studi di Napoli Parthenope and Sustainability, Environmental Economics and Dynamics Studies (SEEDS), Italy*

^d *Dipartimento di Scienze Chimiche, Farmaceutiche Ed Agrarie, Università Degli Studi di Ferrara and Sustainability, Environmental Economics and Dynamics Studies (SEEDS), Italy*

A B S T R A C T

This paper investigates a previously under-explored topic: the impact of Secondary Raw Materials use on firm performance. To this end we construct an original dataset on Italian firms by combining data from a newly developed survey with existing AIDA data covering the period 2021–2022. Focusing on turnover growth as our performance metric, we assess whether firms that adopt secondary raw materials experience different growth trajectories compared to those that do not. To identify the impact under scrutiny, we employ a Propensity Score Matching approach, accounting for other relevant drivers of turnover change over time, such as R&D, number of employees, access to public funds and entrepreneurial education. Our findings suggest that firms integrating secondary raw materials in their production processes tend to perform better in terms of turnover growth, with SRM adopting firms featuring a 10% higher turnover growth in the years under scrutiny. However, the effect appears to be sector-specific, highlighting the role of industry characteristics in determining the benefits of secondary raw material use. Additional dimensions of performance, i.e. water and resource savings, are also analyzed, confirming the presence of sector level evidence and suggesting sector specific policy needs.

1. Introduction

Over the past decade, scholarly discourse on the circular economy has increasingly underscored the critical importance of reducing dependence on virgin raw materials while curtailing the volume of waste directed to landfills. Within this broader framework, the use of Secondary Raw Materials (hereafter SRM), derived through recycling, reclamation, or industrial by-product recovery, has gained prominence as a pivotal component of sustainable manufacturing (European Commission. Directorate General for Environment, 2020). By converting potentially discarded materials into valuable inputs, SRM alleviates mounting pressure on natural resources and can also mitigate cost escalations associated with resource extraction and processing.

Notwithstanding the wide-ranging political and academic attention directed at circular economy paradigms, the operational uptake of SRM in diverse manufacturing contexts is still lagging behind. Several factors may explain this apparent inconsistency. First, fluctuations in both the quality and the availability of recycled materials, stemming from heterogeneous regional waste-collection systems, make consistent supply

challenging. Second, fragmented regulations and a lack of universally accepted standards can inhibit the seamless incorporation of SRM into production lines. Third, market acceptance of SRM-based products frequently hinges on consumer perceptions regarding product safety, quality, and reliability. Consequently, advancing SRM adoption requires cross-sectoral cooperation, technological investment, and strategic managerial guidance at every operational level (Remeikiene et al., 2024; Zu Castell-Rudenhausen et al., 2022).

From a research perspective, the potential economic advantages of SRM use, especially with respect to corporate financial performance, have attracted growing scholarly interest. While extant literature thoroughly investigates the environmental contributions and social responsibility aspects of circular models (Korhonen et al., 2018b), empirical research specifically examining metrics such as revenue or profitability outcomes linked to SRM usage remains comparatively sparse (Antonioli et al., 2022). This gap is especially salient given the ongoing evolution of circular economy theories and the many hypothesized but under-examined pathways by which SRM might contribute to a firm's competitiveness and market positioning.

* Corresponding author.

E-mail addresses: edoardo.quattromini@santannapisa.it (E. Quattromini), elisa.chioatto@unife.it (E. Chioatto), alessio.damato@uniparthenope.it (A. D'Amato), emy.zecca@unife.it (E. Zecca).

<https://doi.org/10.1016/j.jenvman.2026.129275>

Received 22 September 2025; Received in revised form 26 February 2026; Accepted 7 March 2026

Available online 12 March 2026

0301-4797/© 2026 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

In response to these challenges, our paper seeks to determine whether, and under what conditions, SRM adoption positively affects revenue growth in the Italian manufacturing sector. This analysis focuses on the period spanning 2021 to 2022.

To address this question, this study integrates datasets drawn from a comprehensive and original survey by the Italian Institute for Environmental Protection and Research (ISPRA), in collaboration with the Department of Economics and Management of the University of Ferrara, covering 1001 firms, and from the AIDA database, which furnishes a rich compendium of financial indicators. By linking organizational and economic variables (including firm size, R&D intensity, technological capacity, and export orientation), our analysis first addresses the possible determinants and impacts of SRM adoption. Then, a Propensity Score Matching (PSM) methodology is employed to approximate causal effects, mitigating the biases often introduced by non-random, voluntary shifts toward more sustainable practices that are likely to affect survey-based data and, through pairing SRM adopters with observationally similar non-adopters, it allows us to infer the impact of SRM usage on economic performance outcomes in a methodologically robust way.

Our main results show that the integration of SRM usage in production practices may enhance corporate performance. On the other hand, though suggestive of potential synergies between ecological stewardship and economic gains, we cannot warrant immediate large-scale application, due to the heterogeneity of the impacts according to the specific macro-sectors analyzed. Interestingly, by applying a similar methodology to the assessment of SRM adoption on indicators of environmental performance, namely water and resource consumption, we conclude that the sectors where economic performance is not enhanced, namely light consumers goods and chemicals, are those that benefit the most from SRM in terms of environmental performance. These results underscore the complexity of SRMs adoption and signals the importance of deeper investigation before more definitive guidance can be offered, but also suggests the possibility of SRM to be part of a circular transition and highlights the sectors where policy should be more targeted.

Our contribution to the literature rests in the novelty of our research questions: to the best of our knowledge, this is the first paper addressing the impact of SRM adoption on the economic performance of firms. This is, in our view, a relevant question both in empirical terms and for policy implications. Also, novelty traits of our analysis link to our sector level assessment, which provides a better understanding of the heterogeneous benefits accruing from SRM adoption.

Finally, our results are confirmed as robust to existing trends, excluding the possibility that results for SRM adopting are due to pre-existing differences in economic performance, and we are able to disentangle demand and supply side drivers of SRM adoption.

The remainder of the paper is organized as follows: Section 2 surveys focus on the relevant literature and outlines the research question addressed in our study. Section 3 describes data and elaborates on the methodological foundations of the PSM approach, including the selection of covariates, matching algorithms, and validation steps. Section 4 presents the core empirical findings. Finally, Section 5 concludes by discussing the implications of our results from both policy and managerial perspectives, and by proposing pathways for future research and practical application.

2. Literature review and research hypotheses

The adoption of SRM, i.e. raw materials obtained from recycling or recovery processes, is a fundamental element in promoting the circular economy and reducing the pressure on natural resources (Kirchherr et al., 2017). By enabling the closure of material loops, SRM help to both reduce environmental impacts and decrease dependence on virgin raw materials. From a theoretical point of view, SRM can also be interpreted as a lever for process and product innovation, since the need to adapt production plants can generate unprecedented technical solutions. However, the complexity of the circular transition is not limited to the

adoption of new technologies: it affects managerial culture, change management and understanding of market dynamics.

The main challenge lies on the qualitative side, as SRM can have non-uniform physicochemical characteristics, making it difficult to define standardized specifications (Kirchherr et al., 2017). This heterogeneity is influenced by upstream selection and transformation processes, as well as potential impurities in collected waste (Lacy and Rutqvist, 2015), involving issues related to compliance with technical specifications (Witjes and Lozano, 2016), supply side uncertainty (Ghisellini et al., 2016) as well as certification requirements.

- On the demand side, several aspects related to product positioning (Witjes and Lozano, 2016) and perception of product quality (Lacy and Rutqvist, 2016) may matter in driving firms' incentives to use SRM.

On the competitiveness and innovation side, the introduction of SRM could involve a technological adaptation aimed at managing more complex and variable production processes (Porter and Van der Linde, 1995), which include experiments and adaptation to new machineries or processes (e.g. Zhu and Sarkis, 2004; Witjes and Lozano, 2016) as well as staff training (Hart and Glen, 2011).

Another key aspect is the regulatory dimension: Defining the “end-of-waste” criteria and SRM requirements often involves complex and fragmented procedures at both national and international levels (European Commission. Directorate General for Environment, 2020), which may result, for example, in long authorization times (e.g. Ghisellini et al., 2016) and/or rigidity of industry standards (e.g. Kirchherr et al., 2017). In addition, regulatory fragmentation between different countries can complicate the export of products made with SRM.

