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Does Crime Influence Investment in Renewable Energy Sources? Empirical Evidence from Italy

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Abstract: The Sustainable Development Goals are significantly increasing investments in the production of energy from renewable sources (RESs). To this end, the supply of monetary incentives by public institutions has increased sharply. This flow of money inevitably attracts the attention of criminal organizations (henceforth COs) that use their power to increase the volumes of investments, while public authorities might react by deciding not to make investments in RESs in areas at risk of distorted use of incentives. In this context, the research question is as follows: does the presence of COs slow down or encourage investment in RESs? Until now, this topic has received little attention from researchers, at least in the European Union. In particular, the presence of COs is particularly pervasive in the economic system of Italy. Given the heterogeneity of this country, a spatial econometric approach was used, taking into account geographical dependency relationships and their impact on the relevant variables. The main result of the research shows a negative relationship between Italian areas with higher CO levels and RES investments. In other words, investments are discouraged in these regions. This situation is detrimental to the target regions in terms of sustainable development and increasing the gross national product (GNP). Furthermore, we found that micro-crime cannot in any way influence investments in RESs.

Keywords: renewable energy sources; sustainability; organized crime; Italy

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1. Introduction

Starting from the Kyoto Conference in the mid-1990s, problems related to climate change made have led renewable energy sources (henceforth RESs) a topical issue in the political agendas of all governments. Consistently, increased investment in RES generation by several private and public institutions has occurred.

The last report by the International Agency for Renewable Energies (IRENA) [1] outlines that despite prevailing macroeconomic, geopolitical, and supply chain challenges, global investments in energy transition technologies—such as renewable energy, energy efficiency and storage, hydrogen, electrified transport and heat, and carbon capture and storage—surged to USD 1.3 trillion. This value marks a remarkable 19% increase from 2021 levels and a substantial 70% rise from 2019, pre-dating the impact of the COVID-19 pandemic.

To encourage investments in RESs, the European Union (EU), and many other countries have established economic policies as incentives for the transition from traditional sources (especially of fossil origin) to environmentally friendly ones [2–4], and it is commonly assumed that this public support is one of the most critical drivers of the development of RES generation.

Anyway, the experience of some countries shows that subsidies for supporting RESs have also stimulated the interests and appetites of criminal organizations [5–7]. This problem is not new, and even mass media have paid attention to this situation [8,9], underlying that COs are able to attract more investments in RESs for the areas where they are located. Conversely, when COs manifest their intention to catch the investment flows supporting RESs, the main risk is that many private companies are discouraged from investing [10–12]. Similarly, even national or international institutions could decide to reduce or cease their engagement or the facilitations provided, slowing down the process of RES generation [13,14].

Therefore, on the one hand, the presence of COs interested in benefiting from the advantages related to investment flows in RESs could favor investments with advantages for the external context in terms of sustainability and GNP. On the other hand, the presence of COs could discourage investment decisions, with negative effects on the external context.

Specifically, this study assesses how illegal activities influence investments in RESs by focusing on the Italian case. Italy is a country characterized by a rooted but heterogeneous incidence of COs. In 2021, according to the National Statistical Institute of Italy [15], the unobserved economy (black economy and illegal activities) reached about EUR 210 billion, 12.3% of the GDP. From this amount, unlawful activities covered by the national accounts system generated an added value of EUR 16.7 billion, with an increasing trend.

Until now this issue has not been properly addressed because COs are not clearly present in all countries; furthermore, there is often a lack of data to quantify this phenomenon. Moreover, researchers have mainly focused on the effect of corruption, which is only one aspect of criminal behaviors [16]. Gennaioli and Tavoni [17], for instance, examined the relationship between public policy and corruption in the case of wind farms and concluded that the availability of pervasive incentives for RES generation makes it possible for COs to infiltrate and corrupt public officials. Arminen and Menegaki [18] believe that changes in institutional quality (corruption) could have a limited impact on energy and environmental policies. Anyway, other investigations have deepened the intricate relationship between COs and the financial implications on the management of solid urban waste in Italian municipalities or provinces [19,20], underlining the higher costs due to this obscure link.

When considering the mentioned knowledge gap and the large amount of resources allocated by public bodies and private investors in this direction, it is more and more important to understand how COs affect RES investments. The 14th annual Fostering Effective Energy Transition report, just edited by the World Economic Forum, shows that the energy transition is losing momentum. It would be important to understand if this slowdown is also linked to the persistent activity of COs that are further affecting the dynamics of investment flows.

