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Executive summary

This report explores the economic and financial sustainability of regional systems with a focus on Foreign Direct Investment (FDI), trade, and the role of global value chains (GVCs) in fostering circular economy (CE) transitions. By analyzing regional economic structures, environmental sustainability, and investment patterns, key findings and policy recommendations are derived to enhance economic resilience and sustainable growth. This document is organized in two sections. The first one presents simulation Models for Trade, FDI, and Migration Impact on Innovation in Circular Economy (CE) Transition. The second section outlines simulation models for Assessing Trade and GVC Reconfiguration's Impact on CE Transition

The first chapter of Section 1 focuses on the impact of Foreign Direct Investment (FDI) on Circular Economy. The analysis investigates the factors influencing inward FDI in Italian regions, particularly in CE-related sectors. Data from multiple sources, including Eurostat and ISTAT, highlight regional economic, social, and environmental characteristics. Key findings can be summarized as it follows. Market size (GDP) positively correlates with FDI attraction. Environmental quality (emissions per capita) negatively affects total FDI but positively correlates with CE-FDI, indicating that pollution-heavy regions attract sustainability-focused investments. Recycling practices and logistical infrastructure enhance FDI inflows, particularly in CE sectors. High-tech employment is a significant factor in attracting CE-FDI. The robustness of results was tested through cumulative FDI project counts and Poisson regression, confirming that CE investment drivers differ from traditional FDI influences.

The second chapter tackles exposure gaps in environmental impact between domestic and foreign firms. Using ORBIS and EXIOBASE datasets, exposure gaps were assessed based on ownership structures and environmental performance. Key insights are the following. Regions with higher research & development (R&D) investments and better environmental governance exhibit smaller exposure gaps. Foreign multinationals originating from countries with stricter environmental regulations tend to adopt better sustainability practices in their Italian subsidiaries. Higher poverty rates correlate with a greater likelihood of firms relocating polluting activities abroad. Regression analyses confirm that exposure gaps depend on institutional quality, industrial composition, and technological readiness.

The third chapter addresses the role of multinationals in the circular economy transition. Multinational enterprises (MNEs) are found to play a key role in the diffusion of CE practices. Italian MNEs investing abroad are indeed more likely to adopt green investments. Yet, foreign MNE subsidiaries in Italy vary in sustainability adoption based on their home country's regulatory framework. Firms in global value chains (GVCs), particularly in relational linkages, demonstrate greater sustainability engagement. International trade and participation in complex supply chains increase the likelihood of green investment.

The first chapter of the second section deals with the interplay between circular economy, trade, and regional growth. The study builds a simulation model to estimate Domestic Value Added (DVA) growth in CE-related exports across Italian regions. Findings suggest that regions with lower initial DVA in CE trade have higher growth potential. Moreover, exports to developed economies drive CE-related growth, while those to developing countries show weaker effects. Higher institutional quality and selective waste collection expansion correlate with CE trade growth. Finally, Advanced manufacturing (robot adoption) enhances CE competitiveness.

The second chapter analyzes the relationship between global value chains and regional resilience. The External Exposure Indicator (EEI) was developed to assess regional vulnerability to external shocks. The study finds that regions highly reliant on China for plastic waste exports suffered employment losses after China's 2018 waste import ban. Regions with strong waste management infrastructure adapted better to trade disruptions. Ownership linkages and foreign parent companies influence resilience and sustainability adoption.

The findings of the analyses presented in this policy bear relevant policy implications and recommendations. The findings highlight the need for region-specific policies to boost sustainable FDI, enhance CE trade competitiveness, and mitigate external economic shocks. Key recommendations include:

- Encouraging CE investment through incentives for high-tech sectors and recycling initiatives.
- Strengthening institutional frameworks to attract foreign investment in sustainable industries.
- Developing targeted trade policies to support regional resilience in CE sectors.
- Enhancing collaboration between MNEs and local firms to facilitate sustainability diffusion.

This research provides valuable insights for policymakers aiming to create a resilient, sustainable, and inclusive economic landscape in Italy and beyond. Strategic investments in CE sectors, improved institutional governance, and targeted trade policies will be crucial in fostering long-term economic and environmental sustainability.

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1. Simulation models for trade, FDI, and migration impact on innovation in CE transition

1.1 FDI

This contribution is based on the work done for the first deliverable of this project to construct some indicators related to the distribution of FDI and FDI in circular economy (CE)-related activities in Italian regions. In the previous exercise, we collected, analysed, and constructed indicators related to the exposure of Italian regions to such FDI. In this contribution, we move a step further and try to empirically investigate the factors that contribute to shaping such exposure. More specifically, what follows accounts for some of the (conditional or unconditional) correlates of inward FDI in Italian regions. The ultimate goal is to understand the most important dimensions for policy to target if the objective is to attract more FDI in general and more CE-related projects in particular.

Before moving on to the analysis, a few caveats apply to this kind of exercise, which is important to keep in mind before concluding. Small sample size and data limitations, especially for variables directly relevant to the CE domain, limit the capacity to apply robust analysis methods. In addition, while we believe that the relationships we examine are relevant and theoretically sound, also in light of the large existing literature on FDI, what we provide below is a correlational analysis, which cannot be interpreted causally.

The rest of this contribution is structured as follows. We first report a few details about the data (1.1.1) and the indicators (1.1.2) adopted. Next, we discuss the model, and so the relations (1.1.3). Finally, the results of the analysis are reported, inclusive of a few extensions and robustness checks (1.1.4).

1.1.1 Data

This analysis aggregates multiple datasets to examine the territorial characteristics that enhance a region's attractiveness for foreign direct investment (FDI). The unit of analysis is an Italian region, defined as the first administrative unit in the country. The dataset integrates key economic, social, and environmental indicators and is structured to assess dynamics at the regional level. The temporal coverage extends from 2003 to 2021, consistent with the availability of the FDI data currently available from the fDi markets database.[1]

Socioeconomic indicators were primarily obtained from Eurostat[2], covering aspects such as labour markets, education levels, and economic output. Additional indicators were sourced from ISTAT[3] and ARDECO[4], providing regionally disaggregated information on employment trends, workforce qualifications and industrial composition.

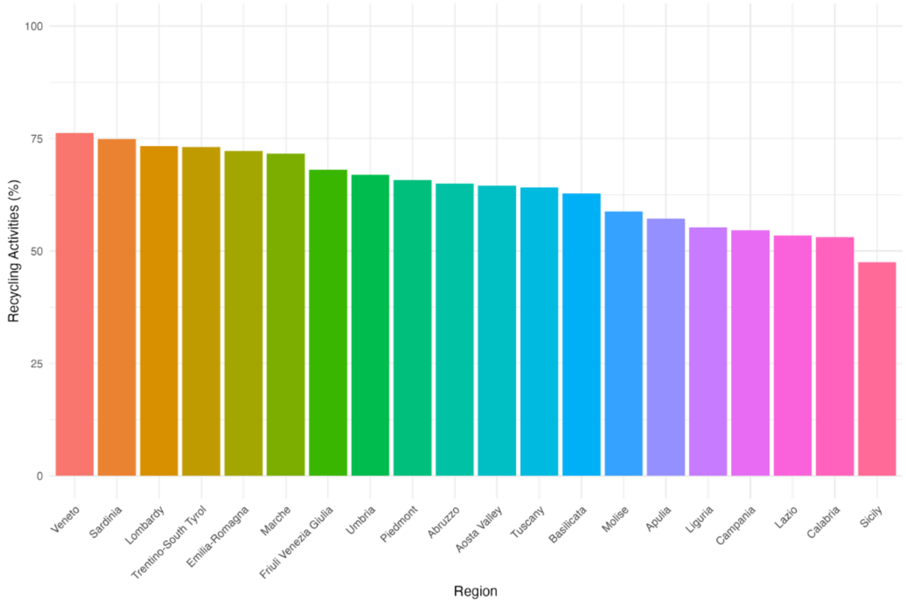
Environmental and circular economy-related information was retrieved from ISPRA[5] and ARDECO, offering a detailed perspective on the status quo of regional performance in some of the key indicators.

More specifically, ISPRA provides granular data on recycling activities, waste management practices, and implementing circular economy principles at the territorial level. These data contribute to a deeper understanding of waste treatment processes, resource efficiency and the effectiveness of sustainability policies across regions. For instance, Figure 1 illustrates the regional waste recycling rates as percentages, showing large variations within the country.

ARDECO supplies the Emissions Database for Global Atmospheric Research (EDGAR), which offers estimates of CO_2 and other greenhouse gases' emissions across different economic activities. These data enable a comprehensive evaluation of the relationship between economic performance, sustainability initiatives, and emissions intensity at the regional level. For instance, Figure 2 plots data on per capita CO_2-equivalent emissions across Italian regions, illustrating regional disparities in emission intensity by normalizing total greenhouse gas emissions using population size.

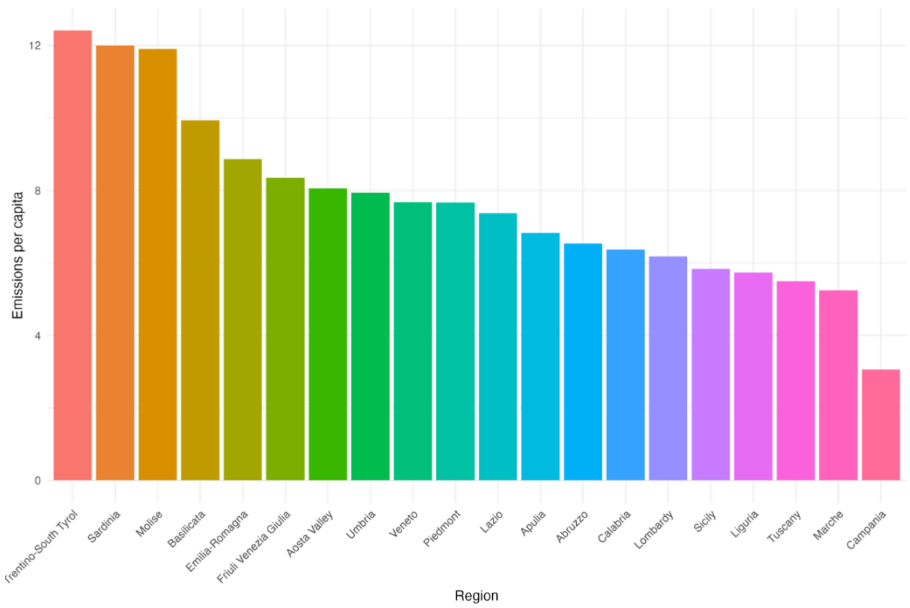
[1] https://www.fdimarkets.com
[2] https://ec.europa.eu/eurostat
[3] http://dati.istat.it
[4] https://knowledge4policy.ec.europa.eu/territorial/ardeco-database_en
[5] https://www.isprambiente.gov.it/it/banche-dati

Figure 1: Recycling Activities per Region in percentage terms – Summary of all years



Notes: This figure presents the average recycling activities (expressed in percentage terms) across all years for each Italian region. The data is sourced from ISPRA (Istituto Superiore per la Protezione e la Ricerca Ambientale). The bars represent the mean recycling rate for each region.

Figure 2: Emissions per Capita in ton CO2eq per person – Summary of all years



Notes: This figure presents the average per capita emissions (expressed in relevant units) for each Italian region over all years. The data is sourced from the EDGAR ARDECO dataset. The bars represent the mean emissions per capita, highlighting regional variations in pollution levels.

1.1.2 Indicators

We have developed a comprehensive set of indicators at the regional level to better understand the exposure of Italian regions to foreign direct investments. These indicators are part of the GRINS project and are further described by Perra and Sanfilippo (2024).

Specifically, we constructed the following indicators using the *number* of inward greenfield FDI projects received by Italian regions over the period available:

- The actual number of FDI projects received by region *i* in year *t*
- The cumulative number of FDI projects received by region *i* in year *t*

In addition, given the project's focus, we have also calculated the two variables that specifically catch the presence of FDI projects related to the Circular Economy (CE).[6]

Considering both the actual and the cumulative number of FDI is useful to obtain a more comprehensive picture of investment dynamics. Actual number of FDI flows represent new foreign investments in a given year, providing insights into short-term trends and how regions are attracting novel capital. The cumulative number of FDI projects, on the other hand, account for past projects that continue to shape a region's economic structure, employment base, and industrial specialization. This distinction is particularly relevant when analysing CE-related FDI. By considering both measures, we can better assess regional positioning in the transition to a circular economy and the long-term integration of sustainable practices into economic activities.

To effectively visualize the data, we utilize the Eurostat R package, which enables access to Eurostat data for mapping and graphical representation. Figure 3 gives a graphical example of some of the basic indicators constructed, mapping the number

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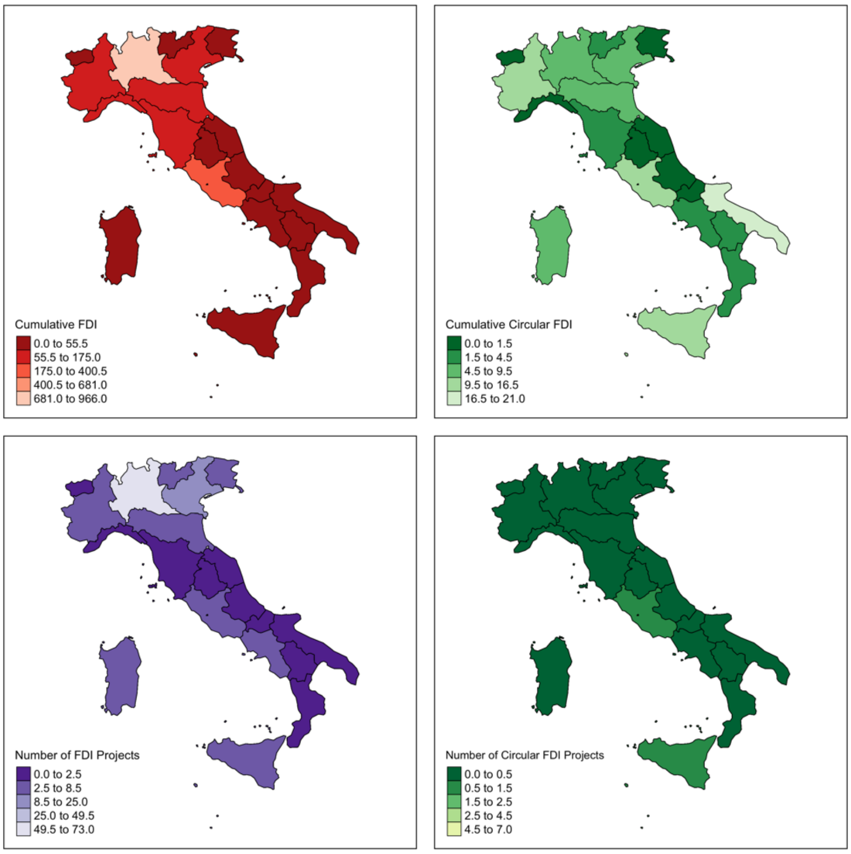
[6] Given the lack of a universally agreed-upon definition of the circular economy, we adopted a selective approach in identifying relevant sectors and activities. While interpretations may vary, we explicitly include waste management and recycling, which align with European Commission definitions, as subsectors and activities closely connected to FDI in the circular economy context. Beyond these, we applied text analysis techniques to explore additional potential alignments. Specifically, we employed the Quanteda package to compute Jaccard similarity coefficients, comparing textual representations of IFDI market subsectors with CE-related definitions from the European Commission. This allowed us to assess connections between sectors and CE principles while maintaining flexibility in classification.

of FDI project, including those related to the CE (top and down, right-side of the picture), in Italian regions over the period for which the data are currently available.