Finally, the adoption of SRM may generate benefits in terms of lower costs or increased revenues. On the costs side, we can indeed expect a reduction in procurement costs and minimize dependence on price fluctuations of virgin resources (Porter and Van der Linde, 1995). Gummerotti et al. (2019), for example, show that drivers of a purely economic nature are the most incisive in encouraging the so-called “linear companies” to embrace more circular business models. Economic benefits may include savings on virgin raw materials (especially in contexts marked by economic volatility and geopolitical instability), as well as improvements in the efficiency in disposal processes (e.g. Ghisellini et al., 2016). Adopting SRM can also act as a lever of innovation that goes beyond the purely technological dimension, enabling forward-looking firms to access new market segments (e.g. Kirchherr et al., 2017) and improving the firm's positioning in the eyes of investors, local communities and institutions (Lacy and Rutqvist, 2015). The use of SRM has a decisive impact on reducing the ecological impact, in particular in manufacturing sectors, as it reduces the consumption of virgin raw materials and the production of waste to be disposed of (Kirchherr et al., 2017), mitigating at the same time exposure to environmental risks.

From the above discussion, it is clear that the introduction of SRM into manufacturing processes presents complex challenges, ranging from setting quality standards to managing consumer confidence and regulatory challenges. Nevertheless, the potential benefits are substantial: cost reduction, creation of new markets, development of innovative solutions and, last but not least, a positive impact on the environment and the social fabric. This leads us to conclude that the impact of SRM adoption on firms' could be characterized by uncertainty given the rather specific features of the challenges and opportunities highlighted here, it may also be sector-specific. This leads to two main research questions.

- RQ1. Do manufacturing firms that adopt Secondary Raw Materials exhibit a higher rate of revenue expansion between 2021 and 2022 compared to those that do not?

RQ2. Does the effect of SRM utilization on firm performance vary systematically across heterogeneous industrial domains, such as light consumer goods, chemical-pharmaceutical production, and metallurgical-mechanical-electronic sectors?

RQ3. To what extent does the adoption of Secondary Raw Materials (SRM) contribute to non-monetary value creation, specifically in terms of environmental performance (water usage and resource consumption reduction), across different industrial sectors?

These questions focus on testing the economic performance consequences of SRM adoption. This fits, in general with the broader literature on the costs and benefits related to such adoption, as well as into the more general works on the Porter hypothesis (Porter and van der Linde, 1995). On the other hand, we think our approach is novel and policy relevant. Also, Italy is a compelling study to test our research questions, as the dynamism of the Italian manufacturing sector plays a decisive role in encouraging the adoption of SRM. Indeed, many small and medium-sized enterprises show a propensity for innovation and decision-making flexibility that allow them to test recycled materials in production cycles, thus generating a virtuous circle between supply and demand for secondary resources.

3. Data and methods

3.1. Data description

The empirical investigation was conducted using an original dataset of Italian SMEs operating in the manufacturing sector. Data have been collected in 2022 by the Higher Institute for Environmental Protection and Research (ISPRA), in collaboration with the Department of Economics and Management of the University of Ferrara, through the elaboration of a national survey. The survey took the form of a CAWI (Computer Assisted Web Interview) through which a structured questionnaire was administered to firms. The questionnaire, aimed at collecting information of both structural and strategic nature, including the employment dimension, the percentage of graduated personnel (with particular regard to managerial and operational roles) the origin of revenues, production capacities and environmental innovation policies. Part of the questionnaire focused on the extent of investments in research and development, with attention to both traditional innovation projects and activities with an environmental vocation. The sample has been stratified by geographical location (macro area, Istat), sector (technological intensity, Eurostat¹), dimension (10-49 employees; 50-249 employees; >250 employees). The final sample counts 1001 Italian manufacturing firms (ATECO codes 10-33, with the exception of 12).

To investigate the relation between the use of SRM within production processes and the economic-financial performance of firms, we, subsequently, complemented the ISPRA dataset with the AIDA database, to acquire a set of variables of economic and managerial importance, including turnover, EBITDA, net profit, capital structure ratios (DEBT/equity, DEBT/liquidity), equity, added value per employee, labor productivity (calculated as the ratio between turnover and number of employees) and operating cash flow, with data available from 2018 to 2023. During the matching process, we did not find a match for 230 companies in the AIDA database and therefore we excluded them from the sample, leaving us with 771 observations. Following the alignment of the two sources, an in-depth verification of the internal consistency of the data was carried out, proceeding to the elimination of any observations characterized by many missing or implausible values. In particular, we adopted turnover as a measure of firms' performance, being it the one available for the largest number of firms, due to their dimensional features in the sample. This choice guarantees

comparability across firms.

The information collected aims to provide the national firms' context in a timely manner both in terms of size, with the presence of small, medium and large companies, and in terms of territorial areas, ensuring a diversified overview of the Italian regions. In addition, the variety of participating firms includes both operators already consolidated in the field of environmental sustainability and firms that, for the first time, approach innovative practices of eco-efficiency and reduction of environmental impact, with a view to a transition towards more circular production models.

Table 1 shows the composition of the sample, while Table 2 reports the number and share of firms adopting SRM.

The table breaks down firms by their use of SRM (Yes/No) and by size class (Small, Medium, Large). In the small firm segment, 79 firms report adopting SRMs, corresponding to 15% within the subsample and 10% of all companies using SRM. Despite the large number of small firms overall, this share reflects the still significant room for growth in the adoption of circular solutions. Among medium-sized companies, 67 report SRM adoption, corresponding to 32% within the group, and 9% of total users.

This pattern may reflect a stronger inclination toward sustainability investments, potentially enabled by greater financial and organizational capacity. In last instance, large firms show the highest adoption rate: 31 firms use SRM, a value equal to 86% within the group, but which accounts for only 4% of the total SRM' users. This high within-group rate likely stems from the availability of resources necessary to implement structured waste management strategies and capitalize on secondary materials.

We can therefore notice that the percentage of firms using SRM increases with firm size, although, in absolute terms, small and medium-sized enterprises continue to represent the majority of the sample of users.

Fig. 1 presents a comparison of the progression in average turnover and in productivity (calculated as turnover per employee) in 2022, based on firms' adoption of SRM as an input of our production process. Notice that SRMs adoption seems to have an impact on average turnover (left part of Fig. 1, although the statistical significance can be questioned), while the impact on productivity (right part of Fig. 1) appears as less relevant. It is important to note that the precise timing of SRM adoption by firms indicating "Yes" is unspecified, hence we cannot confirm whether they were already utilizing SRMs before the timing of our analysis. Nonetheless, from Fig. 1 we can conclude that the impact of SRM adoption on firms' performance deserves more detailed and rigorous analysis.

In addition to economic performance, we extend our analysis to environmental outcomes to capture the multi-dimensional impact of SRM adoption. We employ two binary variables derived from the survey, serving as proxies for process efficiency and environmental footprint reduction: Water Usage Reduction (in Fig. 1c), a dummy variable equal to 1 if the firm declared a reduction in water consumption following the adoption of circular practices, and 0 otherwise. Resource Consumption Reduction (in Fig. 1d) a dummy variable equal to 1 if the firm reported a general reduction in the use of primary resources (materials or energy) in their production process. These variables allow us to test whether

Table 1
Sample composition.

Indicators	Small (10-49)	Medium (50-249)	Large (>249)
Number of Firms	523	212	36
Number of Firms (%)	68%	28%	5%
Workers Share	22%	43%	35%
Value Added (%)	20%	48%	31%
Exporting Firms (%)	51%	41%	8%

Source: own elaboration based on data from ISPRA/UNIFE survey and AIDA data.

¹ Eurostat classification https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries.

Table 2
Distribution of secondary raw materials usage.

SRM introduction	Small	Medium	Large
Yes	79	67	31
No	444	145	5
Partial %	15%	32%	86%
% of total	10%	9%	4%

Source: own elaboration based on data from ISPRA/UNIFE survey and AIDA data.

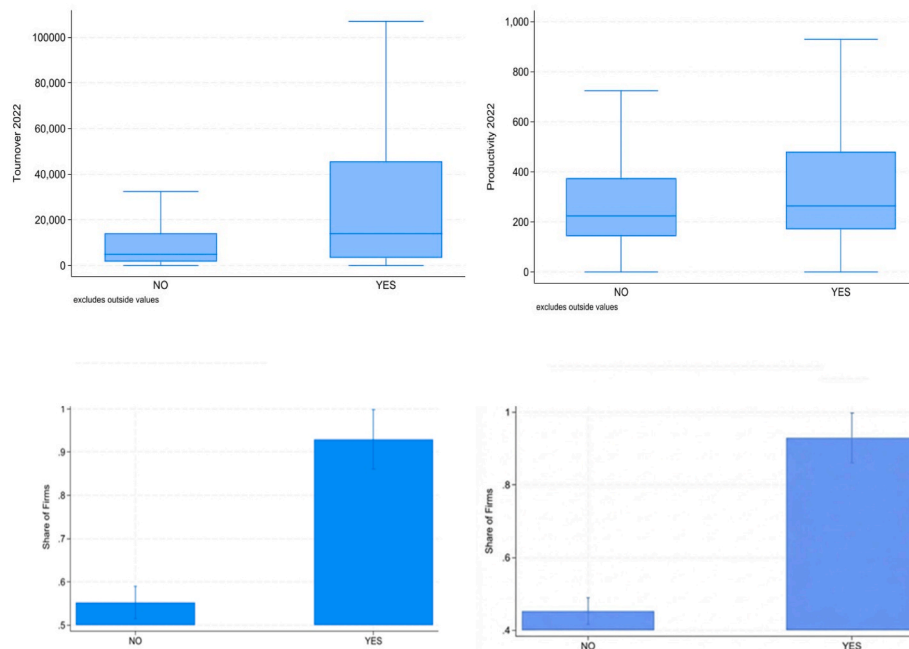


Fig. 1. Turnover and productivity according to SRM adoption. Year 2022.
Source: own elaboration based on data from ISPRA/UNIFE survey and AIDA data.

firms particularly those in sectors where turnover growth is less evident are deriving value through efficiency and sustainability channels.