Consistent with these assumptions, this study aims to verify if the presence of COs quenching or encourages investment in RESs. In particular, the survey verifies whether the presence of criminality is a lever that amplifies investments in RESs or, conversely, whether the presence of closer controls by authorities to tackle COs discourages investments by private companies. Responding to this research question is the first step in creating policy measures that may hinder the destructive operativity of COs.

To this aim, this study first identifies the drivers increasing RES generation among Italian regions with a higher presence of COs, and then it tests if investments in RESs are more likely in those regions. After this introduction, Section 2 remarks on the framework supporting the variables selection process. Section 3 reports the methodology. Section 4 describes the empirical results. Section 5 includes concluding remarks, and the last section reports the limitations and implications.

2. The Framework Supporting the Variables Choice

To detect the variables supporting our investigation, we first collected a set of context variables identified in previous research [2,21] as possible determinants of investments in RESs. We also assumed that the propensity to invest in RESs can affect the productive structure of similar regions, even if they are geographically distant, as long as they are culturally close. In this way, we can also investigate the spillover effects between contiguous regions in terms of geographical and cultural proximity. For this reason, we used longitudinal data of 19 regions (Aosta Valley, the smallest region representing 1% of the Italian spatial extent and 0.2% of the population, has been included in Piedmont (pie)) (NUTS 2) over twelve years.

To these aims, we propose a spatial model, comparing the findings acquired with results obtained by different model specifications:

(i) Panel-corrected standard errors (PCSEs);
(ii) Fixed effect;
(iii) Dynamic models.

Variables were built based on data provided by the Italian Official Statistical Office (ISTAT).

The existing literature explores diverse methodologies for assessing investments in RESs, such as surrogate measures for investments in renewable sources or evaluating investments based on the contribution of RESs to the total energy supply. In this study, we consider the per capita gross non-hydro renewable energy generation (Gwh) as a proxy for investments in RES generation (RenProd) [22]. In terms of RESs, we consider electricity generated from wind, photovoltaics, geothermal energy, and biomass. Hydropower is not considered because the share of generation is now stable, and no investments are planned. The annual regional distribution of renewable generation (RenProd) is reported in Figure 1.