Figure 3: Visualization of our indicators-– Summary of all years

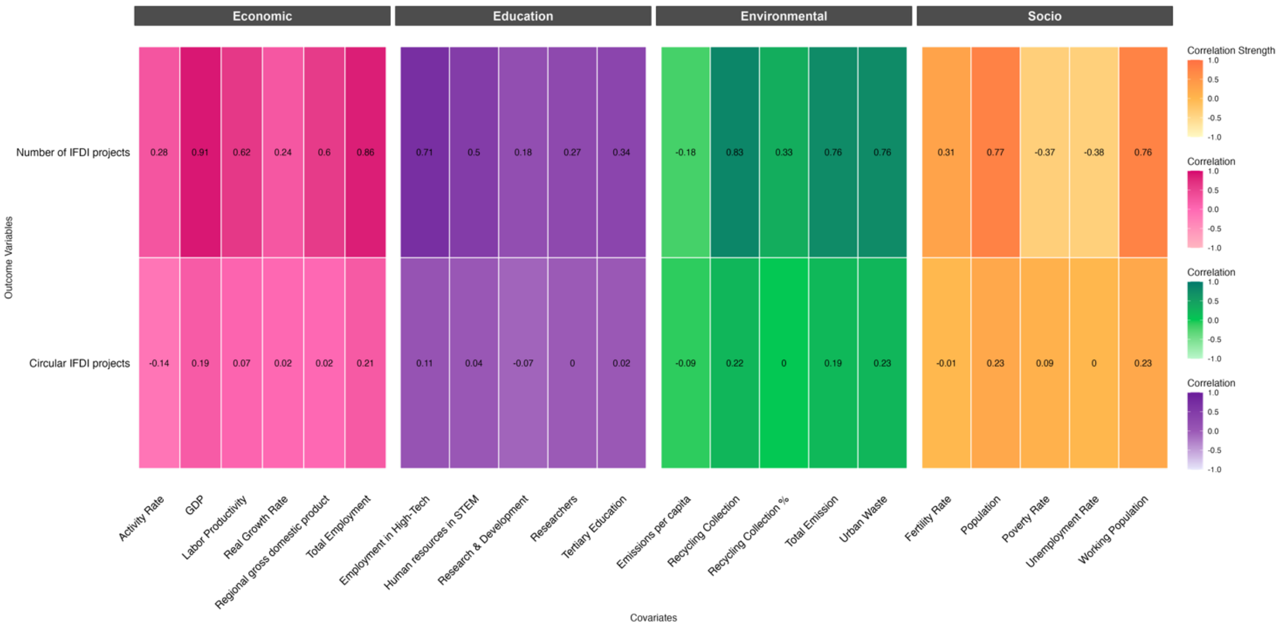


Notes: This figure illustrates foreign direct investment (FDI) stock and flows and circular economy (CE) FDI stock and flows across Italian regions using FDI Markets data, averaged over all years. The top-left map (red) shows cumulative FDI investments, highlighting regional disparities, while the top-right map (green) depicts cumulative circular economy FDI investments. The bottom-left map (purple) represents the number of FDI projects, and the bottom-right map (dark green) shows the number of circular economy FDI projects, revealing the distribution of sustainability-oriented investments.

1.1.3 Models

Before developing a more analytical framework to analyze the relationship between FDI—particularly those linked to the circular economy (CE)—and regional characteristics, we examine the correlation structure of the variables and indicators that we are going to exploit in the rest of this analysis. Given that the objective is to provide evidence on the connection between FDI and the various factors influencing location choices, Figure 4 presents the unconditional correlation between the number of FDI projects, including those related to the CE, and some of their potential drivers. Such variables are grouped according to some broad categories. The figure shows that some of the traditional "location factors" for FDI, such as market size, education, and technology, display high correlations with the number of projects being received by a region. Still, the figure also shows that the same factors do not display high correlations with the number of CE-related projects. This also includes the group of variables that cover some of the relevant dimensions to the CE.

Figure 4: Correlation Matrix between FDI indicators and Covariates



Notes: This figure presents a correlation heatmap between our key indicators and various covariates across economic, education, environmental, and socio-economic dimensions. The covariates include activity rates, real growth rate, regional GDP, total employment, employment in high-tech sectors, human resources, research and development, researchers, tertiary education, and poverty rates from Eurostat. Data on GDP, labor productivity, and emissions come from ARDECO, while recycling activities are sourced from ISPRA. All remaining variables originate from ARDECO. The color gradient represents the strength and direction of correlations, helping to identify key relationships between regional characteristics and the selected indicators.

While Figure 4 reports many indicators, coverage is partial or very low for some of them, especially for the earlier years covered by the FDI data. Hence, in view of the fact that we have 20 regions covered for 19 years, and thus a small theoretical sample, we have to adopt a conservative selection strategy, selecting a few variables based on both their potential interpretation and coverage from each key domain to minimize redundancy and have some statistical power.

Specifically, we include the following variables:

i) Economic Factors:
   a. GDP, which captures regional economic activity and market size;
   b. Cargo transport volume, which is indicative of logistical infrastructure and trade openness.

ii) Environmental and Circular Economy Factors:
   a. Emissions per capita, serving as a proxy for sustainability challenges and industrial structure;
   b. Recycling activities, which serve as a proxy for a region's commitment to sustainable practices and resource efficiency.

iii) Educational Factor: The proportion of high-tech employment, reflecting workforce qualifications and innovation potential.

Next, we employ the following specification:

$$N\_FDI_{it} = \beta X_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

where N_FDI_{it} is one of the outcomes of interest, measured as the actual number of FDI projects received by region *i* (one of the 20 Italian regions) over time *t* (from 2003 to 2021). The variable is log-transformed, adding 1 to account for the presence of zeros in the data. We employ two definitions of this variable, accounting for the presence of CE-projects. The first is the number of actual FDI projects in CE-related activities. The second is the number of FDI projects in other activities. Note that when measuring this outcome, we exclude CE-related projects from the count.

The coefficient β represents the elasticity of the outcome of interest to changes in the control variables X_{it}. α_i captures region fixed effects, thus accounting for region-specific and time-invariant factors (such as geography) that can influence the relation between controls and FDI; λ_t are year fixed effects, which are useful to control for time-specific factors that could have similarly affected all Italian regions. Finally, ϵ_{it} is the error term, accounting for unobserved factors (such as the 2007-2009 financial crisis, or COVID). Standard errors are clustered at the regional level. All specifications are weighted using the total population of the region. Table 1 presents the summary statistics for the covariates and key indicators used in the analysis, capturing their distribution across all years and regions.

Table 1 reports the descriptive statistics for the variables included in the empirical specification.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	**N**	**mean**	**sd**	**min**	**max**
CE FDI projects	380	0.139	0.363	0	2.079
FDI projects	380	1.147	1.083	0	4.304
FDI projcts $_{cumulative}$	380	2.834	1.494	0	6.874
CE FDI projects $_{cumulative}$	380	0.827	0.918	0	3.091
GDP	380	24.67	1.091	22.17	26.69
Recyling Activities	320	12.80	1.298	8.757	15.07
Cargo	361	11.72	7.822	0	18.41
Employment high-tech	185	1.316	0.297	0.588	2.219
Emissions$_{percapita}$	380	2.268	0.330	1.334	3.003

Notes: The values reported in this table represent the summary statistics for the variables used in the regression analysis, following log transformations. CE FDI and FDI projects represent the number of total and Circular Economy-related FDI investments received. CE FDI and FDI cumulative projects indicate their cumulate number. GDP, Employment per Capita, and Emissions per Capita are sourced from ARDECO, where GDP is expressed in millions of euros, emissions per capita in tons of CO_2 equivalent per person, and high-tech employment as a percentage of total employment. Recycling activities data are obtained from ISPRA and are expressed in tons. Cargo transport volume is measured in tons of freight handled, from ISTAT.

1.1.4 Analysis

Table 2 presents the results of the linear fixed effects regression, analyzing the relationship between FDI inflows—distinguishing between CE-related FDI projects (columns (1) and (3)) and the total number of non-CE FDI projects (columns (2) and (4)). While results in columns (1) and (3) maximize the number of observations, in columns (2) and (4) we also report estimates based on a model including also employment in high-tech activities, whose coverage is much smaller compared to other variables.

To reiterate, it is important to keep in mind that due to the relatively small sample size and limited data coverage—especially for key circular economy variables—the statistical power of our regressions is affected. As a result, the findings should be interpreted with caution and seen as indicative of some existing relationships.

The findings indicate that market size (proxied by the regional GDP) is positively associated with the entry of new FDI projects. The coefficient is large and positive across all specifications, but it is statistically significant only for the specification covering projects in non-CE FDI projects.

The size of emissions per capita negatively correlates with total FDI in non-CE activities, suggesting that regions with higher pollution levels may be less appealing to foreign investors, potentially due to sustainability concerns. Still, the sign of the coefficient flips when dealing with CE-related projects, and it is statistically significant in column (3). A possible interpretation for such a reversal is that higher levels of emissions could represent a more attractive market for FDI projects related to the CE. FDI projects in the circular economy might prefer to target regions with higher emissions per capita because these areas tend to have denser industrial activities and more significant waste streams, with more possibilities to end up with larger environmental benefits.

The relative share of recycling positively correlates with FDI inflows, throughout the different categories of projects. Regions with well-developed circular economy practices tend to attract more investments, including in CE-related projects (column 3), highlighting the increasing importance of sustainability in investment decisions and, possibly, the attractivity of CE-projects in regions with records of good practices in the field.

The coefficient on cargo volumes also has a positive association with FDI, indicating that logistical infrastructure and trade openness play a crucial role in attracting foreign capital. This seems relevant to CE projects, too, as better transport infrastructure, such as higher cargo capacities, can foster circular economy projects like recycling by reducing costs and improving efficiency. This might happen not only by favouring the collection and distribution of materials but also by helping reduce environmental impacts by lowering fuel consumption and emissions.

Table 2 Main Results

VARIABLES	(1) **CE IFDI projects**	(2) **IFDI projects**	(3) **CE IFDI projects**	(4) **IFDI projects**
GDP	1.200	2.495**	4.035	1.612
	(1.545)	(0.982)	(2.997)	(1.791)
Emissions $_{percapita}$	0.470	-1.322***	1.245*	-1.170***
	(0.771)	(0.384)	(0.597)	(0.363)
Recycling Activities	-0.035	0.283***	0.356*	0.489***
	(0.140)	(0.039)	(0.204)	(0.122)
Cargo	0.747**	0.397*	0.505	0.604
	(0.308)	(0.212)	(0.404)	(0.459)
Employment $_{high\text{-}tech}$			0.762*	1.193*
			(0.435)	(0.627)
Constant	-40.119	-67.597**	-117.373	-52.741
	(39.369)	(26.070)	(75.038)	(49.082)
Observations	300	300	166	166
R-squared	0.403	0.923	0.461	0.923
Region FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Avg DV	0.32	5.79	0.16	5.93

Notes: This table reports the results of a linear fixed effects regression estimating the relationship between FDI inflows and selected regional characteristics. The dependent variable (DV) is the log+1 of the number of FDI projects received by each region in each year. Columns (1) and (3) present estimates for CE-related FDI projects, while columns (2) and (4) focus on the total number of FDI projects (net of CE projects). The controls include (log) GDP, (log) emissions per capita, recycling activities, cargo transport volume, and high-tech employment (included only in columns (3) and (4)). Region and year fixed effects are included in all specifications. Standard errors clustered at the region level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Finally, columns (3) and (4) introduce high-tech employment as an additional covariate. While this reduces significantly the sample size, results are generally consistent with columns (1)-(2). The variable on high-tech employment has a positive correlation with CE-related FDI. This suggests that a highly skilled and innovative workforce may be a key factor in driving sustainability-focused investments.

1.1.4.1 CE-related FDI projects.

The previous analysis has shown evidence of some of the drivers of FDI in Italian regions. It has also shown that factors driving the entry of FDI projects are often not statistically significant when turning to a specification with CE-related FDI as the dependent variable. We believe this might be because the actual number of FDI in CE activities is still very small and scattered, which affects the statistical power of our specifications. Another potential issue is related to the choice of the control variables, which—as discussed before—is limited by the low number of observations on many different potential controls.

Figure 5 Margin Plot of Regression Coefficients with Confidence Intervals

Note: This figure reports the estimated coefficient of a regression linking CE-FDI to variables on waste management and emissions. Each coefficient comes from a separate regression. Each regression includes region and year fixed effects, and is weighted by the total population. No other controls are included. Urban Waste (in tonnes) comes from ISPRA, while waste infrastructure (e.g., incineration plants, waste facilities, special waste management, composting plants, and water treatment plants) is based on ISTAT ASTI data[7]. Emissions from waste activities, including CH_4 emissions, are sourced from the EDGAR ARDECO dataset[8].

Figure 5 reports the estimated coefficient of a regression in which the dependent variable is the number of CE-related FDI and the control is one dimension related to the CE for which we have (incomplete) data. Note that each coefficient in the figure is estimated from a separate regression, and that no additional controls (except from region and year fixed effects) are added. As it is possible to see, even if most coefficients are not statistically significant, they tend to report a (often very small) positive correlation with the attraction of CE-related projects, which is to some extent in line with the findings that regions equipped with best practices in the realm of the CE attracts also a larger share of FDI in that area

1.1.4.2 Robustness

We run two additional set of regressions to check for the robustness of the results reported in Table 2. In the first two columns of Table 3, we check whether results are confirmed if we replace the actual number of FDI projects with their cumulative amount. This means that for each year *t*, we now include both the investments received by region *i* in that year (as in Table 2) as well the projects received in *t-1*, and so on retrospectively. While this allows to account for lagged responses of FDI to regional characteristics, a potential drawback is that we do not have information about projects that are no longer active. Anyhow, the results appear consistent with the previous ones. A second robustness check has to do with the methodology. The dependent variable measures the number of projects received by each region. The occurrence of zeros is also a potential source of concern, especially with respect to the CE-FDI, which are much less frequent than the other types of projects. To address these two potential issues related to the distributional form of the dependent variables, we replicate our analysis by using a Poisson estimator[9]. Also in this case,

[7] https://asti.istat.it/asti/
[8] https://urban.jrc.ec.europa.eu/ardeco/
[9] More precisely, we use the STATA command "ppmlhdfe", which implements the Poisson pseudo maximum likelihood estimator.

we find no relevant distinctions relative to the main results, confirming their robustness.

Table 3 Robustness Checks

	Linear Regression with the Cumulative number of Projects		**Poisson Regression**	
	(1)	(2)	(3)	(4)
VARIABLES	**CE IFDI projects**	**IFDI projects**	**CE IFDI projects**	**IFDI projects**
GDP	1.078	2.838***	7.597	4.280***
	(1.522)	(0.721)	(4.787)	(1.055)
Emissions $_{percapita}$	0.131	-0.534*	2.834	-1.766***
	(0.490)	(0.272)	(4.493)	(0.308)
Recycling Activities	-0.281*	0.237***	1.396	0.306***
	(0.142)	(0.049)	(0.850)	(0.090)
Cargo	-0.425	0.232	2.844*	0.492
	(0.380)	(0.146)	(1.671)	(0.315)
Constant	-17.330	-73.233***	-252.765**	-112.717***
	(39.537)	(17.970)	(128.762)	(27.740)
Observations	300	300	176	300
R-squared	0.908	0.995	0.3411	0.7947
Region FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Avg DV	3.13	59.25	0.54	5.79

Notes: This table presents robustness checks for the main regression results. Columns (1) and (2) report estimates using the (log+1) cumulative number of FDI projects. Columns (3) and (4) report a Poisson regression model, which accounts for the discrete nature of FDI project counts. The controls include (log) GDP, (log) emissions per capita, recycling activities, cargo transport volume. Region and year fixed effects are included in all specifications. Standard errors clustered at the region level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Finally, but not reported for reasons of space, we also ran the analysis dropping the last year, 2021. This is due to two potential issues. First, the coverage of the FDI data for that year is slightly incomplete (missing the number of projects recorded in December 2021). Second, since this is a year largely affected by the consequences of COVID, its impact on global FDI flows was visible exactly that year. Still, removing 2021 does not affect the substance of our results.