3.2. Methodologies and assumptions

We adopt a PSM strategy, intended to balance pre-existing differences between companies that adopt SRMs and those that do not. This statistical approach aims to isolate the impact of secondary raw material usage by controlling for crucial variables, including firm size, innovation level, financial strength, and investments in research and development. In this way, an attempt is made to assess whether the use of SRM significantly affects the change in turnover between 2021 and 2022.

Employing Propensity Score Matching (PSM) alongside this sector-based division allows more reliable isolation of SRM's effects, controlling for internal sector differences. Indeed, existing literature emphasizes the importance of considering sectoral differences, highlighting that technology, regulation, and market demand significantly influence the adoption of environmental innovations across industries (Horbach et al., 2012). The PSM method allows us to account for potential selection bias by comparing firms that use SRM with similar firms that do not. We justify the use of PSM in light of the non-random nature of SRM adoption and discuss the key covariates influencing both the likelihood of adoption and economic performance outcomes. In other words, the PSM approach is adopted to avoid biases due to factors that push firms to use SRM being the same as those that determine or condition their growth in turnover. The basic idea is to estimate, for each firm, the probability of adopting SRM as a function of a set of specific

characteristics (the so-called confounding factors). This probability, or “propensity score”, is then used to match firms that actually use SRM with those that, on the basis of the propensity score, are *similar* but do not adopt this practice. In this way, the systematic disparity between the two groups due to pre-existing characteristics is reduced, making estimates of the effects of the variable of interest (the use of SRM) more reliable (Garrido et al., 2014).²

To this end, we define firms using SRM in 2021 and 2022 as the ‘processing’ group, while the ‘controlling’ group is composed by firms

not using SRMs in the same period. Next, a logistic regression model is constructed in which the dependent variable is the probability of belonging to the treatment group. The independent variables include several factors considered relevant both for the decision to introduce SRM and for the growth in turnover. Once the propensity score has been calculated for each firm, the treated companies are combined with the control firms that have similar values of this score.

There are several matching techniques (e.g. “Nearest Neighbor”, “Radius” or “Kernel”), but, in general, the goal is to identify pairs or sets of firms that are as similar as possible in terms of propensity score, while ensuring the balance of covariates between the two groups.

In our analysis, we will use in particular the Epanechnikov Kernel, a choice motivated by the fact that this type of kernel allows to attribute a greater weight to the closest units in the propensity score, ensuring an adequate reduction of variance and good efficiency in estimating the effect (Heckman et al., 1997). Compared to other kernels, Epanechnikov tends to be less sensitive to extreme values and, in many cases, represents an optimal intermediate solution between bias and variance (Heckman et al., 1998).

Once the matching phase is over, it is important to check the balance of the covariates between the two groups. A well-executed matching should achieve a reduction in confounding factors means between the treated and control groups, so that differences across SRMs adopting and non-adopting firms can be confidently attributed to the use of SRMs

² Appendix A shows more details on the PSM methodology adopted.

rather than to pre-existing structural disparities.

Our treatment variable is *SRM*; it is a binary variable equal to 1 if the firm declared having used secondary raw materials, and 0 otherwise. Through a logistic regression model aimed at estimating the propensity to treatment, we aim at controlling for the characteristics that may affect the probability that *SRM* equals 1, so that, at the end of the matching, the companies that actually adopt SRM are compared with “peers” that do not use them, minimizing potentially misleading structural differences. This is our strategy to identify the specific link between SRM adoption and firms’ performance.

To measure the impact of SRM adoption on firms’ performance, we adopt the variable *turnover 2021 – 2022*, a continuous variable representing the percentage change in turnover between 2021 and 2022, used as the outcome variable in the analysis. This allows us to estimate the average difference in revenue growth between firms that adopt secondary raw materials and those that do not.

The variables included in the PSM model are selected to account for factors that influence both the likelihood of SRMs adoption and firm performance (according to the literature reviewed in section 2, but see also (Pronti and Zoboli, 2024)). In particular, we consider: *R&D* is a binary indicator that signals whether the company invests in Research & Development. Firms engaged in R&D activities often have a greater propensity to experiment with new solutions, including those based on the reuse of waste or recovered materials. At the same time, investment in R&D is often associated with a positive impact on business growth and competitiveness. *N_employees* is a continuous variable indicating the total number of employees in each firm for the year 2022. The size of the company can affect the ability to implement organizational changes and process innovations, such as the use of SRM, and generally impacts performance variables such as turnover. *Tech* is a categorical variable (with three levels, namely medium-low, medium-high and high) capturing the technological intensity of firms, derived from their ATECO codes in accordance with the Eurostat classification. The variable *Tech* low (low technological intensity) is our reference. Technology-intensive sectors generally show a greater predisposition to innovation and have higher growth potential. This variable makes it possible to grasp the structural differences deriving from the sector to which it belongs. *Graduates* is a continuous variable measuring the share of a firm’s workforce with a university degree in year 2022. Staff qualification can influence the ability to adopt and manage more complex processes, such as those associated with the use of SRM. There is a recognized relationship between the level of human capital and the likelihood of undertaking innovative activities. *Public Funds*, is an indicator of access to public funds for R&D activities. Companies that obtain public funding tend to launch or enhance research and innovation projects, thus encouraging the adoption of more sustainable and advanced solutions. Receiving public funds can also improve financial solidity, affecting the ability to grow. *Company age* is a continuous variable measuring the firm’s age, expressed as the number of years since its establishment. The literature indicates that they are broader, but at the same time they may show greater inertia in adopting practices that more mature companies can benefit from consolidated experience and innovative relational networks. On the other hand, younger companies may be more open to change, while having more limited financial resources and managerial experience. *Liquidity index 2019*, which measures the ability to meet short-term financial commitments in 2019, before the observation horizon considered in the study. Having a good solid base can be crucial for starting experiments or investments in innovative projects, including the adoption of SRM. *Geo* a categorical variable indicating whether the firm is located in the Northeast, Northwest, Central, Southern Italy, or the Isles. The north is considered as our reference. The territory can affect the availability of secondary raw materials and the policy context (e.g., local incentives, Quality of institutions ecc ...), affecting both the use of SRM and the opportunities for revenue growth. Finally, *Turnover Export %*, a continuous variable representing the percentage of turnover generated from exports in 2021. A high degree of internationalization

can reinforce the need to keep up with international environmental and sustainability standards, thereby encouraging the adoption of innovative practices such as the use of SRM. In addition, a greater orientation towards foreign markets can translate into a more marked growth in turnover.

4. Results

To assess the effectiveness of the matching procedure, Table 3 presents the estimated means and variances of the covariates for the two groups, treated (*SRM* = 1) and untreated (*SRM* = 0), both before matching (“Raw”) and after matching (“Matched”).

In terms of differences in means, before matching (Raw), substantial differences are noted in the averages of different covariates between treated and untreated: for example, the R&D variable shows a standardized difference of about 1.17, while the number of employees (*N Employees*, 2022) shows a deviation of about 0.65. These high values of *Std.Dif* (Standard Difference) indicate a clear inhomogeneity between the two groups.

On the other hand, after matching the standardized differences are significantly reduced for most covariates. Taking R&D as an example, the standardized difference collapses to about 0.01. Also, for other variables such as *N Employees 2022*, *Tech*, *Public Funds*, and so on, the deviation is close to zero, signaling a good balance obtained thanks to the matching procedure. This level of standardized differences is consistent with the literature, as similar studies employing propensity score matching indicate that standardized differences below 0.1 demonstrate a satisfactory balance (Austin, 2011).

The table of variances confirms that, between the two “Raw” groups the variances are quite different, while a significant improvement emerges from the matched sample where the two groups are more comparable, with variance ratios closer to 1. Overall, these indicators suggest that the *kernel matching* algorithm effectively constructed a counterfactual sample in which untreated firms exhibit greater similarity to treated firms, compared to the initial unmatched groups, at least as far as the covariates included in the model are concerned. A notable exception is related to the variable *Geo*. South remains notably unbalanced after matching, with a standardized difference of -0.979 . While ideally all covariates should be balanced, it is not uncommon for some variables to remain imbalanced after propensity score matching, especially when they are highly predictive of treatment assignment or when common support is limited. As noted by Stuart (2010), some residual imbalance can be acceptable as long as the majority of key covariates are balanced and the unmatched covariate is accounted for in sensitivity analysis or subsequent regression adjustments.