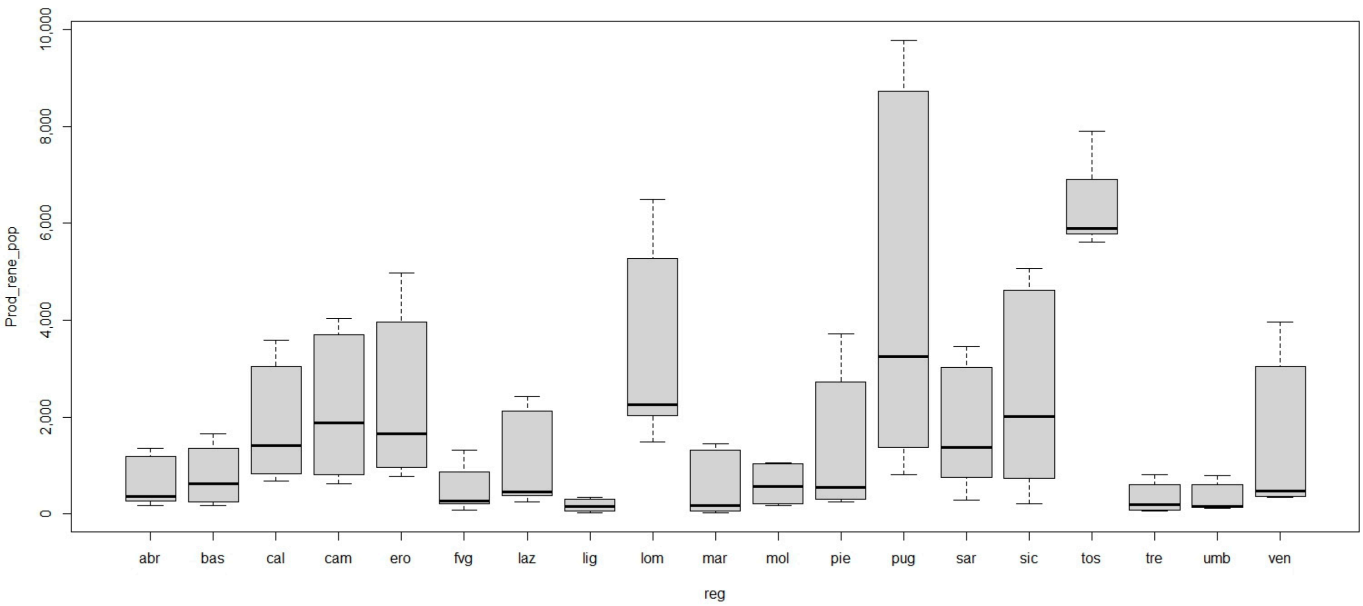

Figure 1. Box Plot of non-hydro renewable generation by regions (abr = Abruzzo; apu = Apulia; bas = Basilicata; cal = Calabria; cam = Campania; ero = Emilia Romagna; fvg = Friuli Venezia Giulia; laz = Lazio; lig = Liguria; lom = Lombardy; mar = Marche; mol = Molise; pie = Piedmont; sar = Sardinia; sic = Sicily; tre = Trentino South Tyrol; tus = Tuscany; umb = Umbria; vda = Aosta Valley; ven = Veneto.) (Yearly distribution of RenProd).

The heterogeneity of RES generation across the Italian regions is visually depicted in the regional box plots illustrating temporal variations. The median values exhibit a considerable fluctuation spectrum, spanning from Liguria to Tuscany as the two extremes. Furthermore, certain regions demonstrate sustained stability in terms of renewable generation, while others represent a notable divergence, with pronounced variations in values. This observed heterogeneity underscores the intricate dynamics of RES generation within the Italian regional context.

Southern regions, specifically Apulia (apu) and Calabria (cal), exhibit elevated levels of RES generation in comparison to certain northern and central regions, notably Liguria (lig) and Friuli Venezia Giulia (fvg). Additionally, noteworthy differentials emerge as higher-income regions, exemplified by Veneto (ven), Umbria (umb), and Lazio (laz), which demonstrate comparatively lower values in terms of the production of energy derived from renewable sources. This underscores a distinct pattern wherein some less economically developed southern regions surpass their wealthier counterparts in terms of RES generation within the Italian context.

A further aspect of interest is the geographical cross-sectional heterogeneity (Figure 2).