1.1.5 Concluding Remarks

Overall, our analysis reveals that while traditional determinants such as regional GDP and cargo transport volumes consistently attract FDI, the drivers for CE-related investments can be different or specific. Regions with higher emissions per capita—less attractive to non-CE investments—emerge as appealing targets for circular economy projects, likely due to the greater potential for environmental impact. Additionally, areas characterized by high levels of high-tech employment tend to attract CE-focused FDI, highlighting the importance of innovation and a skilled workforce in facilitating the transition to a sustainable economic model. These results, though drawn from a limited dataset and not to be interpreted in a causal manner, underscore the need for tailored policy interventions that leverage regional strengths to promote targeted foreign investments in circular economy initiatives.

1.2 Exposure Gap in Environmental Impact in Italy

1.2.1 Data

The data for the exposure gap indicators come from Moody's ORBIS database, which was accessed via its web interface thanks to the CARE-CRUI agreement. All indicators use firm-level information retrieved in July 2023. It is important to highlight the limitations of the ORBIS data, which can be categorized into two main areas.

1. Data Availability: ORBIS relies on the same data as the Infocamere database, meaning it is subject to the same limitations regarding balance sheet data. Specifically, data is only available for firms that are legally required to deposit their balance sheets and make them public in the country where they are incorporated. In the case of Italy, this restriction means we could only access balance sheet data for Società di Capitali (capital companies).
2. Time Span: The standard ORBIS subscription provides limited historical access to firm-level data. Regarding balance sheet data, we were able to access a 10-year window, from 2013 to 2023. However, for ownership structure, the web interface only provides information for the latest available year (2022). As a result, we could not track changes in ownership structure over time.

We use EXIOBASE, a Multi-Regional Environmentally Extended Input-Output table, to collect information on emission intensity and resource usage at the industry level (NACE Rev. 2 – 2 digits). All exposure gaps are then computed with reference to the measures of environmental and resource use intensity extracted from EXIOBASE. In this deliverable, we limit our analysis to the exposure gap against direct CO_2 input requirements.[10] Similar to the ORBIS case, two caveats should be noted:

1. Industry Matching: EXIOBASE only provides the descriptions of the industries rather than the corresponding NACE code identifiers. To match EXIOBASE industry classification to NACE, we manually assigned a NACE 2-digit code to each sector listed in EXIOBASE. This procedure is documented in the code provided with Deliverable 5.3.1.
2. Geographical Detail: Using ORBIS data, we constructed the same indicator at different geographical levels: provincial, regional, and ISTAT-consistent macro-regional levels (NUTS 3, 2, and 1, respectively). To achieve this, we matched and harmonized province and regional details using ISTAT shapefiles for 2022, available on the ISTAT website. Given the limited number of observations and the lack of time variation, we restrict our analysis to the NUTS3 level. More detailed exploration will be possible as the indicators are further developed.

Given the constraints to both ORBIS and EXIOBASE data, we were only able to create a single cross-section for all four indicators considered.

Regarding covariates, we compiled a dataset of additional information from multiple sources, including ISTAT, EUROSTAT ARDECO, The Ministries of the Interior (Ministero dell'Interno) and of Transportation (Ministero dei Trasporti), and the national cadaster of waste (ISPRA). We selected the variables following two principles: on the one side,

[10] As stated in Deliverable 5.3.1, we identified Water Withdrawal, Infrastructure Land Use, and Total Energy Inputs from Nature as potential inputs of interest for our exposure gap, given their relevance to the circular economy. Additionally, we compute the same indicator focusing on those sectors included in the list of circular-economy-sensitive activities by the European Commission. This material is outside the scope of this simple application.

we were constrained by data availability. We limited our selection to the variables with the largest coverage, being this at regional or provincial level. As a matter of facts, not all covariates are available at the more granular level (NUTS 3). For this reason, our dataset includes data at both the regional (NUTS2) and provincial (NUTS3) levels, depending on the source. Table 1.2.1 below lists the variables by source and granularity. On the other side, we selected variables proxying for factors that are susceptible of attracting FDIs or regulate the environmental footprint of a firm and are therefore likely to affect our exposure gap indicators.

Table 1.2.1 – *Variables by source and granularity*

Variable	***Source***	***Granularity***
ExposureGap1	ORBIS (Own elaboration)	NUTS 3
ExposureGap2		
ExposureGap3		
ExposureGap4		
Number of firms	ISTAT	
Per capita GDP (2015 base Y)	ISTAT	NUTS 2
Per capita GDP growth (YoY)	ISTAT	NUTS 2
Waste Collection (recycle)	ISPRA	NUTS 3
Population	ISPRA	NUTS 3
Environmental certificates	ISPRA	NUTS 2
HRST	Eurostat	NUTS 2
Poverty Risk rate	Eurostat	NUTS 2
R&D (GPD %)	Eurostat	NUTS 2
Share of Tertiary Educated	Eurostat	NUTS 2
Real GDP	Eurostat	NUTS 2
Internet Access (headcount)	Eurostat	NUTS 2
Internet Usage	Eurostat	NUTS 2
Real Growth Rate	Eurostat	NUTS 2
Number of Researchers	Eurostat	NUTS 2

Unemployment rate	Eurostat	NUTS 2
Marittime freight	Eurostat	NUTS 2
Airborne freight	Eurostat	NUTS 2
Presence of a port of national relevance	MIT	NUTS 3
Presence of an airport	ENAV	NUTS 3

Notes: HRST = Human resources in science and technology

We collected all covariates in January 2024. To cover a broader time span, we assembled a panel dataset for the years 2013–2023. However, in our empirical application, we only considered covariates for the year 2021 (i.e., with a one-year lag relative to our indicators) due to the cross-sectional nature of our indicators. For the sake of replicability and to support future extensions of this analysis, all scripts related to data cleaning and merging of covariates will be made available on AMELIA. Table 1.2.2 reports the summary statistics for all the covariates.

Table 1.2.2 – *Summary statistics*

	Count	**Mean**	**SD**	**Median**	**min**	**MAX**
ExposureGap1	*104*	*1,00*	*0,11*	*0,98*	*0,74*	*1,59*
ExposureGap2	*104*	*0,99*	*0,10*	*0,96*	*0,80*	*1,37*
ExposureGap3	*56*	*0,91*	*0,53*	*0,70*	*0,35*	*2,62*
ExposureGap4	*92*	*0,74*	*0,33*	*0,65*	*0,22*	*2,31*
Number Of Firms	*107*	*40911*	*49781*	*26571*	*6074*	*347087*
Per Capita Gdp (2015 Base Y)	*107*	*27429,91*	*8297,65*	*29998,30*	*40,90*	*39370,30*
Per Capita Gdp Growth (Yoy)	*107*	*0,11*	*0,01*	*0,11*	*0,07*	*0,12*

	Count	Mean	SD	Median	min	MAX
Population	*107*	*553609*	*604608*	*381091*	*81415*	*4231451*
Waste Collection (recycle, tons)	*104*	*174802,95*	*177128,39*	*119880,98*	*15044,01*	*1160656,15*
Environmental certificates	*98*	*6087*	*4067*	*5462*	*196*	*15429*
HRST	*107*	*35,10*	*4,09*	*35,60*	*28,90*	*42,30*
Poverty Risk rate	*107*	*19,48*	*10,08*	*13,70*	*8,00*	*38,10*
R&D (GPD %)	*107*	*1,34*	*0,47*	*1,29*	*0,54*	*2,16*
Share of Tertiary Educated	*107*	*19,84*	*2,89*	*20,80*	*14,80*	*26,10*
Real GDP	*107*	*30857,94*	*8082,94*	*32900,00*	*18500,00*	*45200,00*
Internet Access (headcount)	*107*	*90,23*	*3,11*	*91,53*	*84,39*	*94,08*
Internet Usage	*107*	*80,10*	*4,67*	*82,01*	*71,59*	*85,16*
Real Growth Rate	*107*	*101,86*	*3,36*	*101,30*	*95,90*	*107,70*
Number of Researchers	*107*	*0,66*	*0,20*	*0,73*	*0,31*	*0,97*
Unemployment rate	*107*	*9,75*	*4,87*	*7,50*	*4,30*	*19,30*
Maritime freight	*107*	*2677,98*	*3762,46*	*689,00*	*0*	*11739,00*
Presence of a port of national relevance	*107*	*0,33*	*0,47*	*0,00*	*0*	*1*
Airborne freight	*107*	*112,44*	*259,65*	*10,00*	*0*	*804,00*
Presence of an airport	*107*	*0,33*	*0,47*	*0,00*	*0*	*1*

1.2.2 Indicators

According to the description provided in Deliverable 5.3.1, we define an *Exposure Gap* as a measure assessing the disparity (or difference) in the environmental performance/resource use/polluting activity between domestic and foreign firms. We generically define the *Exposure Gap* as follows

$$ExposureGap_t = \sum_j \frac{I_{jt} Y_{jt}}{\sum_k I_{kt}} - \sum_j \frac{F_{jt} Y_{jt}}{\sum_k F_{kt}} \qquad (1)$$

Where for instance $I_{jt}$and F_{jt} are the Italian and Foreign owners that are active in country j at time t respectively. Y_{jt} is a measure of environmental impact of the firm's sector.

We further refine the indicator in (1) to express it as a ratio of its two components. This allows us to obtain an *Exposure Gap* where a value of 1 indicates a perfect balance between national and foreign activities on the Italian territory. Consequently, any value below 1 would indicate that business groups headed by a local owner have a lesser impact on the environmental performance/resource use/polluting activity object of the analysis, compared to groups with foreign ownership.

$$ExposureGap_t = \sum_j \frac{\frac{I_{jt} Y_{jt}}{\sum_k I_{kt}}}{\sum_j \frac{F_{jt} Y_{jt}}{\sum_k F_{kt}}} \qquad (2)$$

We propose four variants of the indicators for the exposure gap, based on the perspective adopted when constructing the indicator. These four variants are described below:

- **Exposure gap 1:** Owner's Perspective – Measures how much domestic owners invest in more polluting or environmentally intensive sectors compared to foreign owners.

This is based on the location and industry of other subsidiaries owned by a given group, considering the owner's location within Italy.

- **Exposure gap 2:** Subsidiary's Perspective – Evaluates the extent to which the prevalent industry within an ownership group is more polluting or environmentally intensive, based on the location of each subsidiary within Italy.
- **Exposure gap 3:** Incoming Environmental Stress Perspective – Assesses the degree to which business groups with ultimate owners outside of Italy gravitate toward more (or less) polluting or environmentally intensive sectors within Italy compared to their operations abroad. This indicator is weighted by subsidiary and owner sales in 2022, considering the size of foreign versus domestic operations.
- **Exposure gap 4:** Outgoing Environmental Stress Perspective – Examines the extent to which Italian firms relocate higher-emission operations to countries with potentially less stringent environmental regulations or retain these operations within Italy, where environmental standards may be stricter. This is the counterpart of the "incoming environmental stress" indicator and is also weighted by 2022 sales.

1.2.3 Models

All the indicators described above have significant limitations regarding their use in econometric analyses or simulations. These limitations stem from (a) the cross-sectional nature of the dataset; and (b) the limited sample size, which is constrained by the number of provinces in Italy. While point (b) cannot be addressed, we are actively working on collecting data for a second wave of indicators, incorporating ownership information for the year 2023. This will help mitigate the limitations arising from the small sample size in future applications.

At this stage, and given the existing limitations, the results from a standard regression analysis could potentially be misleading, as it is challenging to address concerns like reverse causality or endogeneity. To offer additional clarity, we present a few correlations using two primary approaches.

First, we report the results from a *Partial Correlation Analysis* (Kim, 2015). Partial correlation measures the relationship between any two variables once the influence of a third variable (or group thereof) is eliminated. In our case, the partial correlation involves either of the four exposure gaps described in the previous section against either of the territorial endowment variables reported in Tables 1.2.1 and 1.2.2. While formally defined as a correlation, partial correlation relies on regressions, more specifically on the estimation of the variances of the two variables that are compared. In short, we compute two simple regressions of the form

$$Y \sim Z, X \sim Z$$

Where Z is the set of covariates whose potential influence over the correlation between y and x we want to control out (in our case, all variables in each table excluding the two we want to test). The correlation coefficient between the residuals of the two linear regressions then is interpreted as the partial correlation between the two dependent variables, X and Y. Like the correlation coefficient, the partial correlation coefficient takes on a value in the range from −1 to 1, where 1 indicates a perfect positive association.

Second, we report the estimates from a standard regression analysis from both OLS and a fixed-effects (FE) estimator. In both cases, the outcome variables consist of the four exposure-gap indicators. The two estimators produce the following estimated equations:

$$EG_p = \alpha + \sum \beta X_p + \sum \Gamma X_r + u_p \qquad (1)$$

For each province index $p = 1, \dots, 110$, EG_p refers to either of the exposure gaps described above. X_p and X_r are the matrices of the covariates – at NUTS 3 and NUTS 2 level respectively – reported in table 5.1.1 and 5.1.2 above, with β and Γ being the vectors of the related coefficients. Finally, u_p represents the heteroskedastic error term. We complement the results from specification (1) with the results from a fixed effects (FE) estimator, where the FE γ_{mr} are specified at macro-region level.[11]

$$EG_p = \alpha + \sum \beta X_p + \sum \beta X_r + \gamma_{mr} + u_p \qquad (2)$$

In the first set of results, we report all the estimated coefficients for each of the covariates described in table 1.2.2 above, which we include individually in equations (1) and (2). Later, we report the estimates related to gradually more demanding specifications, where the potential explanatory variables are included per thematic area. Should be reminded that due to points (a) and (b) above, this latter exercise provides a limited contribution to the understanding of the determinants of the Italian exposure to polluting activities and resource depletion. For this reason, their interpretation will be downplayed, until more waves of the data will be collected.

1.2.4 Analysis

We start with discussing the partial correlations. Table 1.2.3 reports the correlation coefficients between the exposure gap and a territorial endowment variable. To save space, we only report the results for the significant correlations.

[11] In absence of time variability, we use NUTS 2 fixed effects instead of unit (i.e province/NUTS 3) level FE. The latter would in facts absorb all the variability in our data. Additional waves of the indicators will allow to extend the current analysis and allow more complex econometric specifications.

Table 1.2.3 *– Partial Correlation – Only significant correlations (p>0.05)*

Exposure Gap 1	
Population	-0.78
R&D (GPD %)	-0.73
Waste Collection (recycle, tons)	0.65
Presence of an airport	-0.64
Presence of a port of national relevance (R)	-0.59
Exposure Gap 2	
Population	-0.78
R&D (GPD %)	-0.73
Waste Collection (recycle, tons)	0.65
Presence of an airport	-0.64
Presence of a port of national relevance (R)	-0.59
Exposure Gap 3	
R&D (GPD %)	-0.80
Presence of a port of national relevance	-0.78
Presence of an airport	-0.75
Airborne freight	-0.74
Presence of a port of national relevance (P)	0.71
Exposure Gap 4	
HRST	-0.90
Share of Tertiary Educated	0.83
Presence of a port of national relevance (R)	-0.77
Real GDP	0.74
R&D (GPD %)	0.70

Exposure Gap # 1: Owner's Perspective – Investment Patterns in Polluting Sectors

The Exposure Gap 1 evaluates how much domestic owners invest in more polluting or environmentally intensive sectors compared to foreign owners. The positive correlation with the number of companies (0.4437) and the presence of provincial ports (0.4454) suggests that foreign-owned firms are more likely to operate in economically active regions, potentially concentrating their investments in sectors with higher environmental impacts. Conversely, higher population density (-0.3812) and better waste management practices (-0.2730) are associated with lower exposure gaps, indicating that domestic owners in these regions may prioritize less polluting sectors. The presence of regional ports (-0.2556) also appears to reduce disparities, likely due to their role in facilitating balanced economic activities.