4.1. General treatment effect on turnover

The estimation of the effect of the use of secondary raw materials on the dependent variable was carried out by considering three fundamental parameters (Matsouaka et al., 2023): *ATE* (Average Treatment Effect): the average effect of treatment on the entire reference population; *ATT* (Average Treatment Effect on the Treated): the average effect of the treatment on the companies actually treated (those that adopt SRM); *ATC* (Average Treatment Effect on the Controls): the average effect of the treatment on companies that have not adopted secondary raw materials.

In Table 4 the top table shows the distribution of treated firms (those using secondary raw materials) and untreated firms, distinguishing between those successfully matched and those not matched through the propensity score matching process, as well as between controls that were used or unused in the estimation. A total of 609 firms were matched (141 treated and 468 untreated), while only 29 were not matched, indicating high matching quality. Of the 638 total firms, 613 were effectively used as controls in the analysis, confirming the robustness of the matching procedure.

Table 3
Statistics before (Raw) and after (Matched) the matching process.

Means comparison 3a						
Variabile	Raw			Matched		
	Treated	Untreated	Std.Dif	Treated	Untreated	Std.Dif
R&D	0.656	0.158	1.172	0.263	0.259	0.010
N Employees 2022	94.1	38.9	0.649	61.541	53.463	−0.023
Tech medium-low	0.384	0.255	0.279	0.238	0.279	−0.088
Tech medium-high	0.252	0.337	−0.187	0.281	0.314	−0.074
Tech high	0.020	0.031	0.069	0.011	0.018	−0.043
Graduates	22.1	21.2	0.096	20.890	21.134	−0.016
Public Funds	1.159	1.694	−0.283	1.562	1.681	−0.008
Company age	47.6	47.4	0.009	45.212	48.681	−0.162
Liquidity index 2019	1.510	1.592	−0.061	1.489	1.542	−0.040
Geo center	0.152	0.150	0.005	0.136	0.158	−0.064
Geo south	−0.126	0.189	−1.375	−0.212	0.176	−0.979
Turnover Export %	28.0	19.8	0.386	21.884	21.109	0.037
Variance comparison 3b						
Variabile	Raw			Matched		
	Treated	Untreated	Ratio	Treated	Untreated	Ratio
R&D	0.227	0.133	1.704	0.195	0.192	1.016
N Employees 2022	12,046	2399	5.020	5050	6344	0.796
Tech medium-low	0.238	0.190	1.252	0.183	0.202	0.906
Tech medium-high	0.190	0.224	1.181	0.204	0.211	0.967
Tech high	0.020	0.030	0.655	0.011	0.018	0.611
Graduates	0.020	0.030	0.644	0.012	0.018	0.667
Public Funds	1.345	2.128	0.632	0.740	0.425	1.741
Company age	324.2	589.7	0.550	236.6	625.5	0.379
Liquidity index 2019	1.803	1.731	1.042	2.169	1.542	1.407
Geo center	0.130	0.135	0.963	0.118	0.134	0.881
Geo south	0.129	0.188	0.685	0.186	0.145	1.280
Turnover Export %	512.5	384.6	1.333	397.9	400.4	0.994

Table 4
Results of the treatment effect estimation. Propensity-score kernel matching.

Results of the treatment effect estimation (Turnover, 2021–2022)						
	Matched			Controls		
	Yes	No	Total	Used	Unused	Total
Total						
Treated	141	10	151	478	9	487
Untreated	468	19	487	135	16	151
Combined	609	29	638	613	25	638
	Estimate	Std. Error	t value	p value		
Total						
ATE	0.095	0.047	2.00	0.046**		
ATT	−0.075	0.050	1.50	0.135		
ATC	0.101	0.054	1.88	0.060*		

Note: Number of observations = 659 (due to outliers removal in the matching procedure), kernel = epan.

The lower part indicates that ATE is statistically significant at the 5% level, suggesting that if all firms had adopted secondary raw materials, their turnover growth (2021–2022) would have been approximately 10 percentage points higher compared to the scenario without adoption. This result highlights the potential of secondary raw materials to generate economic and environmental benefits, thereby potentially strengthening competitive advantage when integrated effectively into business practices.

In contrast, while ATT exhibits a positive coefficient, it remains statistically indistinguishable from zero. This suggests that for firms engaged in secondary raw material usage, the effect on turnover could not be conclusively isolated from other factors. Possible explanations include heterogeneity in the selection and application of secondary raw materials, as well as market-specific conditions that shape the degree to which these materials can be leveraged for financial gain. Lastly, ATC shows marginal significance at the 10% level, implying that firms

initially not employing secondary raw materials might have experienced a moderate uptick in turnover had they adopted such practices, albeit with greater variability in the results. These findings highlight the importance of considering sector-specific constraints, investment capacities, and strategic objectives when assessing the broader efficacy of secondary raw materials for corporate growth and innovation.

Overall, the results show a potentially positive effect of the adoption of SRMs on revenue growth, with more marked significance for ATE than ATT or ATC. It is possible that the composition of the treated group (perhaps smaller or more heterogeneous) makes the ATT not statistically significant, while the ATE captures a more robust overall average over the whole population.

The matching procedure can be checked by referring to Fig. 2, which compares the propensity scores of treated (SRM = 1) and untreated (SRM = 0) firms before and after matching. This further confirms that our matching procedure is indeed robust. Before matching (Raw), on average, the companies treated show a higher propensity score, concentrated in a range that can exceed 0.5, while the untreated ones are more distributed in the lower bands (below 0.4 or 0.2). This reflects the natural difference in characteristics: companies that adopt SRM had, a priori, a higher probability of being part of the treatment given their structure or their strategic choices. On the other hand, after matching (Matched ATE) the distributions of propensity scores for treated and untreated appear much closer. The ranges of variation also overlap more, thus reducing the risk of extrapolation bias, and this testifies that kernel matching, by adequately balancing the covariates, has made the two groups more comparable.

In addition to the main analyses, a sensitivity analysis was conducted to verify the robustness of the results to the variation of some key parameters of the matching, in particular “caliper” and “bandwidth” (Ho

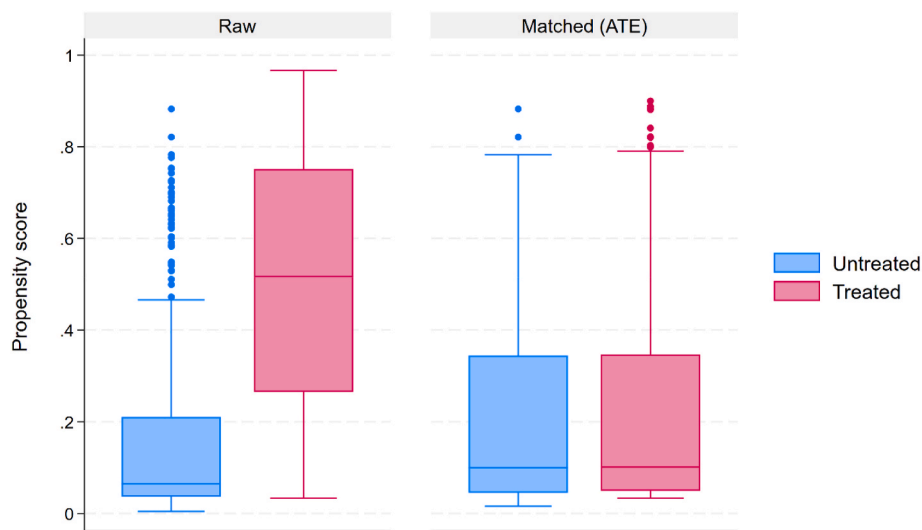


Fig. 2. Box plot of propensity score before and after matching.

et al., 2007).³ Varying both these parameters, it was observed that the main results relating to ATE, ATT and ATC remain substantially unchanged: the estimate of the positive effect of SRM on revenue growth is confirmed, albeit with minimal fluctuations in the coefficients and in the respective confidence intervals. This suggests that the results are not overly sensitive to modest changes in the matching specification.

4.2. Heterogeneity analysis: sector-specific economic impacts

In addition to the main analysis based on the 2021–2022 change in turnover, we extended our analysis to examine the effects of SRM use on the percentage change in turnover from 2021 to 2022, dividing firms into three main industry groups according to specific structural characteristics⁴: a) Sectors Related to “Light” Consumer Goods; b) Chemical, Pharmaceutical Industries; and c) Metallurgical, Mechanical and Electronic Sectors.