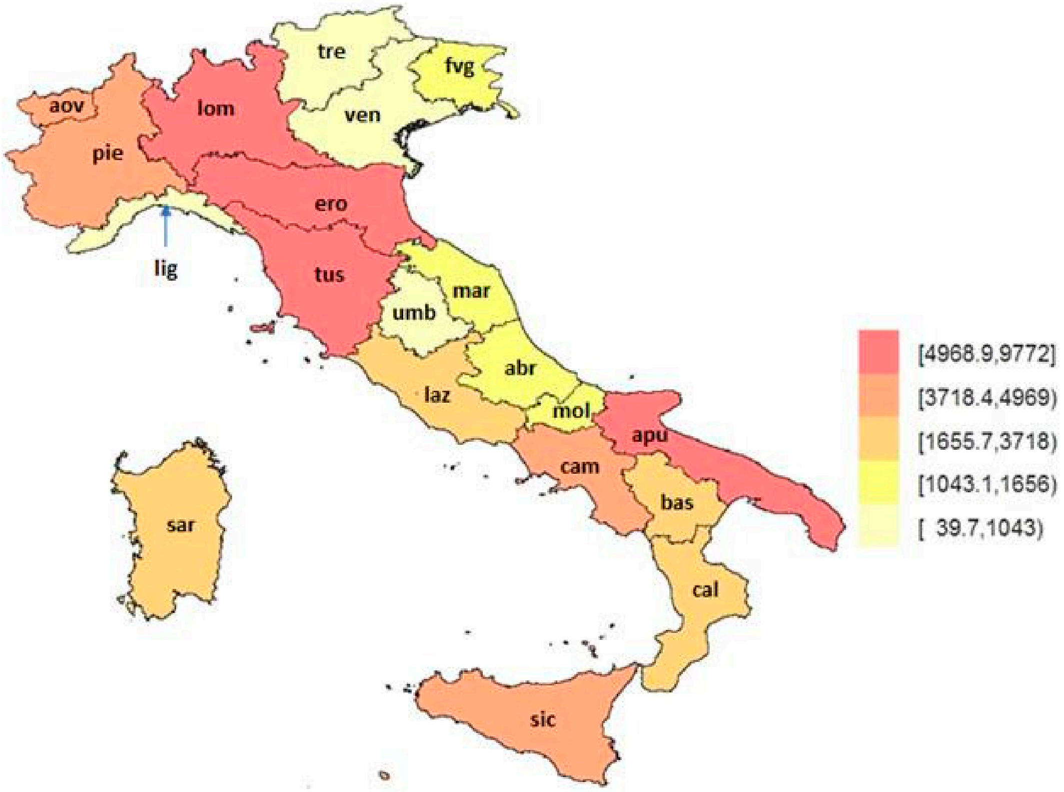

Figure 2. Regional distribution of RenProd (Gwh) (averages 2004–2015).

Specialized literature has studied how illegal activities contaminate the legal economy in several ways, starting from quantifying their presence in the territory [11,23,24]. A way to measure the local presence of illegal activities is to estimate the scale of the shadow economy, periodically provided by the aforementioned ISTAT. We chose not to use this type of indicator because, since the last revision of the methodology used to estimate national accounts, the illegal economy has been directly considered in GDP estimations. For this reason, we use two different proxies of illegal activities on territories represented by the indicators of the presence of organized crime groups (OCrime) as well as small-scale crime (SSCrime) [5,25,26]. The former indicator, OCrime, measures the number of reported organized crime cases (per 1000 inhabitants), while the latter, SSCrime, measures the number of reported common crime cases (per 1000 inhabitants). There is a marked difference between the perception of crime and actual crime; therefore, the territorial framework is very diverse, with regions in which fear and concern represent huge problems.

The two phenomena have marked contraposition; organized crime has mainly infiltrated the southern regions (e.g., Sicily, Campania, and Calabria), while the other regions are characterized by common crime, dedicated primarily to theft and robbery. In these more developed regions, organized crime is still less prominent.

For this reason, a fundamental framework for the illegality spreading in the Italian regions cannot be separated from the knowledge of both statistical indicators, which are based on objective data collected by ISTAT in collaboration with other public authorities. They are the most suitable and exogenous variables (compared to other regressors) to describe this specific aspect that we intend to detect.

Among the independent control variables, there are the following:

(a) Per capita value of investments (Investments);
(b) Per capita regional gross domestic product (GDPpc);
(c) Per capita electric power efficiency, which measures the maximum electrical power (Gwh) that can be supplied by the generating plants in the region (Epower);
(d) Percentage of households complaining about air pollution (Qair);
(e) Percentage of households with at least lower high school education (School).

(a) Investments are a proxy for the intergenerational regional employment rates. Companies' "propensity for investment" improves their business. Although the loss of welfare due to appropriation in areas with COs can be substantial, the spillover effects COs have on regular economic activity can be even bigger quantitatively. Legal businesses that have to pay for protection face higher operation costs, invest less, and bias their investments against anything that can be easily destroyed [27]. Of course, the consideration of the environmental impact of productive activities belongs to the Corporate Social Responsibility pillars that support the relationship between financial performance and shareholders satisfaction. Hence, we expect a positive sign.

(b) The regional GDP (gross domestic product) per capita, measured in EUR, stands as a pivotal and extensively explored indicator in the existing literature, reflecting the income effect [28–30]. Numerous macroeconomic analyses posit a common assumption that wealthier nations possess greater efficacy in fostering investments in RESs facilitated through various forms of grants and incentives [31]. Furthermore, insights from an Italian study on post-war economic development underscore that the presence of organized crime results in a substantial reduction in GDP per capita. This reduction predominantly occurs through a shift from private economic activity to less productive public investment [32]. Nevertheless, in order to maintain citizens' perceived quality of life, it is important to acknowledge that higher income levels might lead to a higher consumption of electricity of fossil origin [30]. Examining the regional perspective, the utilization of GDP allows for control over the dimensional effects of the country and accounts for the heterogeneity in economic growth influencing energy policy choices. A negative sign is expected for GDP, consistent with the prevailing practice of policymakers in endorsing policies that promote economic development in rural and less developed regions [33,34].

(c) Generating plants among regions (Epower) was considered a proxy for regional energy consumption [35]. Increased energy consumption could entice policymakers to increase investments in new RES power plants; thus, a positive coefficient sign is expected. The consumption of electricity is an important variable in such a study because it is an alternative measure of aggregate economic activity, and it is often used to compare unofficial activity across countries. It depends on demand from firms and individuals operating in official and unofficial sectors.