Exposure Gap #2: Subsidiary's Perspective – Sectoral Environmental Intensity

The Exposure Gap 2 assesses the extent to which the prevalent industry within an ownership group is more polluting or environmentally intensive. The strong negative correlations with regional ports (-0.5974) and airports (-0.5514) highlight the role of infrastructure in reducing disparities, as better connectivity enables foreign subsidiaries to integrate into less environmentally intensive sectors. Human capital development (-0.5478) further supports this balance, as skilled labor attracts investments in cleaner industries. However, the positive correlation with regional GDP (0.4492) suggests that economically advanced regions may still experience higher disparities due to the concentration of foreign subsidiaries in resource-intensive sectors. Higher population densities (-0.4358) contribute to reducing the gap, likely due to stricter environmental standards in densely populated areas.

Exposure Gap #3: Incoming Environmental Stress – Foreign Firms' Sectoral Choices in Italy

The Exposure Gap 3 examines the degree to which foreign firms gravitate toward more polluting sectors within Italy compared to their operations abroad. The positive correlation with provincial ports (0.6673) indicates that foreign firms may concentrate their environmentally intensive activities in areas with easier access to logistics. Similarly, the positive correlations with GDP per capita growth (0.4781) and tertiary sector activities (0.4630) suggest that foreign firms are drawn to economically expanding regions and advanced industries, which may have higher environmental impacts. However, the presence of regional ports (-0.4311) mitigates these disparities by promoting a more balanced distribution of foreign investments across sectors.

Exposure Gap #4: Outgoing Environmental Stress – Relocation of High-Emission Operations

Finally, the Exposure Gap 4 evaluates whether Italian firms relocate higher-emission operations abroad or retain them in Italy. The strong negative correlation with human capital (-0.7406) suggests that regions with a more educated workforce are better equipped to retain environmentally sustainable operations. In contrast, poverty (0.7009) is positively correlated with the exposure gap, reflecting the challenges faced by disadvantaged regions in retaining low-emission activities. Regional GDP (0.6485) and GDP per capita (0.6103) also show positive correlations, indicating that economically advanced regions may relocate high-emission operations abroad to comply with stricter local regulations. The presence of regional ports (-0.6624) continues to play a mitigating role, likely by supporting the retention of operations within Italy.

In terms of policy implications, these findings highlight the need for targeted policies to address the unique dynamics of each Exposure Gap indicator. Enhancing infrastructure, particularly through regional ports and airports, can reduce disparities by fostering balanced economic integration. Investments in human capital development are essential to attract sustainable and diversified investments, particularly in regions with high poverty levels. Finally, policies should focus on aligning foreign and domestic investments with environmental and social sustainability goals, ensuring that economically advanced and disadvantaged regions alike benefit from balanced and responsible economic activities.

We finally report the results from the regression analysis. We report the results for both the OLS and the FE estimators alongside each other for a series of specifications. While all estimates control for the condition of the labor market, the size of the productive ecosystem (proxied by the number of firms officially active in each region), the size of the market, and the bureaucratic requirements (in terms of certificates needed to operate businesses in a given region), we focused on the role (i) GDP and each region's growth perspective; (ii) presence of a port or airport suitable for commercial purposes; (iii) presence and spread of fast internet connection; and (iv) extent of the waste recycling, which proxies for the receptiveness of a territory for more ecologically conscious activities. As we expected, given the limited numerosity of the sample and the relatively limited data availability in general, estimates are largely insignificant, both in magnitude and in statistical terms. This, joined with the limited explanatory model of each model, makes this exercise remains largely uninformative.

For this reason, we will only report the estimates for the first and the third indicator (Owner perspective and Incoming Environmental stress).[12]

Table 1.2.4 – Growth and Economic Potential on Exposure Gap #1

	GDPc		*ΔGDPc (YoY)*		*Real ΔGDP*	
	OLS	**FE**	**OLS**	**FE**	**OLS**	**FE**
GDP (see column header)	-0.021	0.125	-1.899	-0.503	**-0.011***	-0.002
	-0.199	-0.257	-1.291	-1.434	**-0.006**	-0.009
Isole		-0.015		-0.007		-0.006
		-0.068		-0.075		-0.079
Nord-est		**-0.142*** **		**-0.132*** **		**-0.131*** **
		-0.04		**-0.043**		**-0.047**
Nord-ovest		**-0.101****		**-0.085****		**-0.087****
		-0.045		**-0.042**		**-0.041**
Sud		-0.043		-0.044		-0.039
		-0.058		-0.059		-0.072
Constant	0.964	-0.412	1.094**	0.936*	1.735**	1.063
	-2.059	-2.622	-0.493	-0.496	-0.71	-0.89
Observations	98	98	98	98	98	98
Adjusted R2	-0.063	0.036	-0.039	0.034	-0.029	0.034
F Statistic	0.174	1.325	0.485	1.313	0.615	1.309

Notes: Macroregional FE. Base Macroregion: Central Italy. Measures of Growth (source and summary statistics) described in Table 1.2.1 and 1.2.2.

[12] The estimates for the other two indicators will be available upon request.

Table 1.2.6 – Influence of internet connectivity and impact on Exposure Gap #1

	Internet Access		*Internet Usage*	
	OLS	**FE**	**OLS**	**FE**
Internet	0.004	0.001	0.005	0.0002
	-0.007	-0.007	-0.005	-0.006
Isole		-0.018		-0.016
		-0.069		-0.071
Nord-est		**-0.138*** **		**-0.137*** **
		-0.039		**-0.042**
Nord-ovest		**-0.091** **		**-0.091** **
		-0.039		**-0.039**
Sud		-0.05		-0.051
		-0.055		-0.064
Constant	0.425	0.71	0.262	0.821
	-0.782	-0.798	-0.622	-0.676
Observations	98	98	98	98
Adjusted R2	-0.061	0.033	-0.05	0.033
F Statistic	0.208	1.304	0.345	1.300

Notes: *ISTAT consistent Macroregional FE. Base Macroregion: Central Italy. Measures of Internet Connectivity (source and summary statistics) described in Table 1.2.1 and 1.2.2.*

Table 1.2.6 – Comparison between maritime and airport connectivity and impact on Exposure Gap #1

	MARITIME FREIGHT						*AIRBORNE FREIGHT*					
	OLS	**FE**	**OLS**	**FE**	**OLS**	**FE**	**OLS**	**FE**	**OLS**	**FE**	**OLS**	**FE**
Freight	0.00001*	0.00001			**0.00001***	0.00001	0.0001	0.00003			0.00003	–0.00005
	0	–0.00001			**–0.00001**	–0.00001	–0.0001	–0.0001			–0.0001	–0.0001
Port/Airport of national relevance			0.03	0.028	0.042	0.033			0.0003	0.001	–0.012	–0.009
			–0.028	–0.027	-0.037	-0.036			–0.031	–0.029	–0.032	–0.031
Freight x (Air)Port					0	0					0.0001	0.0001
					–0.00001	–0.00001					–0.0001	–0.0001
Isole		-0.016		–0.02		-0.016		–0.022		-0.017		–0.021
		-0.068		–0.068		-0.07		-0.071		–0.069		–0.071
Nord-est		**–0.128*** **		**–0.138*** **		**–0.126*** **		**–0.135*** **		**–0.138*** **		**–0.137*** **
		-0.042		**–0.039**		**–0.043**		**–0.041**		**–0.039**		**–0.042**
Nord-ovest		**–0.079***		**–0.091****		**–0.076***		**–0.094****		**–0.091****		**–0.095****
		–0.043		**–0.039**		**–0.044**		**–0.041**		**–0.039**		**–0.041**

Sud		-0.026		-0.051		-0.022		-0.056		-0.052		-0.054
		-0.068		-0.054		-0.068		-0.057		-0.055		-0.057
Constant	0.616	0.755*	0.841*	0.931**	0.663	0.827*	0.756*	0.843**	0.748	0.846*	0.758*	0.863**
	-0.439	-0.441	-0.445	-0.426	-0.456	-0.456	-0.436	-0.42	-0.451	-0.432	-0.451	-0.433
Observations	98	98	98	98	98	98	98	98	98	98	98	98
Adjusted R2	-0.031	0.038	-0.05	0.045	-0.038	0.028	-0.053	0.034	-0.064	0.033	-0.062	0.029
F Statistic	0.586	1.344	0.334	1.418	0.603	1.218	0.304	1.307	0.172	1.300	0.366	1.224

Notes: Macroregional FE. Base Macroregion: Central Italy. Measures of Freight and (Air)port presence (sources and summary statistics) described in Table 1.2.1 and 1.2.2.

Table 1.2.7 –Impact of Waste management on Exposure Gap #1

	Waste Recycling (log tons)		*Waste Recycling (% waste collection)*	
	OLS	**FE**	**OLS**	**FE**
Recycling	-0.077	-0.04	-0.147	-0.089
	-0.066	-0.071	-0.134	-0.139
Isole		-0.01		-0.006
		-0.069		-0.07
Nord-est		**-0.131*** **		**-0.131*** **
		-0.041		**-0.041**
Nord-ovest		**-0.087** **		**-0.089** **
		-0.04		**-0.039**
Sud		**-0.053**		**-0.048**
		-0.055		-0.055
Constant	0.839*	0.891**	0.967**	0.979**
	-0.442	-0.428	-0.479	-0.469
Observations	98	98	98	98
Adjusted R2	-0.048	0.037	-0.049	0.038
F Statistic	0.367	1.334	0.347	1.344

Notes: Macroregional FE. Base Macroregion: Central Italy. Measures of recycling activity (sources and summary statistics) described in Table 1.2.1 and 1.2.2.

Table 1.2.8 – Growth and Economic Potential on Exposure Gap #3

	GDPc		***ΔGDPc (YoY)***		***Real ΔGDP***	
	OLS	FE	OLS	FE	OLS	FE
GDP (see	-0.605	-0.546	-1.859	1.197	-0.009	-0.017
column header)	-1.863	-2.724	-8.686	-12.351	-0.042	-0.065
Isole		-0.29		-0.34		-0.235
		-0.621		-0.714		-0.672
Nord-est		0.108		0.073		0.146
		-0.279		-0.304		-0.342
Nord-ovest		-0.065		-0.12		-0.051
		-0.324		-0.345		-0.332
Sud		-0.202		-0.195		-0.09
		-0.444		-0.479		-0.525
Constant	1.288	0.787	-4.151	-4.844	-3.79	-2.966
	-18.414	-26.872	-3.875	-4.581	-5.062	-6.965
	51	51	51	51	51	51
Observations	0.103	0.031	0.102	0.03	0.102	0.031
Adjusted R2	1.820	1.144	1.809	1.140	1.808	1.147

Notes: Macroregional FE. Base Macroregion: Central Italy. Measures of Growth (source and summary statistics) described in Table 1.2.1 and 1.2.2.

Table 1.2.9 – Influence of internet connectivity and impact on Exposure Gap #3

	Internet Access		*Internet Usage*	
	OLS	**FE**	**OLS**	**FE**
Internet	0.038	0.037	0.019	0.033
	-0.068	-0.077	-0.043	-0.059
Isole		-0.336		-0.199
		-0.619		-0.642
Nord-est		0.08		0.158
		-0.26		-0.288
Nord-ovest		-0.091		-0.049
		-0.273		-0.287
Sud		-0.137		-0.003
		-0.425		-0.515
Constant	-8.028	-7.895	-6.344	-7.56
	-7.014	-7.767	-5.088	-6.333
Observations	51	51	51	51
Adjusted R2	0.107	0.035	0.105	0.038
F Statistic	1.857	1.167	1.838	1.178

Notes: ISTAT consistent Macroregional FE. Base Macroregion: Central Italy. Measures of Internet Connectivity (source and summary statistics) described in Table 1.2.1 and 1.2.2.

Table 1.2.10 – Comparison between maritime and airport connectivity and impact on Exposure Gap #3

	MARITIME FREIGHT						***AIRBORNE FREIGHT***					
	OLS	**FE**	**OLS**	**FE**	**OLS**	**FE**	**OLS**	**FE**	**OLS**	**FE**	**OLS**	**FE**
Freight	–0.0003	–0.00003			–0.0002	0.0002	0	–0.00001			–0.0001	–0.0001
	-0.001	-0.001			-0.001	-0.001	–0.00004	–0.0001			–0.0001	–0.0001
Port/Airport of national relevance			–0.302	–0.287	–0.302	–0.328			0.239	0.217	0.126	0.02
			–0.204	-0.214	–0.228	-0.241			–0.206	-0.219	–0.224	–0.248
Freight x (Air)Port					0.0001	0.0001					0.0001	0.0001
					-0.001	-0.001					–0.0001	–0.0001
Isole		–0.294		–0.249		–0.336		–0.274		–0.274		–0.603
		–0.655		–0.605		–0.658		–0.645		-0.61		-0.67
Nord-est		0.084		0.103		0.135		0.059		0.099		-0.164
		–0.274		–0.255		–0.277		-0.317		–0.258		–0.337
Nord-ovest		–0.096		–0.058		–0.089		-0.13		–0.052		–0.288
		–0.287		–0.269		–0.288		–0.333		–0.275		–0.348
Sud		-0.166		-0.152		-0.21		–0.223		-0.132		–0.233
		–0.444		-0.411		–0.446		-0.521		-0.417		-0.51

Constant	-4.599	-4.552	-5.15	-5.058	-5.112	-5.073	-4.46	-4.269	-3.933	-3.91	-2.561	-2.294
	-3.269	-3.437	-3.226	-3.382	-3.302	-3.465	-3.458	-3.851	-3.284	-3.456	-3.557	-3.906
Observations	51	51	51	51	51	51	51	51	51	51	51	51
Adjusted R2	0.109	0.03	0.144	0.073	0.105	0.027	0.101	0.03	0.128	0.054	0.129	0.073
F Statistic	1.877*	1.140	2.206*	1.355	1.651	1.107	1.803	1.142	2.050*	1.257	1.823*	1.305

Notes: Macroregional FE. Base Macroregion: Central Italy. Measures of Freight and (Air)port presence (sources and summary statistics) described in Table 1.2.1 and 1.2.2.

Table 1.2.11 –Impact of Waste management on Exposure Gap #3

	Waste Recycling (log tons)		*Waste Recycling (% waste collection)*	
	OLS	**FE**	**OLS**	**FE**
Recycling	0.465	0.409	0.299	0.183
	-0.546	-0.617	-1.13	-1.232
Isole		-0.338		-0.314
		-0.616		-0.62
Nord-est		0.029		0.079
		-0.274		-0.268
Nord-ovest		-0.115		-0.103
		-0.273		-0.274
Sud		-0.177		-0.183
		-0.418		-0.426
Constant	-5.288	-5.175	-5.076	-4.848
	-3.358	-3.545	-3.757	-3.978
Observations	51	51	51	51
Adjusted R2	0.116	0.041	0.102	0.03
F Statistic	1.934*	1.192	1.813	1.142

Notes: Macroregional FE. Base Macroregion: Central Italy. Measures of recycling activity (sources and summary statistics) described in Table 1.2.1 and 1.2.2.

1.3 Multinationals in the in Circular Economy Transition

The transition toward a circular economy is an important step for sustainable development and requires firms to invest in practices that reduce environmental impact. The institutional pressure in this direction is strong all over the world, but in particular within European Countries such as Italy. The recent European Commission Circular Economy Action Plan (see European Commission, 2008; 2015; 2020 for the different regulatory stages) aims to stimulate the adoption of good practices for sustainable production, re-manufacturing, and recycling. In this context, a major contribution is expected from Multi-National Enterprises (MNEs). Thanks to their involvement in global business and multi-tier supply chain networks, these organizations dominate the European as well as worldwide economy, coordinate resource-intensive global supply networks and might promote a more efficient use of resources and contribute to an effective adoption of sustainable practices (Calzolari et al., 2021).

Although a growing consensus on the key role of MNEs in promoting more sustainable production practices in their supply chains seems to be arising (Calzolari et al. 2021; Ajwani-Ramchandani et al. 2021), the main driver behind the adoption of sustainable practices for MNEs and local firms has not been assessed systematically. From the literature, potential conflicts emerge among MNEs' practices in-house and abroad, even stronger when their subsidiaries are located in emerging countries. The Stakeholder theory suggests that consumers and other social groups are often perceived as weaker stakeholders (Ajwani-Ramchandani et al., 2021) in the host countries in comparison to those in their home countries: this creates the incentive for MNEs to relax CSR and environmental-friendly activities during their operations abroad (Chen et al., 2016).