This approach allows a deeper evaluation of how secondary raw material usage may create meaningful differences in production outcomes, potentially linked to the intrinsic properties of primary resources and specific production processes. Factors such as resource availability, process efficiency, and associated environmental impacts are fundamental to assessing the practical and sustainable effectiveness of integrating secondary raw materials across different industry contexts.

Specifically, by dividing the dataset into these three sector groups we take into account the distinct structural, technological, and market-related characteristics that uniquely influence the adoption and economic impact of SRMs in different production environments.

The first group, sectors Related to “light” consumer goods primarily target final consumers and depend significantly on aesthetics, brand perception, and perceived product quality. SRM adoption may be more

strongly driven by market dynamics and communication strategies rather than direct technical efficiencies, resulting in economic outcomes that differ from those in other sectors. The chemical and pharmaceutical industries,⁵ by contrast, are characterized by stringent regulatory standards and purity requirements, which create substantial technological barriers to the integration of heterogeneous secondary raw materials. Finally, the metallurgical, mechanical, and electronic sectors, typically exhibit production processes that are more compatible with SRM integration due to well-established practices of material recovery and recycling. Consequently, measurable economic impacts of SRM adoption might be more evident.

Table 5 shows the values of ATE, ATT and ATC (table below), together with their p-values and confidence intervals, derived from propensity-score kernel matching (treatment: SRM = 1, table above).

In the first group, comprising industries oriented toward “light” consumer goods, the estimated effects remain statistically insignificant, indicating that the integration of secondary raw materials between 2021 and 2022 did not produce a discernible impact on turnover. Such an outcome can be attributed to several sector-specific determinants: for instance, supply chains in this segment may be designed to optimize aesthetic or brand-based value propositions, leading to a diminished emphasis on resource efficiency or sustainable sourcing. Additionally, consumer purchasing decisions in these industries often pivot more on design and marketing appeal, which may dilute the direct economic benefits of adopting alternative inputs. Consequently, companies in these fields might find it challenging to justify investments in secondary raw materials without clear evidence of a significant return or alignment with overarching brand narratives.

In the second group, encompassing chemical and pharmaceutical industries, results continue to exhibit a lack of statistical significance. Despite the theoretical advantages that secondary raw materials can offer, including cost reductions or an enhanced sustainability profile, their adoption often encounters barriers rooted in stringent regulations, high standards for quality and purity, and the overarching need for consistent production processes. Moreover, research and development costs associated with integrating untested or less conventional raw materials may contribute to a lower propensity to experiment, thereby mitigating any immediate economic outcomes that could otherwise be observed.

A notably different pattern emerges within the third group, comprised of metallurgical, mechanical, and electronic sectors, where

³ The caliper indicates a maximum distance threshold (generally in the metric of the propensity score or its logit) within which the matching between a treated and a control is allowed. Increasing or decreasing the caliper affects the number of controls actually selected and, therefore, the quality of the matching. A very tight caliper reduces the risk of bad matches, but can limit the number of matches available, while a larger caliper increases the likelihood of finding a match but can introduce more heterogeneity. In kernel matching, bandwidth (or window width) determines how rapidly the weight assigned to control units that are more and more distant, in terms of propensity score, decreases with respect to the treated unit. A smaller bandwidth reduces the amount of relevant controls, making the matching more “severe”, while a larger bandwidth makes the matching “wider” and could introduce less similar matches.

⁴ The detail of the division is reported in Appendix B.

⁵ Detailed results are reported in Appendix C.

Table 5

Propensity-score kernel matching for each of the three industry groups.

	Matched			Controls			Bandwidth
	Yes	No	Total	Used	Unused	Total	
Group 1							
Treated	49	5	54	193	0	193	0.0830338
Untreated	187	6	193	46	8	54	0.0147863
Combined	236	11	247	239	8	247	
Gruop 2							
Treated	56	0	56	118	4	122	0.0703584
Untreated	118	4	122	56	0	56	0.0705058
Combined	174	4	178	174	4	178	
Gruop 3							
Treated	44	0	44	190	0	190	0.2684267
Untreated	184	6	190	30	14	44	0.0251044
Combined	228	6	234	220	14	234	
	Coefficient	Std. err.	t	P> t			
1							
ATE	0.0689284	0.084446	0.82	0.415			
ATT	−0.0052284	0.0634873	−0.08	0.934			
ATC	0.0883598	0.0956896	0.92	0.356			
2							
ATE	−0.0187545	0.0898329	−0.21	0.835			
ATT	0.0778475	0.0744211	1.05	0.296			
ATC	−0.0645995	0.1213912	−0.53	0.595			
3							
ATE	0.1233661	0.0545525	2.26	0.024**			
ATT	0.1283816	0.0656649	1.96	0.05**			
ATC	0.1221667	0.0615784	1.98	0.048**			

Number of observations = 659 (due to outliers removal in the matching procedure), kernel = epan.

The top part of Table 5 reports the number of treated and untreated units matched in each subgroup, as well as the number of control observations used. It also shows the bandwidth applied during kernel matching, which determines the similarity threshold for matches.

the estimates either meet or closely approach the 5% significance benchmark. From a quantitative standpoint, the projected turnover gains hover around 12% when secondary raw materials are effectively incorporated, suggesting a meaningful competitive edge for firms inclined to adopt more sustainable and potentially cost-efficient inputs. One plausible explanation for this robust outcome lies in the structural compatibility between secondary raw materials and manufacturing workflows that prioritize recycling, modular design, and resource optimization. In these industries, incremental improvements in efficiency or reductions in material costs can substantially influence profitability, particularly when supported by supply-chain partners and accompanied by consumer demand for ethically produced goods. Furthermore, this alignment may encourage innovation not merely in materials but also in production techniques, as organizations seek to leverage the full spectrum of benefits associated with a circular economy model.

Overall, the heterogeneous findings observed across these three groups underscore the complexity inherent in evaluating the practical impact of secondary raw materials. While certain sectors, such as metallurgical, mechanical, and electronic, appear predisposed to leverage both economic and strategic gains, others face structural or regulatory impediments that limit the detectability of similar benefits. This discrepancy highlights the importance of tailored policy measures, collaborative efforts among stakeholders, and sector-specific research, all of which may clarify the conditions under which secondary raw materials can be most effectively harnessed to support sustainable growth, enhance competitive positioning, and meet evolving market demands for responsible innovation.

In terms of the extent of this effect, an increase in turnover of more than 12% in just one year represents a significant result, both from an economic and managerial point of view. The metallurgical, mechanical and electronic sectors would therefore seem to be particularly predisposed to benefit from the use of secondary raw materials, perhaps thanks to production processes more compatible with the use of recovered

materials (e.g. regenerated scrap metal) and possible cost and supply savings. Motivation could also include the possibility of more easily adhering to “green” certification standards or making use of targeted incentives.

Ultimately, empirical evidence shows a heterogeneous effect of SRM depending on the context of the sector. While in the first two groups there is no statistically evident impact, the metallurgical, mechanical and electronic sectors appear to be able to derive a net and significant benefit, with a potential increase in turnover on an annual basis of more than 10%.

4.3. General results on environmental performance

While turnover growth represents the market realization of circular practices, the immediate impact of SRM adoption is often found in process efficiency and resource footprint reduction. To capture this multi-dimensional value, we extended the Propensity Score Matching analysis to two key environmental proxies derived from the survey: *Water Usage Reduction* and *Resource Consumption Reduction*.

On the aggregate sample, the results suggest that the adoption of SRM is associated with a general improvement in process efficiency, though with different degrees of statistical strength. Table 6 reports the matching estimates for both variables.

Regarding Water Usage Reduction, the Average Treatment Effect (ATE) is statistically significant ($p = 0.038$), suggesting that if the entire population adopted SRM, water efficiency would improve by approximately 7.9%. The effect on the treated (ATT) is also positive (+7.4%) and marginally significant ($p < 0.10$).

Similarly, regarding Resource Consumption Reduction, the analysis points to a positive association with SRM adoption, indicating a general tendency towards the optimization of primary material and energy inputs.

Overall, these aggregate findings signal a potential benefit in terms

Table 6
General environmental impact.

Outcome Variable	Estimate	Coef.	Std. Err.	t	P> z
Water Usage Reduction	ATE	0.1469	0.0853	1.72	0.086*
	ATT	0.0807	0.0305	2.65	0.008**
	ATC	0.1665	0.1057	1.57	0.116
Resource Cons. Red.	ATE	0.1860	0.08853	2.1	0.036**
	ATT	0.1371	0.0435	3.15	0.002*
	ATC	0.2004	0.1089	1.84	0.066*

Propensity Score Matching estimates (Kernel = Epanechnikov).