(d) Among the elements representing the environmental features of the countries, we involve the share of households complaining about air pollution (Qair). This variable may mirror the environmental degradation [31] that citizens feel. Consequently, greater attention is paid by the public to the possibility of replacing polluting energy sources with greener ones. Some studies have confirmed that the process of energy innovation has positive effects on environmental pollution [36]. That is why we expected a positive sign for this indicator.

(e) Some researchers have demonstrated that individuals with higher levels of education tend to exhibit stronger inclinations toward environmental concerns and protection (see, e.g., [37]). Therefore, we considered a variable measuring the percentage of households with at least a lower high school education (School). This variable serves as a potential proxy for gauging the population's preference for environmentally friendly policy management, essentially acting as an indicator of 'green sentiment'. Consequently, the anticipated sign of the coefficient associated with this variable is expected to be positive, reflecting a positive correlation between educational attainment and a proclivity towards environmentally conscious attitudes. Furthermore, some scholars (see, e.g., [38]) have observed that schools in southern regions are not only characterized by a lower initial level of skills but also exhibit lower value added (Some authors have questioned this claim [39], assuming that higher income is positively correlated with higher levels of consumption and a greater carbon footprint).. This additional insight underscores the multifaceted nature of the School variable, suggesting that it may capture nuances related to educational attainment and regional disparities in skill levels and value addition.

For a more detailed overview of the analyzed variables, Table 1a–c provides descriptive statistics, offering valuable insights into the characteristics and distributions of the variables under consideration in our study.

Table 1. (**a**) Descriptive statistic (mean, standard deviation, and interquartile range). Year 2004–2015. (**b**) Descriptive statistics (mean, standard deviation, and interquartile range). Year 2004–2015. (**c**) Descriptive statistics (mean, standard deviation, and interquartile range). Year 2004–2015.

(a)

	RenProd			*GDPpc*			*Investments*		
Italian Regions	***Mean***	***Standard Deviation***	***Interquartile Range***	***Mean***	***Standard Deviation***	***Interquartile Range***	***Mean***	***Standard Deviation***	***Interquartile Range***
Abr	0.485	0.370	0.670	30,109	1720	1636	5.688	0.591	0.838
Apu	1.143	0.892	1.730	68,842	1893	1669	3.163	0.263	0.303
Bas	1.298	0.991	1.790	10,970	452	529	4.403	0.394	0.405
Cal	0.936	0.596	1.025	32,440	985	1028	3.729	0.509	0.585
Cam	0.368	0.238	0.480	101,196	2808	2435	3.305	0.603	0.918
Ero	0.548	0.367	0.623	139,374	7759	8495	6.597	0.865	1.403
Fvg	0.422	0.360	0.460	34,759	1374	1346	5.870	0.501	0.765
Laz	0.195	0.157	0.300	180,739	6066	4219	5.627	0.450	0.608
Lig	0.113	0.078	0.135	46,777	1783	1498	5.258	0.509	0.898
Lom	0.350	0.186	0.293	337,908	18,493	21,378	6.723	0.695	0.858
Mar	0.371	0.405	0.795	39,457	1409	958	4.939	0.612	0.980
Mol	1.936	1.227	2.613	6323	358	541	5.091	0.730	1.090
Pie	0.313	0.301	0.493	129,222	3986	4817	6.303	0.355	0.463
Sar	1.048	0.722	1.300	32,407	1177	1109	4.679	1.021	1.775
Sic	0.493	0.381	0.758	87,130	2754	2863	3.141	0.492	0.743
Tre	0.322	0.278	0.485	36,154	2948	3950	9.728	0.436	0.538
Tus	1.744	0.184	0.240	104,679	4790	4168	5.190	0.528	0.800
Umb	0.388	0.298	0.473	21,468	762	927	4.983	0.869	0.903
Ven	0.308	0.304	0.505	144,991	5827	5852	6.006	0.589	0.983

(b)