Previous evidence and theories substantially fail to understand the adoption mechanism for the common firms (i.e., not MNEs and not involved in the global supply chain). What drives the adoption of sustainable practices is still an open question, and the underlying mechanisms remain unclear. The resource-based approach suggests that investment in sustainable practices requires a minimum amount of resources (i.e., a minimum threshold) to be able to invest. Most productive firms should be the subgroup more prone to adopt green and CE practices

Existing literature typically focuses on case studies or small samples of firms, in most cases very similar: MNEs are often analyzed separately, and large samples of heterogenous firms (MNEs, local, suppliers of global supply chains) are rarely explored for the difficulties to collect reliable data on environmental practices.

In this study, we provide insights into the determinants of firms' circular as well as green economy investments while emphasizing the heterogeneous role of multinational enterprises in driving these transitions. This study further explores how firm characteristics, such as the Multinational status, the origin country, and participation in global value chains shape sustainable investment decisions by firms. To understand the mechanisms through which sustainability standards transmit across borders, we leverage several micro datasets on Italian firms. These rich datasets include granular details on firms' sustainable investments, international linkages, and FDIs.

We find that Italian firms that engage in foreign direct investments abroad (i.e., Italian MNEs) are significantly and positively linked to sustainable investments. For what concerns inward FDIs (i.e., foreign MNEs), instead, we disentangle the origin of foreign direct investment and find significant heterogeneity in the adoption of circular economy practices across foreign subsidiaries. The effects seem stronger for MNEs originating from countries with more stringent environmental regulations. Hence, these MNEs serve as channels for the diffusion of advanced sustainability standards while transmitting their knowledge and practices from high-regulation home countries to their subsidiaries. Specifically, subsidiaries linked to countries with higher environmental policy stringency exhibit a greater likelihood of investing in circular economy initiatives. This indicates that being part of a foreign MNE alone does not drive the diffusion of sustainable practices; rather, this diffusion occurs specifically when firms are subsidiaries of parent companies headquartered in high-stringency countries.

Relationships with foreign partners can also lead to higher investments in circular economy as their partners may face strict environmental standards in trade. Building on this, we find that both exports and imports of Italian firms are positively associated with green and circular economy practices. We also extend our analysis to investigate the importance of the complexity of GVC linkages. Firms can participate in many tasks in value chains. By differentiating these tasks and identifying different GVC modes, we show that firms that are part of relational GVCs are the ones engaging more in sustainability investments. However, there is not any significant link to these investments for firms that participate in GVCs through simpler tasks like competitive pricing. These findings suggest that firms strongly involved in GVCs relationship might be able to share resources and risks within the supply chain, with an increasing likelihood of making circular economy investments.

1.3.1 Data

This piece of work relies on the merging of multiple datasets to provide a complete perspective on our research questions at the micro-level. The first dataset is the MET Survey, which provides information on Italian firms' involvement in sustainable investments. The second dataset is AIDA, which provides detailed information about the sectors and locations of firms. The third dataset is the ownership information provided by ORBIS. The final dataset is the OECD Environmental Policy Index for the countries. We match all four datasets to construct a panel of firms for this paper.

1.3.1.1 The MET dataset

The first dataset is the MET Survey, a comprehensive dataset for Italian firms that provides insights into their activities and characteristics. Most importantly, it enables tracking firms' circular and green economy investments in the most granular way. As the questions related to sustainability are available only for 2021 and 2023, we use data from these two years in our analysis. In addition to variables related to circular investments, this survey also allows us to identify whether a firm participates in a GVC or not. Moreover, the survey provides information on the firm's international trade activities.

First of all, we identified firms that adopted sustainable practices according to their decision on Green and Circular Investments. This first definition depends on whether a firm is answering "yes" to different questions regarding their investments in circular economy practices, such as recovery, reuse, recycling, investments in durability and repairability, optimization of non-energy material use, and significant changes in products or services to align with environmental sustainability guidelines. The second definition encompasses all types of green investments, that include also energy saving, reduction of transport costs, and other strategies directed to reduce pollution. The details of these questions are provided in Appendix A.

Second, we identified firms that are Multinationals because firms also reported whether they belong to a business group. Additionally, they indicate whether the group is based in Italy, within the European Union, or outside the European Union. This dimension of the data allows us to investigate the link between the firm and the origin of the foreign direct investment. Hence, we can identify Italian subsidiaries of foreign multinationals that engage in FDIs in Italy (i.e., foreign multinationals or inward FDIs) as well as Italian firms that invest abroad (i.e., Italian multinationals or outward FDIs). Moreover, we differentiate between subsidiaries of European firms and subsidiaries of multinationals located in non-European countries. As to the identification of Italian multinationals, the survey contains information about the outward foreign direct investments made in the previous three years and in the past (outward FDIs). We have thus detailed information on both outward and inward FDIs.

Finally, we can identify firm-level GVC Participation and the quality of such participation. To achieve this, this section classifies both GVCs and further examines the scope of GVC relationships based on the MET Survey. The firm responses in this survey are implemented to identify whether a firm is a GVC participant or not, following Brancati et al. (2017). According to this study, a firm is classified as part of a GVC if it engages in both importing inputs and exporting final goods, if it exports semi-finished goods and components, or if it either imports inputs or exports products but at the same time maintains long-term and significant relationships with foreign firms. However, this rich dataset enables further classification of the complexity of GVC linkages into different modes of GVC participation, namely, arm-length, hierarchical, quasi-hierarchical, and relational relationships. According to Brancati et al. (2017), we classify the four types of GVC participation modes, as outlined in Table 1.

The first and simplest mode, arm-length, focuses on competitive pricing. This relationship is characterized by relatively low levels of integration and collaboration. The second mode, quasi-hierarchy, describes trade relationships where the firm is connected to a value chain but does not contribute to developing the final product. Compared to arm-length, these relations with GVCs are not spot but they are typically based on long-term contracts. The third mode is hierarchy, which occurs when firms are subsidiaries tightly connected to their parent companies through direct ownership. The fourth mode, relational, is the most complex due to its demanding requirements. This mode is primarily associated with firm involvement in the design of the product, and requires knowledge exchanging, high competence, cooperation capabilities, and ultimately more symmetry among the different actors involved in the value chain.[13]

Type of GVC	**Underlying Relationship with Foreign Firms**
Arm length	Pure trade links dominated by competitive pricing
Quasi-hierarchy	Trade links with no significant role in the value chain
Hierarchy	Subsidiaries of leading firms
Relational	Active partners in the value chain

Table 1.3.1: Participation Modes to Global Value Chains

1.3.1.2 The AIDA dataset

The AIDA dataset is provided by Bureau van Dijk (Moody's) and contains detailed yearly financial and other information on Italian firms. Using firms' tax codes, the information contained in MET is merged with several variables related to structural and financial aspects of firms included in AIDA.[14] We retrieve information on the sector of the firm from its ATECO 2007 code, which aligns with the NACE framework, allowing sector identification at the six-digit level. The establishment date of the firm, provided

[13] See Brancati et al. (2017) for more details on the identification of the above four categories using the MET dataset.
[14] This merge has been conducted by MET, as MET data are anonymized for privacy reasons.

in AIDA, is used to calculate the firm's age, which is used as a control in our regressions. We then use the AIDA dataset to compute total factor productivity (TFP) estimates, inserted as controls in the regressions. The availability of multiple years of observations of the AIDA dataset (2010-2023) allows us to construct accurate time-varying firm-level TFP measures. To obtain our TFP estimates we use the information on value added, the number of employees, tangible fixed assets, and expenditure on intermediate inputs and follow the methodology developed by Ackerberg et al. (2015) (abbreviated as "ACF").[15]

1.3.1.3 The ORBIS dataset (ownership information)

The ORBIS dataset is provided by Bureau van Dijk and contains detailed financial and other information for firms located in more than 200 countries of the globe. We exploit this dataset to obtain ownership information for the Italian firms in the matched MET-AIDA dataset which are indicated as subsidiaries of foreign firms. In other words, we use the ORBIS dataset to identify the origin country of the parent company that owns the firm identified as a foreign-group subsidiary in the MET dataset. This is crucial for understanding how MNEs and their foreign subsidiaries operate within Italy and whether there are differences based on the country of origin of the parent company.

1.3.1.4 OECD environmental policy stringency index

MET allows us to track whether a company is a subsidiary of an MNE and how it engages in green and circular economy investments. However, an important aspect of our research question is whether stringent environmental regulations diffuse to host countries. In this context, we have information on the nationality of the parent company from the ORBIS dataset. We then match this data with the Environmental Policy Stringency Index provided by OECD (2024). This matching enables us to distinguish between MNEs with varying levels of environmental stringency. By combining these

[15] See Appendix C for details on TFP estimates.

datasets, we can investigate whether a firm is part of an MNE that prioritizes green investments.[16]

1.3.2 Indicators

The descriptive statistics for the key indicators relative to the matched panel are reported in Table 2, based on 11,914 observations. We report the key variables related to circular economy participation in Panel A. 28% of firms in our sample have invested in circular economy practices, while 41% have engaged in sustainable green strategies.

	Obs.	Mean	Std	Min	Max
Panel A: Circular Economy					
Circular Economy	10,243	28.21	45.01	0	100
Green Economy	10,243	41.18	49.21	0	100
Panel B: MNEs					
Outward FDI	10,243	3.43	18.15	0	100
Inward FDI: European	10,243	3.61	18.59	0	100
Inward FDI: non-European	10,243	2.88	16.75	0	100
Panel C: GVC Participation					
GVC	10,243	37.87	48.51	0	100
Panel D: GVC Modes					
Arm-Length	10,243	13.24	33.90	0	100
Quasi-hierarchy	10,243	11.31	31.68	0	100
Hierarchy	10,243	6.87	25.29	0	100
Relational	10,243	9.59	29.45	0	100

Table 1.3.2: Main indicators & descriptive Statistics

[16] Note that this index provides a comparable measure of environmental policy stringency across 40 countries.

In Panel B, we focus on outward and inward FDIs. 90% of the sampled firms are not engaging in foreign direct investments, while 430 firms are Italian MNEs that have invested abroad and 814 firms are subsidiaries of a foreign group operating in Italy. For 452 of them, the parent company is headquartered in a country member of the European Union, while the remaining 362 are subsidiaries of a multinational company located outside the European Union. Panel C presents GVC participation. Based on our sample, almost thirty-eight percent of the firms participate in global value chains. Panel D provides the statistics for different modes of GVCs.

1.3.3 Models

In this section, we examine the role of different explanatory variables drawn from hypotheses development (i.e., outward vs inward FDIs, international trade, and participation in global value chains in shaping green and circular investment decisions according to specific model specifications. These aspects are very important given their potential to direct the transition toward sustainability. To address this, we rely on two definitions of sustainability from the MET surveys, which include general green investments and the stricter subset of investments in circular economy. The use of these two dependent variables allows us to capture a robust measure of sustainability.

In the subsequent regression models, we adopt a structured approach, starting with the issue of MNEs' ownership structures and progressively moving toward other specific configurations. This allows us to disentangle the role of MNEs in fostering sustainability and further investigate the investments made by foreign affiliates. We look at how different types of FDI (Italian MNEs vs foreign MNEs) affect the chances of firms making sustainable investments. Additionally, we broaden our analysis to investigate the role of the regulatory contexts and the global chain participation. In particular, we include as potential explanatory variables the international trade connections (i.e., imports or exports) as well as whether the different modes of GVC participation affect firms' decisions to make sustainable investments.

The baseline regression model is defined as follows:

$$SustInvestment_{i,t} = \beta_0 + \beta_1 OutwardFDI_{i,t} + \beta_2 InwardFDI_{i,t} + \beta_3 Size_{it} + \beta_4 Age_{it} + \beta_5 TFP_{it} + \lambda_i + \delta_t + \eta_{it} + \epsilon_i \quad (1)$$

where the dependent variable, $SustInvestment_{i,t}$ is the investment in sustainability practices of firm *i* in year *t*. In each regression, we use two different dependent variables: green economy investment and circular economy investment. *OutwardFDI* identifies Italian multinationals that, by definition, invest abroad, while *ForeignSubsidiary* accounts for inward FDIs done by foreign multinationals in Italy. We include classical key control variables such as size, age, and TFP that account for the dimension (measured by the logarithm of the number of employees), the age of the firm (measured in years), and TFP of the firm.[17] Controlling for TFP is crucial due to the strong connections between the multinational status and the expected higher productivity, documented by many studies (Alfaro et al., 2004; Javorcik, 2004; Keller and Yeaple 2009; Altomonte et al., 2013, and Alfaro, 2017).

All the regressions include numerous fixed effects to control for potential confounding factors in particular we include includes fixed effects for size (five classes), industry (three-digit ATECO 2007 classification), province (λ_i), and year (δ_t), as well as year-size, year-industry, and year-region interactions (η_{it}) to control for specific region-sector-size trends. Along with the empirical analysis, the other aspects of interest (i.e., the detailed multinational origin, the level of environmental stringency, the involvement in international trade/GVC, and the GVC participation modes) are investigated according to this baseline model that is substantially stable in terms of controls and fixed-effects structure.

1.3.4 Analysis of the results

In this section, we focus on the empirical results from the estimation of econometric models on the role of multinationals in shaping circular economy practices. To do so, we first explore whether the location of a parent company's headquarters influences a

[17] See Appendix C for details of how we computed TFP.

subsidiary's likelihood of adopting sustainable practices. Hence, we aim to investigate the heterogeneity across MNEs. We divide foreign subsidiaries into two categories: European and non-European. This differentiation allows us to assess how differences in environmental regulatory environments relate to firm behavior.

This distinction is particularly relevant, as the European Union has established itself as a global leader in circular economy policies, promoting the most comprehensive frameworks for minimizing waste and maximizing resource efficiency. On the other hand, firms with non-European parent companies can be exposed to different regulations. Therefore, we use the parent company's location as a proxy for circular-economy regulations.

	Dependent Variable	
	(1)	(2)
VARIABLES	Green Economy	Circular Economy
Italian MNE	0.113***	0.081***
	(0.028)	(0.027)
Foreign MNE	-0.024	-0.018
	(0.022)	(0.022)
Size	0.057***	0.040***
	(0.008)	(0.007)
TFP index	0.031***	0.018**
	(0.009)	(0.008)
Firm's Age	0.002***	0.001***
	(0.000)	(0.000)
Constant	0.056	0.059*
	(0.038)	(0.035)
Observations	10,243	10,243
R-squared	0.148	0.110

Table 1.3.3: Investment Origin

Notes: This table displays the estimated coefficients and SE in parentheses for the model (1). All estimates account for size (five classes), industry (three-digit ATECO 2007 classification), province (λ_i), and year (δ_t), as well as year-size, year-industry, and year-region interactions (μ_{it}) fixed effects. Significance levels are indicated as follows:

$*p < 0.05$, $**p < 0.01$, and $***p < 0.001$.

According to Table 3, the coefficients for outward FDIs are positive and statistically significant across all three sustainability definitions, while inward FDIs do not seem to be associated with green or circular economy investments, as they exhibit a negative but not statistically significant coefficient.[18]

The results for the control variables are of a certain interest, since they show that sustainable investments increase with a firm's size, age, and TFP.

Table 4 separates inward FDIs according to the nationality of the foreign parent company. Interestingly, for non-European subsidiaries we observe a negative and statistically significant coefficient, suggesting that implementing sustainability strategies in Italy is not a priority for those multinational companies.[19]

	Dependent Variable	
	(1)	(2)
VARIABLES	Green Economy	Circular Economy
Italian MNE	0.113***	0.081***
	(0.028)	(0.027)
UE MNE	0.001	0.008
	(0.029)	(0.028)
Extra-UE MNE	-0.057*	-0.051*
	(0.031)	(0.031)
Size	0.058***	0.040***
	(0.008)	(0.007)
TFP index	0.031***	0.018**
	(0.009)	(0.008)
Firm's Age	0.002***	0.001***
	(0.000)	(0.000)
Constant	0.056	0.059*
	(0.038)	(0.035)
Observations	10,243	10,243
R-squared	0.148	0.110

[18] Descriptive statistics highlight that 64% of Italian MNEs invested in green economy, compared to a percentage of 50% for foreign MNEs and 40% for domestic firms. A similar pattern emerges for circular economy investments.
[19] The non-EU countries that invest more in Italy are the US, Switzerland, the UK, and Japan, while the EU countries that have more subsidiaries in Italy are Germany, France, the Netherlands, Sweden, Luxembourg, and Spain.