Note: N = 667. ***p < 0.01 **p < 0.05, *p < 0.10. The table reports the estimated effects of SRM adoption on the probability of reducing water usage and general resource consumption.

of sustainability. However, treating the sample as a monolith may obscure the specific trade-offs faced by different industries, as in the case of our economic performance analysis. Therefore, to fully understand where these benefits are concentrated, it is necessary to inspect the results at the sector level.

4.4. Sectoral heterogeneity analysis: environmental performance

The sectoral decomposition of economic results presented in Section 4.2 revealed a sharp contrast in how different industries capture economic value from Secondary Raw Materials (SRM). While “Heavy” industries (Group 3) showed robust turnover growth, the “Light Consumer Goods” (Group 1) and “Chemical/Pharmaceutical” (Group 2) sectors did not exhibit significant economic gains. This disparity raises a fundamental question: are these firms failing to derive any benefit from SRM adoption, or is the value being generated through non-monetary, environmental channels?

To address this, we extended the Propensity Score Matching analysis to our environmental proxies, strategically aggregating Group 1 and Group 2 into a single macro-category. By focusing on this combined group of sectors that lacked immediate turnover growth, we can test whether their adoption of circular practices yields operational value instead of direct market expansion.

The results, presented in Table 7, reveal a striking dichotomy. While these firms do not translate SRM adoption into short-term revenue, they achieve statistically significant improvements in process efficiency. Specifically, for the combined sample of Light Consumer Goods and Chemical/Pharmaceutical industries, water usage reduction shows a significant positive impact with an ATT of 0.1098 (p = 0.020). Furthermore, resource consumption reduction exhibits a highly significant effect, with an ATT of 0.1530 (p = 0.003).

This evidence suggests that for lighter and chemical industries, the primary driver for SRM adoption is operational efficiency and compliance rather than immediate market expansion. In other words, unlike heavy industries, which leverage established recycling value chains to boost sales, these sectors appear to use SRM to optimize their resource footprint and potentially reduce input reliance. This does not exclude the possibility for those sectors to also contribute to future competitive advantages, if environmental gains act as precursors to long-term

Table 7
Environmental Performance Effects for Sectors Lacking Immediate Economic Returns (Group 1 & Group 2) Propensity Score Matching estimates (Kernel = Epanechnikov).

Outcome Variable	Coefficient (ATT)	Std. Err.	T-stat	P-value	[95% Conf. Interval]
Water Usage Reduction	0.1098	0.0471	2.33	0.020**	0.017 – 0.2024
Resource Consumption Reduction	0.1530	0.0505	3.03	0.003***	−0.0654 – 0.2523

Propensity Score Matching estimates (Kernel = Epanechnikov).

market benefits.

4.5. Robustness checks and mechanism analysis

To rule out the possibility that our results are driven by pre-existing trends or unobserved historical superiority of the treated firms, we conducted a temporal placebo test. We applied the same Propensity Score Matching specification using firm level data from the pre-adoption/pre-pandemic period (2018–2019), and using again, as a treatment, the observed adoption of SRM in 2021–22. The estimated Average Treatment Effect on the Treated (ATT) for this placebo period was statistically insignificant, confirming that SRM-adopting firms did not exhibit superior growth trajectories prior to the analysis period. This validates our identification strategy, supporting the claim that the performance premium observed in 2021–2022 is causally linked to SRM adoption and not to structural firm differences.⁶

To address the mechanisms driving the observed turnover growth specifically distinguishing between supply-side factors (e.g., cost efficiency) and demand-side factors (e.g., green marketing) - we analyzed additional survey evidence regarding production costs. We constructed a ‘Perceived Cost Increase’ indicator combining responses from adopters and non-adopters regarding the impact of SRM on their cost structures.

Contrary to the hypothesis of cost reduction often associated with circular efficiency, in Table 8 we conducted a t-test analysis that reveals that SRM adopters report significantly higher perceived production costs (Mean = 3.97) compared to non-adopters (Mean = 3.43; p < 0.001). This finding is crucial: since SRM firms exhibit higher turnover despite facing higher production costs, the positive performance premium cannot be attributed to cost-cutting (supply-side). Instead, it points to demand-side drivers, and is a hint in favour of the ability to command a ‘green premium’ or an expanded market share driven by corporate reputation and consumer preference for sustainable products.

5. Concluding remarks

Our paper is among the very few (to our knowledge) investigating the link between firms performance (namely growth in turnover per employee) and the adoption of SRM in production. Overall, our analysis conducted using a PSM highlighted a potential positive effect of the adoption of SRM on company performance, though with some caveats and sector level heterogeneities.

For the whole sample, the change in turnover for the period 2021–2022 shows a significant average treatment effect, indicating that, on average, companies adopting SRM recorded a greater increase in turnover than in a scenario without SRM. Intra-group differences and non-uniform impacts are however suggested by our empirical analysis. Dividing the sample into three groups of sectors with different structural characteristics shows a positive and statistically significant economic effect only for the metallurgical, mechanical, and electronic sectors (“Heavy Industries”).

Table 8
Mechanism analysis: T-test on perceived production costs.

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]
No	592	3.434	0.052	1.258	3.332 – 3.535
Yes	170	3.97	0.091	1.193	3.789 – 4.151
Combined	762	3.553	0.045	1.263	3.463 – 3.643
Difference		−0.536	0.108		−0.748 – 0.3239
T-statistic		−4.9557			
P-value		0.0000			

⁶ For detailed results see the Table in Appendix D.

Conversely, for “Light” consumer goods and chemical/pharmaceutical sectors, results do not show significant turnover coefficients. However, our extended analysis reveals that these sectors are not failing to capture value; rather, they capture it differently. While Heavy industries monetize SRM adoption immediately, Light industries (Group 1) exhibit significant gains in environmental efficiency, particularly in water usage reduction and resource optimization. This suggests a strategic dichotomy: heavy industries derive economic returns driven by mature recycling markets, whereas light industries currently focus on process compliance and efficiency, which may serve as precursors to long-term competitiveness.

Furthermore, our mechanism analysis sheds light on the drivers of the observed turnover growth. By analyzing survey data on production costs, we found that SRM adopters report significantly higher perceived production costs compared to non-adopters. This finding challenges the traditional assumption that circular economy adoption is purely a cost-cutting strategy. Instead, it suggests that the revenue growth observed in successful firms is driven by demand-side factors: firms appear to be leveraging circular practices to justify a price premium or access new market segments, thereby increasing turnover despite the higher operational complexity and costs associated with SRM.

From a theoretical perspective, the economic success of the heavy sectors aligns well with the circular economy paradigm (Korhonen et al., 2018a; Blomsma and Brennan, 2017), which emphasizes a closed-loop approach. In heavy industry, the economic incentives for material recovery, larger production scales, and opportunities for cost savings through energy efficiency further encourage firms to integrate SRM. Indeed, previous research has consistently highlighted how process-oriented firms in metallurgy and machinery can more easily adopt recycling and recovery practices (Pisano and Adams, 2009). As a result, the historical momentum toward material reuse in these sectors naturally fosters a favorable environment for SRM. We expect these conclusions to be of immediate relevance for companies operating in the investigated fields and for political or financial decision-makers. In terms of policies, our results support the role of public incentives for circular economy projects not just as economic boosters, but as essential support for sectors (like light industries) where the benefits are primarily environmental rather than financial in the short term. The policy stimulus for the construction of plants capable of processing increasingly complex waste streams (Ministero dello Sviluppo Economico, 2020) may complement private incentives. Industrial symbiosis also emerges as a potential tool to maximize the use of SRM and minimize non-recyclable waste (Chertow, 2000).

Our empirical conclusions, which are robust to changes in matching parameters and validated by a temporal placebo test ruling out pre-existing trends, are intended to be a starting point for more detailed analysis.

We acknowledge limitations of our study, particularly regarding the 2021–2023 timeframe featuring market volatility, and our binary

treatment variable. While we provided evidence of a “Green Premium” mechanism via perceived costs, future research should aim to validate this using granular, quantitative cost accounting data. Additionally, further investigation into intra-sector differences could help verify if the environmental efficiency observed in light sectors eventually translates into financial performance over a longer time horizon. All these extensions are left for future research.

CRediT authorship contribution statement

Edoardo Quattromini: Writing – review & editing, Writing – original draft, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Elisa Chioatto:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Data curation, Conceptualization. **Alessio D'Amato:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Formal analysis, Conceptualization. **Emy Zecca:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Data curation, Conceptualization.

Ethical standards

This study does not involve human participants or animals. Therefore, ethical approval was not required.

Funding information

This project is the result of a joint research collaboration between ISPRA and the Department of Economics and Management of the University of Ferrara, formalized through an agreement signed on September 13, 2022. The project did not receive direct financial support from any funding agency.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The survey data on which this paper is based were funded on the basis of an agreement between the Department of Economics and Management of the University of Ferrara and the Italian Institute for Environmental Protection and Research (ISPRA); this funding did not influence the design, analysis, or interpretation of the results.

Acknowledgments

This work was supported by the Higher Institute for Environmental Protection and Research (ISPRA), Italy, in collaboration with the University of Ferrara, Italy.

Appendix A. Mathematical Formalization of Propensity Score Matching (PSM)⁷

Propensity Score Matching (PSM) is a non-parametric technique widely used to estimate causal effects in observational studies where treatment assignment is not randomized. The main objective is to reduce selection bias by comparing treated units with untreated units that exhibit similar characteristics. At the core of the method lies the propensity score, defined as the conditional probability of receiving the treatment given a vector of observed covariates:

$$e(X) = P(D = 1|X)$$

where.

⁷ See, among others, [Caliendo and Kopeinig \(2008a,b\)](#).

- $D \in \{0, 1\}$ indicates treatment assignment (1 if the firm adopts SRM, 0 otherwise),
- X is the vector of observed covariates,
- $e(X)$ is the propensity score.

Based on this definition, it is possible to estimate several types of average treatment effects:

ATT (Average Treatment Effect on the Treated):

$$ATT = E[Y(1) - Y(0)|D = 1]$$

ATC (Average Treatment Effect on the Controls):

$$ATC = E[Y(1) - Y(0)|D = 0]$$

ATE (Average Treatment Effect):

$$ATE = E[Y(1) - Y(0)]$$

Since it is not possible to observe both $Y(1)$ and $Y(0)$ for the same unit, PSM approximates the unobserved counterfactual by matching each treated firm with one or more untreated firms with similar values of $e(X)$ (Rosenbaum and Rubin, 1983).

In this study, matching is performed using **kernel matching** with the **Epanechnikov kernel** function, which assigns higher weights to control units that are closer in terms of the propensity score (Heckman et al., 1998). The estimate of the counterfactual outcome for treated unit i is given by:

$$\hat{Y}_i(0) = \sum_{j \in C} w_{ij} Y_j$$

where.

- $w_{ij} = K\left(\frac{e(X_i) - e(X_j)}{h}\right)$ are kernel weights based on the distance between propensity scores,
- h is the bandwidth parameter,
- C is the set of control units.

Likewise, for untreated units, the counterfactual outcome can be estimated to obtain ATC. The aggregate treatment effects are then estimated as follows:

$$ATT = \frac{1}{N_1} \sum_{i \in T} (Y_i - \hat{Y}_i(0))$$

$$ATC = \frac{1}{N_0} \sum_{j \in C} (\hat{Y}_j(1) - Y_j)$$

$$ATE = \frac{N_1}{N} \cdot \widehat{ATT} + \frac{N_0}{N} \cdot \widehat{ATC}$$

where.

- N_1 and N_0 are the number of treated and untreated firms, respectively,
- $N = N_1 + N_0$

This formulation allows estimation of the average treatment effect on the entire observed population, as well as on specific subgroups. The combined use of ATT, ATC, and ATE thus provides a more complete and nuanced view of the impact of SRM adoption on firm performance.

Appendix B. Sectoral decomposition

Sectors Related to “Light” Consumer Goods (mainly use of Paper, Plastic, Textiles, Wood)

- 10 Food Industries
- 11 Beverage Industry
- 13 Textile Industries
- 14 Clothing Packaging
- 15 Manufacture of Leather Goods
- 16 Wood Industry
- 17 Paper Making
- 18 Printing
- 31 Furniture Manufacturing
- 32 Other manufacturing industries

Chemical, Pharmaceutical Industries (mainly use of plastic, glass, various chemicals)

- 24 Metallurgy
- 25 Manufacture of Metal Products
- 26 Manufacture of Electronic Products
- 27 Manufacture of Electrical Equipment
- 28 Manufacture of Machinery and Apparatus
- 29 Manufacture of motor vehicles
- 30 Manufacture of Other Means of Transport
- 33 Repair and Maintenance of Machines and Equipment

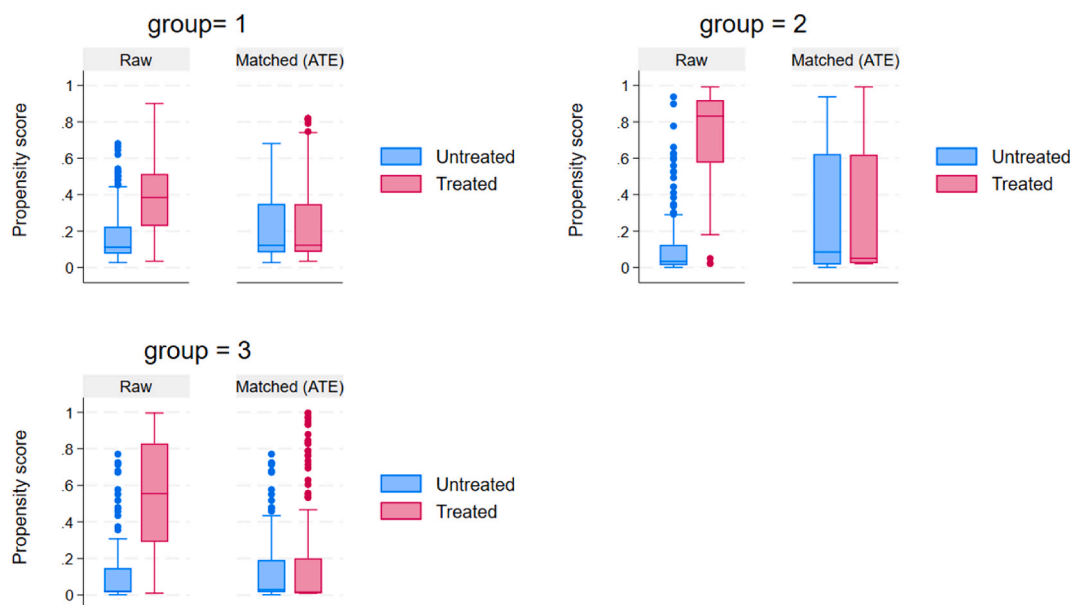
Metallurgical, Mechanical and Electronic Sectors (mainly use of metals, aluminum, plastic components/alloys)

- 19 Coke Manufacture
- 20 Manufacture of Chemical Products
- 21 Manufacture of Pharmaceutical Products
- 22 Manufacture of Plastics
- 23 Manufacture of Non-Metallic Mineral Processing Products

Appendix C. Detailed statistics before (Raw) and after (Matched) the matching process. in the three sectors case

Variable	Group 1			Group 2			Group 3		
	Treated	Untreated	StdDif	Treated	Untreated	StdDif	Treated	Untreated	StdDif
Raw									
R&D	9	2.784	0.604	15.446	3.080	1.1578	16.841	2.571	1.4394
Employees2022	106.54	46.04	0.6076	71.02	28.21	0.6455	110.23	35.89	0.8532
TECH MediumLow	0	0	.	0.6786	0.4444	0.4825	0.4773	0.3927	0.1701
TECH MediumHigh	0	0	.	0.3036	0.5238	-0.4559	0.4773	0.5497	-0.1443
TECH High	0	0	.	0.0179	0.0317	-0.089	0.0455	0.0576	-0.0546
Graduates2022	18.54	19.58	-0.0609	24.88	23.19	0.0943	22.32	20.812	0.1156
Public Funds	1.27	1.69	-0.9299	1.09	1.77	-1.882	1.11	1.64	-1.2829
Company Age	48.71	53.27	-0.1818	43.93	47.25	-0.1726	49.77	41.267	-0.476
liquidity index2019	1.38	1.46	-0.0546	1.71	1.77	-0.0481	1.36	1.57	-0.1744
GEO.Center	0.27	0.22	-0.1194	0.09	0.16	-0.211	0.09	0.08	-0.025
GEO.South	0.14	0.25	-0.2648	0.13	0.26	-0.3499	0.114	0.115	-0.0048
Turnover Exp %	23.52	20.86	-0.1312	27.77	15.74	0.5618	31.82	20.50	0.5363
Matched									
R&D	4.20	4.18	0.0014	6.33	7.77	-0.1349	4.53	4.81	-0.029
Employees2022	52.14	55	-0.0287	28.25	38.77	-0.1586	28.38	43.18	-0.1698
TECH MediumLow	0	0	.	0.7648	0.5096	0.5261	0.2362	0.4239	-0.3773
TECH MediumHigh	0	0	.	0.2263	0.4663	-0.4968	0.7438	0.5250	0.4358
TECH High	0	0	.	0.0088	0.0241	-0.098	0.02	0.0511	-0.1397
Graduates2022	23.81	20.22	0.235	19.74	21.34	-0.0892	17.53	21.49	-0.304
Public Funds	1.61	1.61	-0.0065	1.56	1.55	-0.04	1.63	1.58	0.1339
Company Age	48.48	53.08	-0.1833	44.28	47.14	-0.1481	39.49	43.037	-0.1984
liquidity index2019	1.515	1.451	0.045	1.26	1.65	-0.3036	1.71	1.52	0.1573
GEO.Center	0.26	0.22	0.0953	0.0419	0.1256	-0.254	0.02	0.08	-0.2082
GEO.South	0.29	0.24	0.1304	0.12	0.21	-0.2455	0.018	0.1054	-0.2736
Turnover Exp %	23.35	21.26	0.1029	10.42	13.96	-0.1655	32.16	22.11	0.4762

Note: Propensity Score Matching - Covariates balance.