Table 1.3.4: Detailed Investment Origin

Notes: This table displays the estimated coefficients and SE in parentheses for the model $SustInvestment_{i,t} = \beta_0 + \beta_1 ItalianMNE_{i,t} + \beta_2 UE\_MNE_{i,t} + \beta_3 ExtraUE\_MNE_{i,t} + \beta_4 Size_{it} + \beta_5 Age_{it} + \beta_6 TFP_{it} + \lambda_i + \delta_t + \eta_{it} + \epsilon_i$. All estimates account for size (five classes), industry (three-digit ATECO 2007 classification), province (λ_i), and year (δ_t), as well as year-size, year-industry, and year-region interactions (μ_{it}) fixed effects. Significance levels are indicated as follows:

$*p < 0.05$, $**p < 0.01$, and $***p < 0.001$.

The findings from Tables 3 and 4 underline the crucial role of investment origin in influencing firm-level sustainability practices. Italian multinationals are more likely to engage in sustainability practices, while non-EU multinationals operating in Italy are not related to these investments possibly due to less regulatory pressures on renewables compared to Europe.[20]

To elaborate more on this, we investigate the role of environmental stringency for inward FDIs. To do so, we use the OECD Environmental Stringency Index which measures the intensity of environmental policies in a given country and provides a metric to compare the environmental stringency across countries. Using this information, we identify countries that show a stringency index higher than the OECD average and we construct a dummy for catching MNEs that originate from a high-stringency country. Table 5 presents the results of regressions in which the dummy indicating foreign subsidiaries has been interacted with the dummy indicating high environmental stringency index, thus including the interaction term *Foreign_MNEs*High_stringency*.

We find the coefficient on the interaction term positive and significant, but our conclusions on this point are very cautious for the weak statistical significance and the proxy used for both the identification of high-stringency countries and firm-level ownership limitations[21].

[20] It is important to note that Italy is among the countries with the highest environmental stringency: according to the 2020 OECD Environmental Policy Index, Italy ranked eighth.

[21] The identification of the origin country has not been possible for the entire subset of foreign MNEs due to data limitations. Using the partial information from the MET survey we reconstruct missing origin countries with the average stringency indicators for the aggregated area (EU vs non-EU final owners).

	Dependent Variable	
	(1)	(2)
VARIABLES	Green Economy	Circular Economy
Italian_MNE	0.113***	0.081***
	(0.028)	(0.027)
Foreign_MNE	-0.047	-0.042
	(0.035)	(0.035)
ForeignMNEs * high stringency	0.035*	0.036*
	(0.020)	(0.021)
Size	0.057***	0.040***
	(0.008)	(0.007)
TFP index	0.031***	0.018**
	(0.009)	(0.008)
Firm's Age	0.002***	0.001***
	(0.000)	(0.000)
Constant	0.056	0.060*
	(0.038)	(0.035)
Observations	10,243	10,243
R-squared	0.148	0.110

Table 1.3.5: Environmental Stringency

Notes: This table displays the estimated coefficients and SE in parentheses for the model $SustInvestment_{i,t} = \beta_0 + \beta_1 ItalianMNE_{i,t} + \beta_2 Foreign\_MNE_{i,t} + \beta_3 Foreign\_MNE*High\_stringency_{i,t} + \beta_4 Size_{it} + \beta_5 Age_{it} + \beta_6 TFP_{it} + \lambda_i + \delta_t + \eta_{it} + \epsilon_i$. All estimates account for size (five classes), industry (three-digit ATECO 2007 classification), province (λ_i), and year (δ_t), as well as year-size, year-industry, and year-region interactions (μ_{it}) fixed effects.

Significance levels are indicated as follows: $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$.

These findings are intriguing and are suggestive of a process of diffusion of sustainable practices from firms headquartered in countries with higher stringency to their subsidiaries operating abroad.

1.3.4.1 International trade, GVCs, and sustainability investments

The results presented so far highlight the role of Italian MNEs as well as foreign MNEs linked to regions with higher environmental regulations in implementing green and circular economy strategies in the Italian territory. This section extends the above analysis to investigate the role of international trade, for both MNEs (undertaking both outward and inward FDIs) and domestic firms that do not engage in foreign direct investments. In particular, we enrich our baseline regression by including imports and exports of Italian firms. Similar to the significant diffusion observed from MNEs to their subsidiaries, international trade might force firms in partner countries to align with regulations. Hence, gaining access to foreign markets can be an incentive for firms to invest in sustainability.

	Dependent Variable			
	(1)	(2)	(3)	(4)
VARIABLES	Green Economy	Circular Economy	Green Economy	Circular Economy
Exporter	0.054***	0.046***	---	---
	(0.013)	(0.012)		
Importer	0.105***	0.095***	---	---
	(0.014)	(0.013)		
GVC	---	---	0.115***	0.098***
			(0.012)	(0.011)
Italian MNE	0.085***	0.056**	0.080***	0.052*
	(0.028)	(0.027)	(0.028)	(0.028)
UE MNE	-0.013	-0.004	-0.014	-0.005
	(0.029)	(0.028)	(0.029)	(0.028)
Extra-UE MNE	-0.071**	-0.064**	-0.071**	-0.063**
	(0.031)	(0.030)	(0.031)	(0.030)
Size	0.049***	0.033***	0.052***	0.036***
	(0.007)	(0.007)	(0.007)	(0.007)
TFP index	0.024***	0.013	0.025***	0.013
	(0.009)	(0.008)	(0.009)	(0.008)
Firm's Age	0.002***	0.001*	0.002***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.052	0.056	0.041	0.047
	(0.037)	(0.034)	(0.037)	(0.034)
Observations	10,243	10,243	10,243	10,243
R-squared	0.158	0.119	0.156	0.117

Table 1.3.6: International Trade

Notes: This table displays the estimated coefficients and SE in parentheses for the model $SustInvestment_{i,t} = \beta_0 + \beta_1 Exporter_{i,t} + \beta_2 Importer_{i,t} + \beta_3 GVCs_{i,t+} \beta_4 ItalianMNE_{i,t} + \beta_5 UE\_MNE_{i,t} + \beta_6 ExtraUE\_MNE_{i,t} + \beta_7 Size_{it} + \beta_8 Age_{it} + \beta_9 TFP_{it} + \lambda_i + \delta_t + \eta_{it} + \epsilon_{i.}$. All estimates account for size (five classes), industry (three-digit ATECO 2007 classification), province (λ_i), and year (δ_t), as well as year-size, year-industry, and year-region interactions (μ_{it}) fixed effects. Significance levels are indicated as follows: $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$.

It is interesting to observe that regressions in Table 6 show positive and statistically significant coefficients for both imports and exports, indicating that firms that are involved in export/import activities are more likely to adopt sustainable practices.

Relationships with foreign firms can be more complex than simply importing or exporting intermediate/final goods. To account for this, we investigate whether participation in GVCs has an impact on the firm's decision to adopt green and circular economy practices. Firms engaged in GVCs might be forced to align their practices with the requirements and standards of their partners. Thus, these upstream and downstream linkages can be a critical criterion for trade and production activities. We extend therefore the baseline exercise by adding regressors related to the GVC participation of Italian firms (again, for both multinational companies and domestic firms).

The findings are reported in Table 6. In each specification, GVC turns out to be positively related to sustainable investments. Hence, GVC participation amplifies the role of firms in driving sustainable practices. This result is likely due to the compliance requirements with environmental standards set by partners in the value chain. As a result, findings in Table 6 suggest the importance of regulatory upstream and downstream linkages in shaping firm behavior.

As outlined in data section, our dataset allows decomposing GVC participation to investigate whether deepening in GVCs is somehow related to firms' green and circular economy investment decisions. Specifically, we can categorize the complexity of GVC relationships into four classes by applying additional criteria beyond mere participation. The four types of GVCs are arm-length, quasi-hierarchy, hierarchy, and relational.

The findings shown in Table 7 indicate that firms participating in relational GVCs are more likely to follow sustainability practices. Participation modes that involve longlasting relationships and active contributions to the conception and definition of the final product for the market show greater involvement in responsible sourcing and other related green and circular strategies. A positive effect, but of a lower magnitude, is also found for subsidiaries involved in value chains that respond to the directives of the parent companies.

	Dependent Variable	
	(1)	(2)
VARIABLES	Green Economy	Circular Economy
GVC Arm-length	0.050	0.034
	(0.037)	(0.036)
GVC Quasi-hierarchy	0.035	0.027
	(0.039)	(0.038)
GVC Hierarchy	0.058**	0.067**
	(0.025)	(0.026)
GVC Relational	0.123***	0.097***
	(0.017)	(0.018)
Italian MNE	0.086***	0.057**
	(0.028)	(0.027)
UE MNE	-0.039	-0.034
	(0.033)	(0.032)
Extra-UE MNE	-0.099***	-0.096***
	(0.033)	(0.032)
Size	0.054***	0.038***
	(0.007)	(0.007)
TFP index	0.031***	0.018**
	(0.009)	(0.008)
Firm's Age	0.002***	0.001**
	(0.000)	(0.000)
Constant	0.047	0.052
	(0.037)	(0.035)
Observations	10,243	10,243
R-squared	0.157	0.117

Table 7: Different GVC Participation Modes

Notes: This table displays the estimated coefficients and SE in parentheses for the model $SustInvestment_{i,t} = \beta_0 + \beta_1 GVC\_AL_{i,t} + \beta_2 GVC\_QH_{i,t} + \beta_3 GVC\_Hs_{i,t} + \beta_4 GVC\_Hs_{i,} + \beta_5 ItalianMNE_{i,t} + \beta_6 UE\_MNE_{i,t} + \beta_7 ExtraUE\_MNE_{i,t} + \beta_8 Size_{it} + \beta_9 Age_{it} + \beta_{10} TFP_{it} + \lambda_i + \delta_t + \eta_{it} + \epsilon_i$. All estimates account for size (five classes), industry (three-digit ATECO 2007 classification), province (λ_i), and year (δ_t), as well as year-size, year-industry, and year-region interactions (μ_{it}) fixed effects. Significance levels are indicated as follows: $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$.

Conversely, less complex relationships based only (arm-length) or mostly on pricing (quasi-hierarchy) are not significantly associated with investments in sustainability. Therefore, the findings demonstrate that as a firm's involvement in GVCs deepens, it becomes more strongly associated with green and circular economy strategies. Our results suggest that also if we consider the mode – that is, intensity – of participation to GVC: more qualified modes, such as relational or hierarchical, are the only ones that remain statistically significant and positive when we focus on the kind of relationship within GVC. In other words, more complex relationships, such as those involving strategic partnerships, are more likely to be built with sustainable partners. Such forms of collaboration facilitate the exchange of knowledge and best practices, which can be related to circular economy principles.

2. Simulation models for assessing trade and GVC reconfiguration's impact on CE transition

2.1 Circular Economy, Trade and Regional Growth

The European Union (EU) has made CE a priority and has been adopting action plans since 2014 (EU, 2014, 2015). CE was turned into a core component of the European Green Deal (EU, 2020). This transition to CE is expected to reduce pressure on natural resources, to create sustainable growth and jobs, to achieve the EU's 2050 climate neutrality target and to halt biodiversity loss (European Commission, 2024). However, little is known about how this transition to CE can take place, and its economic and social consequences.

From an optimistic viewpoint, according to EMF (2013), this transition leads to significant economic and environmental advantages at global level. CE can allow resilient growth, reduced dependency on resource markets and lower exposure to resource price shocks and external costs in developed countries. Emerging countries, in their turn, can benefit from circular setups by avoiding 'lock-in' and benefiting from greater material savings.

Very little is known on the flows and dynamics of CE trade. Moreover, no evidence is available at the sub-national level. This is an important limitation, since the growth of domestic value-added in CE exported in GVCs can be different in the different regions according to local structural (institutions and technological) factors related to the CE promotion and to the network of trade partners. From this perspective, **the aim of this work is to build a simulation model to explore the growth trajectories of the Domestic Value Added (DVA) in CE sectors in Italian regions under different assumptions on the changes in new trade patterns within GVCs and in structural characteristics related to CE promotion**.

2.1.1 Data

The aim of the model is to estimate and simulate DVA growth between 2014 and 2018[22], based on the expression:

$$CE\ DVA\ growth = \frac{(CE\ DVA_{2018} - CE\ DVA_{2014})}{CE\ DVA_{2014}} \quad (1)$$

In order to build the indicator, DVA in circular economy in different regions (*CE DVA*) and time span has to be known. This is obtained from global OECD input-output matrices set for 2014 and 2018[23]. The choice for OECD matrices stems from the fact that they have been widely available, overtime, in comparison to other matrices found in the literature. Furthermore, they have been used by OECD to derive Trade in Value-Added (TiVA).

Sector 'x' in country 's' produces a good i that can be used as intermediate production factor in the production of another good or to meet final demand in country s or in country r, abroad, in the inter-country input-output context. Mathematically, this association is expressed as:

$$x_i^s = \sum_{s=1}^{n} \sum_{j=1}^{m} z_{ij}^{sr} + f_i^{sr} \quad (2)$$

Wherein, x_i^s is total production, z_{ij}^{sr} represents inter-industry sales by sector i in region s to sector j in region r, and f regards final demand.

The matrix columns provide information on production technology and point out the amounts of intermediate goods needed to produce the total product; it reflects both domestic and foreign intermediates used in production. This technology is fixed, at least in the short run, and it can be expressed by the following technical coefficient:

$$a_{ij}^{sr} = z_{ij}^{sr} / x_j^r \quad (3)$$

[22] In 2014, DVA took into account inflation in the EU between 2018-2014, since the database of OECD matrices is expressed in current values.

[23] Although this database holds information regarding years after 2018, we have carefully followed the accuracy of this year's data, which are in compliance with the national input-output matrices obtained by OECD - the most recent years were also estimated based on 2018.

By isolating z_{ij}^{sr} in equation (2), replacing it into equation (1) and rewriting the system in the matrix form we find:

$$X = AX + Y \tag{4}$$

By solving it for total product X:

$$X = (I - A)^{-1}Y \tag{5}$$

Wherein, $(I - A)^{-1}$ is the Leontief inverse, denoted as L, and A is the matrix of technical coefficients and I is an identity matrix.

It is necessary having a value-added vector, v, where each element represents the rate of value-added (w) per unit of product (x) by country *r* and sector *i*, to calculate the DVA embodied in gross exports:

$$v_i^r = w_i^r / x_i^r \tag{6}$$

An important observation concerns the value-added vector, which was crucial to capture DVA in CE and non-CE trade, in Italy. DVA in CE was calculated by using value-added measures recorded for CE-related sectors, as defined by Prognos (2022) in the 4-digit NACE, which includes the primary, industrial and services sectors.

Since the OECD input-output matrix is defined at 2-digit NACE level, it was necessary to estimate the value-added share of the CE sectors from the 4-digit to the 2-digit NACE. It was done by dividing the sectoral employment in CE sectors at NACE 4-digit level by their corresponding sectoral employment at 2-digit NACE level for 2018, based on the Istat employment database.

The shares resulting from this division were applied to the value-added vector, W, recorded for 2014 and 2018. This approach kept the proportionality of CE sectors in these two years, which allowed comparing changes in DVA without influencing employment changes, such as productivity gain or decrease. The total value-added for the remaining sectors in non-CE trade was taken into account, i.e., these sectors were not seen as CE sectors by Prognos (2022).