Appendix D. Placebo Test Results (Turnover Growth, 2018-2019)

	Coefficient	Std. Err.	T-stat	P-value	[95% Conf. Interval]
ATE	-0.034	0.036	-0.96	0.335	-0.105 – 0.036
ATT	0.018	0.02	0.94	0.35	-0.020 – 0.058
ATC	-0.051	0.044	-1.15	0.252	-0.139 – 0.036

Data availability

The authors do not have permission to share data.

References

- Antonioni, D., Ghisetti, C., Mazzanti, M., Nicolli, F., 2022. Sustainable production: the economic returns of circular economy practices. *Bus. Strat. Environ.* 31 (5), 2603–2617. <https://doi.org/10.1080/00273171.2011.568786>.
- Austin, Peter C., 2011. An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behav. Res.* 46 (3), 399–424. <https://doi.org/10.1080/00273171.2011.568786>.
- Blomsma, Fenna, Brennan, Geraldine, 2017. The Emergence of Circular Economy - A New Framing Around Prolonging Resource Productivity. *Journal of Industrial Ecology* 21. <https://doi.org/10.1111/jiec.12603>.
- Caliendo, Marco, Kopeinig, Sabine, 2008a. Some practical guidance for the implementation of propensity score matching. *J. Econ. Surv.* 22 (1), 31–72. <https://doi.org/10.1111/j.1467-6419.2007.00527.x>.
- Caliendo, Marco, Kopeinig, Sabine, 2008b. Some practical guidance for the implementation of propensity score matching. *J. Econ. Surv.* 22 (1), 31–72. <https://doi.org/10.1111/j.1467-6419.2007.00527.x>.
- Chertow, Marian R., 2000. Industrial symbiosis: literature and taxonomy. *Annu. Rev. Energy Environ.* 25 (1), 313–337. <https://doi.org/10.1146/annurev.energy.25.1.313>.
- European Commission. Directorate General for Environment, 2020. 2020 Circular Economy Action Plan. Publications Office. <https://data.europa.eu/doi/10.2779/603655>.
- Garrido, Melissa M., Kelley, Amy S., Paris, Julia, et al., 2014. Methods for constructing and assessing propensity scores. *Health Serv. Res.* 49 (5), 1701–1720. <https://doi.org/10.1111/1475-6773.12182>.
- Ghisellini, Patrizia, Cialani, Catia, Ulgiati, Sergio, 2016. A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems. *J. Clean. Prod.* 114 (February), 11–32. <https://doi.org/10.1016/j.jclepro.2015.09.007>.
- Gusmerotti, Natalia Marzia, Testa, Francesco, Corsini, Filippo, Pretner, Gaia, Iraldo, Fabio, 2019. Drivers and approaches to the circular economy in manufacturing firms. *J. Clean. Prod.* 230 (September), 314–327. <https://doi.org/10.1016/j.jclepro.2019.05.044>.
- Hart, Stuart L., Glen, Dowell, 2011. A natural-resource-based view of the firm: fifteen years after. *J. Manag.* 37 (5), 1464–1479. <https://doi.org/10.1177/0149206310390219>.
- Heckman, J.J., Ichimura, H., Todd, P.E., 1997. Matching as an econometric evaluation estimator: evidence from evaluating a job training programme. *Rev. Econ. Stud.* 64 (4), 605–654. <https://doi.org/10.2307/2971733>.
- Heckman, James J., Ichimura, Hidehiko, Todd, Petra, 1998. Matching as an econometric evaluation estimator. *Rev. Econ. Stud.* 65 (2), 261–294. <https://doi.org/10.1111/1467-937X.00044>.
- Ho, DE, Imai, K, King, G, Stuart, EA, 2007. Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference. *Political Analysis* 15 (3), 199–236. <https://doi.org/10.1093/pan/mpl013>.
- Horbach, Jens, Rammer, Christian, Rennings, Klaus, 2012. Determinants of eco-innovations by type of environmental impact — the role of regulatory push/pull, technology push and market pull. *Ecol. Econ.* 78 (June), 112–122. <https://doi.org/10.1016/j.ecolecon.2012.04.005>.
- Kirchherr, Julian, Reike, Denise, Hekkert, Marko, 2017. Conceptualizing the circular economy: an analysis of 114 definitions. *Resour. Conserv. Recycl.* 127 (December), 221–232. <https://doi.org/10.1016/j.resconrec.2017.09.005>.
- Korhonen, Jouni, Nuor, Cali, Feldmann, Andreas, Birkie, Seyoum Eshetu, 2018a. Circular economy as an essentially contested concept. *J. Clean. Prod.* 175 (February), 544–552. <https://doi.org/10.1016/j.jclepro.2017.12.111>.
- Korhonen, Jouni, Nuor, Cali, Feldmann, Andreas, Birkie, Seyoum Eshetu, 2018b. Circular economy as an essentially contested concept. *J. Clean. Prod.* 175 (February), 544–552. <https://doi.org/10.1016/j.jclepro.2017.12.111>.
- Lacy, P., Rutqvist, J., 2016. Waste to Wealth: the Circular Economy Advantage. ResearchGate. <https://doi.org/10.1057/9781137530707> ahead of print, January.
- Lacy, Peter, Rutqvist, Jakob, 2015. Circular business models: evaluation, enablers, and ecosystems. In: Lacy, Peter, Rutqvist, Jakob (Eds.), *Waste to Wealth: the Circular Economy Advantage*. Palgrave Macmillan UK. https://doi.org/10.1057/9781137530707_9.
- Matsuoka, Roland A., Liu, Yi, Zhou, Yunji, 2023. Variance estimation for the average treatment effects on the treated and on the controls. *Stat. Methods Med. Res.* 32 (2), 389–403. <https://doi.org/10.1177/09622802221142532>.
- Ministero dello Sviluppo Economico, 2020. Decreto 11 Giugno 2020. Criteri E Modalità per La Concessione Di Agevolazioni Volte a Sostenere Progetti Di Ricerca E Sviluppo per La Riconversione Dei Processi Produttivi Nell'Ambito Dell'Economia Circolare. <https://www.gazzettaufficiale.it/eli/id/2020/07/14/20A03740/sg>.

- Pisano, G.P., Adams, P., 2009. VF Brands: Global Supply Chain Strategy. Harvard Business School Case, 610-022.
- Porter, Michael E., Van Der Linde, Claas, 1995. Toward a new conception of the environment-competitiveness relationship. *J. Econ. Perspect.* 9 (4), 97–118. <https://doi.org/10.1257/jep.9.4.97>.
- Pronti, A., Zoboli, R., 2024. Institutional Quality, Trust in Institutions, and Waste Recycling Performance in the EU27. *Sustainability* 16 (2), 892. <https://doi.org/10.3390/su16020892>.
- Remeikiene, Rita, Gaspareniene, Ligita, Matulienė, Snieguolė, Szarucki, Marek, 2024. Secondary Raw Materials in the Circular Economy: A Multi-Perspective Study. <https://doi.org/10.12797/9788383681252>.
- Rosenbaum, Paul R., Rubin, Donald B., 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70 (1), 41–55. <https://doi.org/10.1093/biomet/70.1.41>.
- Stuart, E.A., 2010. Matching methods for causal inference: A review and a look forward. *Stat. Sci.* 25, 1–21. <https://doi.org/10.1214/09-STS313>.
- Witjes, Sjors, Lozano, Rodrigo, 2016. Towards a more circular economy: proposing a framework linking sustainable public procurement and sustainable business models. *Resour. Conserv. Recycl.* 112 (September), 37–44. <https://doi.org/10.1016/j.resconrec.2016.04.015>.
- Zhu, Q., Sarkis, J., 2004. Relationships between Operational Practices and Performance among Early Adopters of Green Supply Chain Management Practices in Chinese Manufacturing Enterprises. *J. Operations Manage.* 22, 265–289. <https://doi.org/10.1016/j.jom.2004.01.005>.
- Zu Castell-Rudenhause, M., Wahlstrom, M., Nelen, D., Dams, Y., Paleari, S., Zoboli, R., Wilts, H., Bakas, I., 2022. Investigating Europe's secondary raw materials markets. European Environment Agency, Luxembourg, 63. 10.2800/48962. <https://hdl.handle.net/10807/230085>.