It was necessary to provide an interregional export vector, e, which represented the exports from one country to the other in order to calculate DVA in CE and non-CE trade. This vector was found through equation (6), based on Koopman et al. (2014):

$$E_{s*} = \sum_{r\neq s}^{G} E_{sr} = \sum_{r\neq s}^{G}(A_{sr}X_r + Y_{sr}) \quad (7)$$

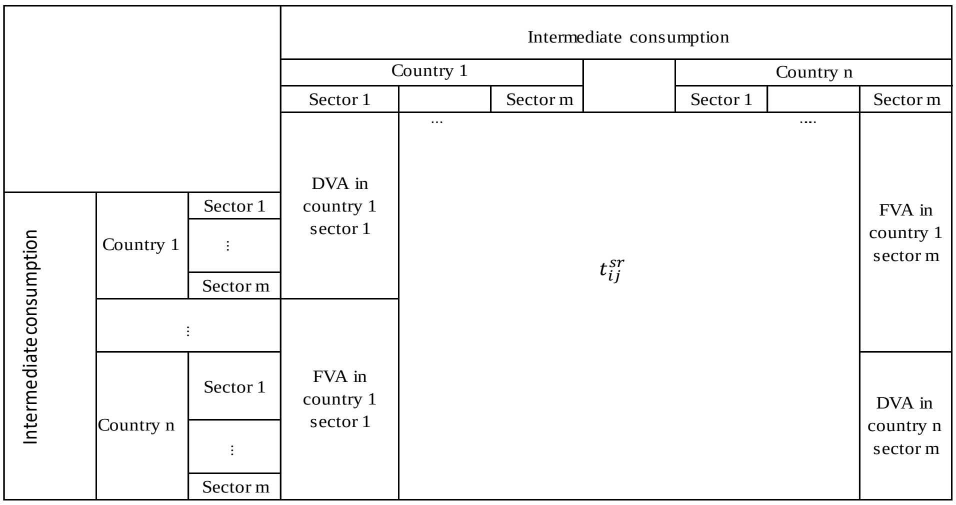
DVA embodied in gross exports could be calculated from T by diagonalizing both vectors v and e:

$$T = \begin{pmatrix} T_{11}^{11} & \dots & T_{1n}^{mm} \\ \vdots & \ddots & \vdots \\ T_{n1}^{1m} & \dots & T_{nn}^{mm} \end{pmatrix} = \begin{pmatrix} v^1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & v^m \end{pmatrix} \begin{pmatrix} L_{11}^{11} & \dots & L_{1n}^{mm} \\ \vdots & \ddots & \vdots \\ L_{n1}^{1m} & \dots & L_{nn}^{mm} \end{pmatrix} \begin{pmatrix} e^1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & e^m \end{pmatrix} \quad (8)$$

Figure 1 depicts an updated UNCTAD (2013) T-matrix for 'm' sectors and 'n' countries.

According to the T matrix, DVA in gross exports represents the value created in a country through the production of goods and services for export. Essentially, it shows the fraction of the value recorded for the exported product coming from the exporting country itself; it was done by focusing on the production taking place within the country's borders. This measure encompasses both the direct and indirect value-added generated by Italy's exports in CE and non-CE sectors. The direct value-added for CE trade was defined based on the method by Prognos (2022), whereas the indirect value-added stemmed from other sectors linked to CE trade. In contrast, when it comes to non-CE trade, direct value-added emerges from sectors outside the CE framework, and indirect values, from CE.

Figure 1. T matrix used to calculate DVA in CE and non-CE trade



Source: elaborated by the authors.

Finally, DVA related to CE and non-CE trade was regionalized to NUTS2 regions in Italy. This regionalization was based on the employment rate in each 2-digit NACE sector linked to the national total recorded for 2018 by using data available at the IstatData database. This process involved multiplying the national DVA by the rate of employment recorded for each sector at regional level. The 2018 shares were kept constant to calculate the regional DVA for 2014 and 2018.

2.1.2 Indicators

The indicators of trade in CE, calculated with the methodology discussed in the previous section, are complemented with other indicators on selected regional characteristics of CE promotion. These characteristics are assumed to impact the regional capability of developing CE trade, i.e. possibility for a region of increasing the DVA produced and traded within GVCs by CE sectors.

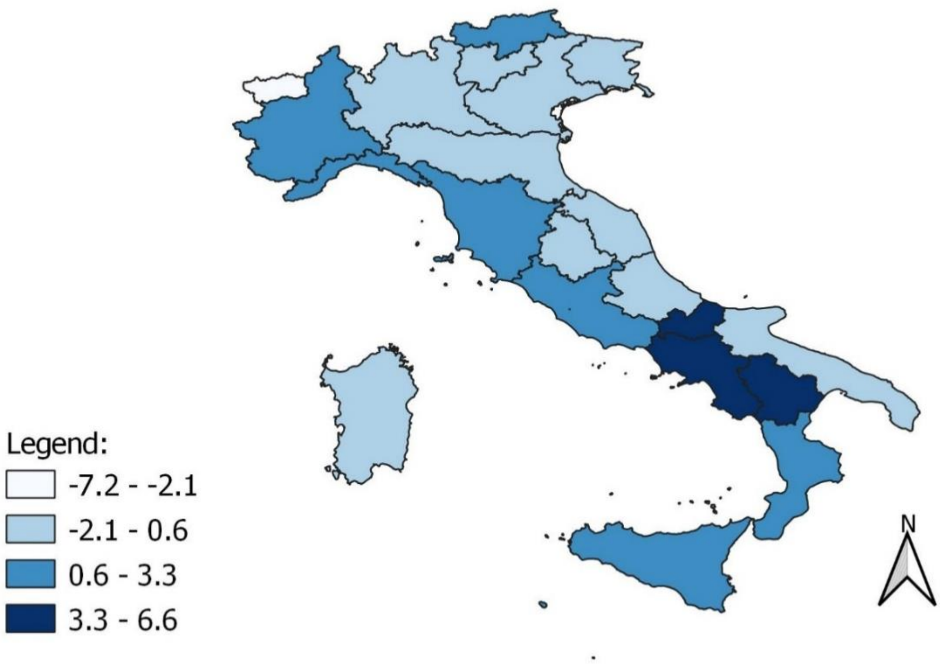
Table 1. Indicators for the simulation model (*r* = NUTS2 region)

Variables	Indicator (Formula)	Year	Source
Initial DVA in CE	*See section 2.1.1*	2014	OECD inter-country
DVA growth in CE trade	*See section 2.1.1*	2014 - 18	OECD inter-country
GDP *per capita*	$GDP_r/Population_r$	2014	Eurostat
Tertiary education	$Pop.with\ tertiary\ educ._r/Pop._r$	2014	Eurostat
Share of exports to EU countries	$Export\ to\ EU_r/Tot.export_r$	2013	OECD / EUREGIO
Share of exports to China	$Export\ to\ China_r/Tot.export_r$	2013	OECD / EUREGIO
Rule of law	*Composite indicator*	2014	IQI database
Growth in selective waste collection	$\Delta selective\ waste\ collection_r$	2014-18	ISPRA
Patents per employee	$Patents_r/Tot.employment_r$	2013	OECD / Eurostat
Robots per employee	$Robots\ adopted_r/Tot.employment_r$	2014	Capello and Lenzi (2021)

Table 1 reports the list of these indicators, which will serve as inputs in the simulation model. They include the overall economic development of a region (per capita GDP), the quality of human capital (population with tertiary education) and institutions (rule of law), and the level of technological adoption (patents and robots per capita). A second group of indicators capture the structure of the international trade network of Italian NUTS2 regions, either oriented towards EU countries, or towards China. Finally, the increase in waste collection measures local behaviors oriented towards sustainability and CE.

Figure 2 shows the growth of DVA in CE between 2014 and 2018. Interestingly enough, DVA growth in CE does not follow the traditional prevalence of Northern Italy in trade within GVCs (Capello et al., 2024). The Central and Southern regions also captured value-added from CE trade between 2014-2018, highlighting Piedmont and Campania, and Veneto, Friuli-Venezia Giulia, Puglia regions. Lombardy is an interesting case of DVA degrowth – mainly due to losses in the machinery and equipment sector, not elsewhere classified (28).

Figure 2. Italian regional DVA growth rates in CE (2014 - 2018)



2.1.3 Model

The simulation model takes the following form:

$$\begin{aligned}\triangle\, DVA\ related\ to\ CE\ trade_{r,i} &= \beta_0 + \beta_1 initial\ level\ of\ DVA\ in\ CE_{r,\,t-1} \\ &+ +\beta_2 GDP\ per\ capita_{r,\,t-1} + \beta_3 tertiary\ education_{r,\,t-1} + \beta_4 \begin{matrix} share\ of\ exports\ to \\ developed\ countries \end{matrix}_{r,\,t-1} \\ &+ +\beta_5 share\ of\ exports\ to\ developing\ countries_{r,\,t-1} \\ &+ \beta_6 rule\ of\ law_{r,t-1} + \beta_7 growth\ of\ waste\ selective\ collection_{r,t} \\ &+ \beta_8 patents\ per\ employee_{r,t-1} + \beta_9 robots\ per\ capita_{r,t-1} + c_{macro\_i} + c_{macro\_r} + \epsilon_{r,i}\end{aligned}$$

Wherein, *i* are the sectors and *r* the Italian NUTS2 regions, *t-1* is the initial period (2014) and *t* is the final one (2018). Variables were used to represent market, institutions and technological factors, and their association with DVA growth in CE trade, as discussed in section 2.1.2.

2.1.4 Analysis

Results presented in Table 2 are consistent with the assumptions on the association between the regional factors related to CE promotion and DVA growth related to CE trade. Notably, the initial DVA level in CE trade showed negative correlation to its growth, pointing out that regions with lower initial DVA in CE trade had the potential for higher growth.

External demand, mainly from developed countries, play central role in promoting DVA growth related to CE trade. On the other hand, domestic market factors, such as GDP per capita and tertiary education level, did not appear to have statistically significant influence, which is understandable, given the focus on international trade, within this context.

Institutional efficiency, as reflected by the rule of law, has a positive effect on DVA growth related to CE trade, and it suggesting that higher quality of institutions supports CE-related activities. Similarly, selective waste collection expansion contributes to DVA growth in CE trade. This finding highlights the crucial role of CE policies in facilitating international trade in CE, which is likely to grow in importance, overtime, and should be a key target in future research.

Table 2. Regression results: innovative milieu related-factors and DVA growth in CE and non-CE trade

VARIABLES	DVA growth in CE trade	DVA growth in non-CE trade
Initial DVA in CE	-0.009**	-0.014**
	(0.003)	(0.004)
Rule of law	1.653*	-6.724
	(0.699)	(3.515)
GDP *per capita*	46.312	442.931*
	(29.697)	(171.344)
Tertiary education	-0.015	-0.564
	(0.079)	(0.418)
Selective waste collection growth	0.184'	-1.513*
	(0.091)	(0.622)
Robots *per capita*	17.942**	-75.118*
	(4.324)	(27.935)
Patents per employee	0.444	0.420
	(1.836)	(13.081)
Share of exports to developed countries	1,267.564***	-1,724.084***
	(27.558)	(104.529)
Share of exports to developing countries	247.617***	-2,971.051***
	(18.261)	(106.986)
Constant	-24.703***	124.706***
	(2.022)	(7.426)
Observations	816	816
R-squared	0.020	0.155

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1, 'p<0.12.

Although patents do not show direct impact on this growth, the density of robots per capita emerges as potential factor capable of increasing DVA in CE trade. Automation, based on using robotics, provides a route to produce goods and manage processes based on reduced environmental impact, which is in line with the CE principles.

Another scenario is presented for non-CE trade. In this case, DVA growth is positively correlated to regions' GDP per capita, while the density of robots and exports to developed and developing countries has a negative association with the dependent variable. This suggests that CE and non-CE trade within GVCs are stimulated by different territorial characteristics of the regions.

Simulations can be run assuming different values for the different independent variables. Knowing the estimated beta coefficients, the new values of domestic value added growth in CE sectors is obtained.

2.2 Global Value Chains and Regional Resilience

Understanding the external exposure of regional economies to international trade and policy shocks related is important in assessing their resilience and adaptability. The **External Exposure Indicators (EEI)** developed in this study provide a framework to measure such vulnerabilities at the **Local Labor System (LLS)** level in Italy. These indicators capture regional susceptibility to foreign shocks through two key channels **Global Value Chain (GVC) Linkages and Ownership Linkages.**

These indicators allow for a comprehensive analysis of how external shocks propagate through regional economies, particularly in industries relevant to the **Circular Economy (CE).** By linking trade dependencies to employment and production structures, they provide insights into how different regions respond to disruptions in global markets.

We present an application analyzing the impact of **China's plastic waste import ban in 2018**, which represents a significant external shock to regions that relied on China as a destination for plastic waste exports. By leveraging our EEI through GVC, we examine how regions with varying degrees of exposure to the Chinese market experienced different employment dynamics in industries related to **waste management and recycling, and manufacturing of plastic more generally**. This analysis provides insights into how trade restrictions in the circular economy sector may reshape regional labor markets and the broader waste management infrastructure.

2.2.1 Data

The indicator based on GVC contribution and reliance, we use publicly available data on global trade in value added from **Trade in Value Added (TiVA),** provided by the OECD, at the country-ISIC rev 3 industry level. Correspondence tables are used to convert it to NACE. Complementary data on employment and population at the LLS level, and employment at 3-digit NACE industry-region level are available from **ISTAT**. We weigh employment at 3-digit NACE industry-region level using LSS regional population shares to proxy employment by industry at LSS, and identify 611 unit of LLS.

To construct the indicators based on Ownership linkages, we rely on data from **Orbis** provided by Bureau Van Dijk, subject to access agreements with Bocconi University, including information on firms' ownership linkages. Namely, for each firm the database provides two ownership connections: (1) with its direct majority share owner (ISH), and with its Global Ultimate Owner (GUO), and this information is available in the last available year. We consider observations in 2022/2023 as the last available year. The database also provides information on firm location (NUTS3, postcode), industry (NACE 4-digits), and firm performance. Using the postcode information for each Italian affiliate, we are able to match the firm to its LLS. We consider the following industries in waste-related activities:

Table 1: Waste-related industries

NACE code	**Description**
46.77	Wholesale of waste and scrap
20.16	Manufacture of plastics in primary forms
22.29	Manufacture of other plastic products
38.32	Recovery of sorted materials

Notes: This table presents all industries we consider related to the Chinese plastic waste import ban, defined at 4-digit industry codes.

2.2.2 Indicators

These indicators capture regional susceptibility to foreign shocks through two key channels:

A. EEI through Global Value Chain (GVC) Linkages

The EEI GVC indicator quantifies a region's integration into international production networks by assessing its reliance on foreign value-added in production processes (intermediate inputs) and access to foreign markets (output). It considers both the domestic value added in exports and the foreign value added in imports. For a given area (LLS), EEI_GVC is the weighted sum of GVC exposure in circular economy related sectors, where the weight is given by the LLS's or Province's labor share. In particular, GVC is the average of two components. The first component is the share of the Domestic Value Added (DVA) content of Italy's total exports in each of the sectors at a certain destination to total DVA. The second component is the share of latter's Import Value Added (VA) in each sector to total VA, i.e. the foreign content of exports.

Denoting by r the LLS, k the industry, and c the counterpart country or region, EEI_GVC is thus given by:

$$\mathrm{EEI\_GVC}_{\,r} = \sum_k \frac{L_{rk}}{L_r} * averageExp_k$$

Where L denotes employment and:

$$averageExp_k = mean(\frac{DVA_k^c}{DVA_k}; \frac{VA_{IMP}{}_k^c}{VA_{IMP}{}_k})$$

For the purpose of the analysis, we present the indicator as the exposure of SLL to GVC dynamic of China in the sector of trade in waste, directly linked to the ban of plastic imports (NACE 46.7). We also focus on the year before the shock, hence 2017. In this sense, we can analyze the impact of this particular dependency on LLS employment. The indicators is computed as follows:

$$\mathrm{EEI\_GVC}_{\,r} = \frac{L_{r,k=467}}{L_r} * averageExp_{k=467}$$

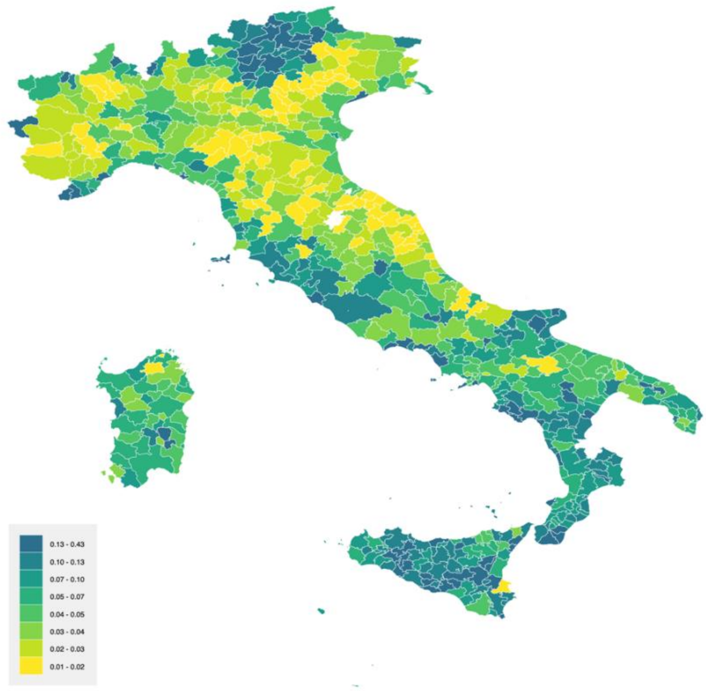
Where L denotes employment and:

$$averageExp_{k=467} = mean(\frac{DVA_{k=467}^{CN}}{DVA_{k=467}}; \frac{VA_{IMP}{}_{k=467}^{CN}}{VA_{IMP}{}_{k=467}})$$

We present in Figure 1, a map that provides a visual representation of the relative reliance of each LLS on China as an export destination for its production of plastic waste. The color gradient, ranging from dark blue (high exposure) to light green (low exposure), highlights significant geographic variation in dependencies. There is higher exposure for Northern and Southern areas like Trentino-South Tyrol, Lombardy, Sicily and Calabria, while there is low to moderate exposure in Central regions like in

Emilia-Romagna. There is also notable variations within regions. Even within highly exposed regions like **Lombardy and Veneto**, there are pockets of lower exposure. This points to potential differences in **sectoral specialization**, where some areas are more engaged in processing and exporting recyclable waste, while others rely more on localized circular economy practices.

Figure 1: External Exposure Indicator to Trade in Waste with China at LSS in 2017



Source: Authors' calculations using data from TiVA and ISTAT

Notes: This figure provides a visual representation of the relative reliance of each of the 611 LLS on China as an export destination for its production of plastic waste. The color gradient, ranging from dark blue (high exposure) to light green (low exposure), highlights significant geographic variation in dependencies. The External Exposure Indicator considers both the domestic value added in exports and the foreign value added in imports, of waste.

B. EEI through Ownership Linkages

The EEI Ownership indicator measures the extent to which firms in a given LLS are exposed to foreign economies due to ownership structures. It accounts for direct and indirect majority ownership, as well as common parent relationships, to determine how deeply embedded a region is in international corporate networks.

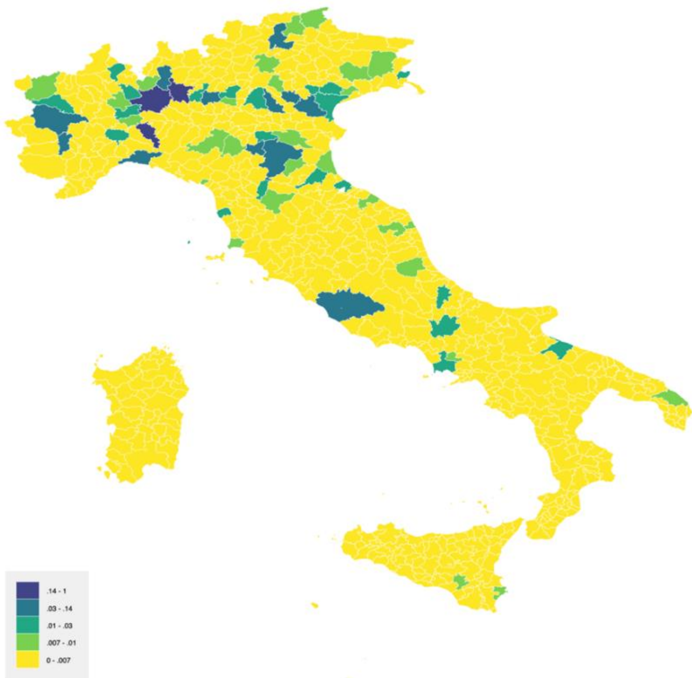
The indicator is constructed as a region- and/or sector-specific index on exposure to foreign affiliates operating in a country c in a specific sector through Italian affiliates. Thus, it can be expressed as the share of ownership links related to foreign country *c* in sector *k* at region *r* in total links in sector *k* with country *c*, computed as follows:

$$EEI\_O_{rk,c} = \frac{\sum_i OLinks_{irk,c}}{OLinks_{k,c}}$$

Where $\sum_i OLinks_{irk,c}$ is the sum of links for all firms *i* in sector *k* in region *r* and foreign country *c*. Accordingly, $OLinks_{k,c}$ is the total number of links in sector *k* from all over Italy with country *c*.

Figure 2 presents the map of the exposure to BGs with Chinese affiliate operating in a waste-related industry by SLL. Exposure to these affiliates seems to be mostly concentrated in Milan, Bergamo, and Voghera. Other cities such as Rome, Turin, Bologna, and Genoa are also among the most exposed LLS, although the level of exposure is not nearly as high.

Figure 2: EEI to China ownership in waste at LSS in 2022-2023



Source: Authors' calculations using data from Orbis

Notes: This figure provides a visual representation of the relative exposure of each of the 611 LLS to the waste industry and China through the share of Italian affiliates with ownership linkages with

Chinese affiliates operating in the waste industry. The color gradient, ranging from dark blue (high exposure) to light green (low exposure), highlights geographic variation in exposure.

2.2.3 Mechanisms

The impact of China's plastic waste import ban on regional economies can be approached through theoretical frameworks that examine **trade disruptions and global production networks**. The following mechanisms, outlined in seminal literature on trade shocks and global value chains, help explain how such a policy change could affect industries related to waste management and recycling:

- **Trade shock transmission:** Theoretical models of **global trade shocks** (Autor et al., 2013; Baldwin & Freeman, 2020) show how abrupt policy changes disrupt established trade flows, leading to shifts in supply and demand. The plastic waste import ban severs a major processing destination, resulting in an oversupply of plastic waste in exporting countries and regions, and a reduction in the global market value of plastic scrap. Firms and LLS engaged in waste collection and processing are expected to face declining revenues, leading to potential contractions in industry employment.

- **Reallocation within Supply Chain:** The literature on **import substitution and trade reallocation, namely** Fajgelbaum et al. (2020), suggests that when a major trade partner imposes restrictions, exporting firms must seek alternative markets or adapt their production processes. Hence, Italian areas that previously exported large volumes of plastic waste to China could be forced to find alternative destinations, at lower prices, or invest in domestic recycling infrastructure. Those with diversified trade relationships would be better positioned to mitigate the shock, while those with high dependence on China should face larger disruptions.

- **Value Chain fragmentation:** Studies on **supply chain interdependencies** (Pierce & Schott, 2016) show that disruptions in upstream industries can have cascading effects on downstream sectors. The sudden restriction on plastic waste exports reduces the availability of low-cost recycled materials, potentially increasing input costs for industries that rely on secondary plastics. These constraints could lead to price volatility and adjustments in production strategies across the **waste management and recycling value chain**.

By applying these frameworks, we can anticipate that regions highly reliant on China for plastic waste exports would likely experience significant disruptions after the shock, while those with more diversified trade networks had greater resilience. We should also expect to see this effect not only within the same industry, but also the effect is likely to propagate along other closely related industries within the supply chain. The GVC EEI indicator allow us to quantify these effects by linking regional exposure to changes in global trade patterns, providing a structured approach to assessing the economic consequences of circular economy policies.

2.2.4 Analysis

This section presents a preliminary empirical analysis on the impact of the China Plastic import ban in 2018 on employment at LLS level. We use data on employment at industry and LLS level from 2015 to 2022 as described in the data subsection. As discussed in the mechanisms section, we expect a negative effect of the ban on imports of waste on revenues and hence a pressure on employment contraction in closely related industries. To test this, we estimate the following Difference-in-Differences model:

$$Y_{LLS,t} = \beta_1 Post_t \times EEI\ GVC_{LLS} + \delta_{LLS} + \delta_{r,t} + \varepsilon_{LLS,t} \qquad (1)$$

Where $Y_{LLS,t}$ represents a set of dependent variables at LLS: (i) employment in plastic waste trade, (ii) employment in manufacturing of primary plastic, (iii) manufacture of plastic final products, and (iv) the sum of employment over the three latter industries. $Post_t$ is a dummy, equals one starting from 2018 and zero before. $EEI\ GVC_{LLS}$ is the external exposure indicator reflecting the relative reliance of each LLS to trade in plastic waste with China, as described in section 2.1.2. Fixed effects at the LLS level δ_{LLS}, and at the aggregate region-year level $\delta_{r,t}$ are used to control for time-invariant city characteristics and shocks and time-variant characteristics at the region level, respectively. This ensures that general regional attributes, specialization, and population composition and its evolution are accounted for. $\varepsilon_{LLS,t}$ $is\ the$ error term. Standard errors are clustered at the LLS level to allow for dependency between outcomes at that level. Given this model, the coefficient on the interaction β_1 is expected to be negative as the higher the exposure to Trade in waste with China pre-treatment, the bigger the magnitude of the impact on employment should be.

Table 2 presents results of the estimation of equation (1). As expected, controlling for market characteristics at the LLS and shocks at a more aggregate regional level, we observe a differential impact of the import ban in China depending on the level of GVC exposure. LLS that are highly exposed to GVC, experience a bigger employment contraction in related industries, especially in plastic waste trade.

Table 2: The impact of the China Plastic import ban on employment at LLS level

	(1)	**(2)**	**(3)**	**(4)**
	Employment			
Dependent variable:	**Plastic waste**	**Manuf plastic**	**Plastic product**	**Total related**
$Post_t \times EEI\ GVC_{LLS}$	-0.4482***	-0.2432***	-0.4003***	-0.4524***
	(0.0951)	(0.0436)	(0.0732)	(0.0979)
Observations	6,688	6,688	6,688	6,688
Adj R-squared	0.9976	0.9991	0.9989	0.9979
LLS FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES

Notes: This table reports the estimated coefficient of equation (1) on employment in industries related to plastic waste trade and collection (column 1), employment in manufacturing of primary plastic (column 2), manufacturing of plastic final products (column 3), and total employment in the aforementioned industries (column 4). $Post_t$ is a dummy, equals one starting from 2018 and zero before. $EEI\ GVC_{LLS}$ is the external exposure indicator reflecting the relative reliance of each LLS to trade in plastic waste with China, as described in section 2.1.2. Standard errors are clustered at the SLL level and reported in parentheses. Significance level is expressed as follows: *** p<0.01, ** p<0.05, * p<0.1.

Although the last table shows the differential impact that is predicted by previous literature, the identification of the overall effect remains ambiguous. Hence, we estimate the following model to uncover the overall effect of the Chinese import ban on employment, depending on the level of dependency on it as an export market:

$$Y_{LLS,t} = \sum_{i=1}^{i=4} \beta_i \, Post_t \times EEI\ GVC_{\ LLS}\, Q_i + \delta_{LLS} + \delta_{r,t} + \varepsilon_{LLS,t} \tag{2}$$

Where $EEI\ GVC_{\ LLS}\, Q_i$ for i=1 to i=4 represents quartile dummies, with $EEI\ GVC_{\ LLS}\, Q_1$ reflecting the lowest exposure category and $EEI\ GVC_{\ LLS}\, Q_4$ the highest. This fully interacted model provides direct estimates of the overall effect of the policy on each group post-treatment.

Table 3 presents results of the estimation of equation (2), where we find that SLL in the highest 3 quartiles of exposure to China, experience significant job loss in all 3 industries directly and indirectly affected from column (1) to (3). While SLL in the first quartile that are the least exposed to China experience job creation on all those industries. These results are interesting as they shed light on a regional adjustment mechanism. Regions that didn't experience the shock as intensely start emerging as alternative hubs for plastic waste processing and recycling. This suggests that in the absence of China as the dominant global buyer, less-exposed regions were able to absorb a portion of the displaced market activity, potentially benefiting from increased demand for domestic waste processing and recycled materials.

These findings align with theoretical predictions from trade literature. When a major trade disruption occurs, regions that are **less integrated into the disrupted trade network** may experience an **opportunity effect**, as demand for their domestic production rises to compensate for supply chain dislocations elsewhere (David, Dorn & Hanson, 2013). In this case, the absence of heavy reliance on China allowed first-quartile SLLs to attract new investment and expand local waste processing capacity, leading to employment gains.

From a policy perspective, these findings emphasize the need for **targeted interventions** to support regions disproportionately affected by trade shocks in the circular economy. Strategies such as investment in **domestic recycling infrastructure**, **incentives for market diversification**, and **enhanced trade partnerships with alternative destinations** could help stabilize employment in vulnerable areas while fostering **long-term resilience** in waste management industries.

These insights contribute to a broader understanding of how regions adjust to **disruptions in global value chains,** providing empirical evidence on the employment consequences of trade restrictions in the circular economy. Future research could further investigate the long-term trajectories of these regions, particularly whether the newly emerging waste processing hubs sustain their growth or face **competitive pressures as global markets stabilize.**

Table 3: The impact of China Plastic import ban on employment at LLS level, by EEI GVC quartile

	(1)	(2)	(3)	(4)

Dependent variable:	**Employment**			
	Plastic waste	**Manuf plastic**	**Plastic product**	**Total related**
$Post_t \times EEI\ GVC_{LLS}\ Q_1$	1.2987*	0.8830*	1.1973*	1.3243*
	(0.7574)	(0.4595)	(0.6197)	(0.7729)
$Post_t \times EEI\ GVC_{LLS}\ Q_2$	-0.8296*	-0.6768**	-0.7962*	-0.8372*
	(0.4627)	(0.3413)	(0.4147)	(0.4705)
$Post_t \times EEI\ GVC_{LLS}\ Q_3$	-1.1894**	-0.9062**	-1.1217**	-1.2029**
	(0.5825)	(0.3928)	(0.5053)	(0.5936)
$Post_t \times EEI\ GVC_{LLS}\ Q_4$	-1.5621**	-1.0290**	-1.4342**	-1.5877**
	(0.6793)	(0.4271)	(0.5656)	(0.6923)
Observations	6,688	6,688	6,688	6,688
Adjusted R-squared	0.9976	0.9991	0.9989	0.9979
LLS FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES

Notes: This table reports the estimated coefficient of equation (2) on employment in industries related to plastic waste trade and collection (column 1), employment in manufacturing of primary plastic (column 2), manufacturing of plastic final products (column 3), and total employment in the aforementioned industries (column 4). $Post_t$ is a dummy, equals one starting from 2018 and zero before. $EEI\ GVC_{LLS}Q_i$ for i=1 to i=4, is the external exposure indicator quartile dummies reflecting the relative reliance of each LLS to trade in plastic waste with China, as described in section 2.1.2. $EEI\ GVC\ _{LLS}\ Q_1$ reflects the lowest exposure category and $EEI\ GVC\ _{LLS}\ Q_4$ the highest. Standard errors are clustered at the SLL level and reported in parentheses. Significance level is expressed as follows: *** p<0.01, ** p<0.05, * p<0.1.