	Epower			*School*			*Air*		
Italian Regions	***Mean***	***Standard Deviation***	***Interquartile Range***	***Mean***	***Standard Deviation***	***Interquartile Range***	***Mean***	***Standard Deviation***	***Interquartile Range***
Abr	1.938	0.541	1.168	75.345	3.030	4.548	23.590	2.394	1.880
Apu	2.448	0.604	1.123	71.573	2.700	3.413	37.732	2.289	1.813
Bas	1.483	0.593	1.085	71.823	3.304	4.365	21.414	4.201	7.103
Cal	2.863	0.885	1.460	72.340	2.601	4.403	20.673	1.773	2.098
Cam	0.845	0.186	0.250	74.499	2.984	4.800	45.275	4.354	7.445
Ero	1.812	0.269	0.538	75.675	3.938	6.418	39.950	4.757	7.253
Fvg	2.287	0.358	0.165	78.658	3.273	4.198	29.313	3.067	4.495
Laz	1.663	0.117	0.173	82.097	2.531	3.255	44.520	4.381	5.095
Lig	1.979	0.200	0.060	78.740	2.697	4.278	32.716	3.661	5.528
Lom	2.001	0.108	0.115	78.895	2.709	3.260	52.747	4.263	7.508
Mar	0.831	0.303	0.613	74.348	3.367	5.348	27.768	2.103	1.463
Mol	4.843	1.418	0.950	72.700	3.208	4.900	16.291	3.609	5.650
Pie	2.240	0.325	0.563	77.055	2.996	4.343	30.998	3.175	4.915
Sar	2.793	0.340	0.563	75.593	2.855	4.513	17.425	2.564	2.823
Sic	1.611	0.269	0.470	72.699	3.118	4.748	35.155	3.024	1.865
Tre	3.504	0.254	0.475	80.434	2.838	3.645	30.948	4.654	7.335
Tus	1.391	0.155	0.230	73.252	3.424	5.605	32.890	3.715	6.360
Umb	1.783	0.205	0.318	75.652	3.154	5.370	26.127	3.991	6.378
Ven	1.529	0.179	0.265	76.825	3.846	6.160	40.663	4.536	7.775

Table 1. *Cont.*

(c)						
	OCrime			*SSCrime*		
Italian Region	*Mean*	*Standard Deviation*	*Interquartile Range*	*Mean*	*Standard Deviation*	*Interquartile Range*
Abr	2.510	0.663	0.905	18.828	1.162	1.513
Apu	2.661	1.303	0.880	20.493	1.155	1.963
Bas	3.322	2.821	1.050	7.476	0.827	1.305
Cal	3.864	1.107	1.415	13.618	1.169	1.303
Cam	3.767	0.769	0.998	18.783	1.514	1.940
Ero	1.123	0.361	0.408	34.048	2.946	3.260
Fvg	1.528	0.655	0.488	17.666	1.474	2.310
Laz	2.208	0.546	0.685	34.469	4.097	4.325
Lig	1.720	0.797	0.778	30.983	4.000	4.965
Lum	1.463	0.749	0.425	31.478	1.747	2.223
Mar	2.027	0.475	0.513	17.599	1.232	1.898
Mol	4.080	2.100	2.263	11.538	1.220	0.883
Pie	1.106	0.498	0.733	22.200	2.261	3.793
Sar	1.183	0.362	0.378	13.677	1.201	1.303
Sic	3.223	0.895	0.770	20.504	1.432	2.925
Tre	2.335	2.324	2.065	16.861	1.714	3.420
Tus	1.696	0.328	0.230	27.540	2.128	2.545
Umb	3.774	3.851	1.568	20.735	1.632	2.230
Ven	1.404	0.489	0.363	23.678	2.463	4.163

3. Methods

The limitations inherent in the classical panel approach, when applied to examining macroeconomic phenomena pertaining to administrative regions or countries, rather than individuals, are universally acknowledged in scholarly discourse [40–42]. Analyzing proximity correlations in this context introduces several econometric challenges. Specifically, if cross-sectional correlation impacts a phenomenon under investigation, it necessitates utilizing a model that accounts for this form of dependence when studying its determinants.

In the field of economic research, spatial modeling has emerged as a systematic approach to comprehending the spatial distribution of economic activity across various scales, from local to global. Researchers employ this method to explore the interplay between geographic dependence and its impact on relevant variables. However, when dealing with administrative regions, spatial modeling encounters intricacies beyond mere physical proximity. These complexities arise from factors such as economic, social, and cultural considerations, which influence dependencies related to similarity and proximity. Recognizing these nuances is crucial for refining the methodological approaches employed in studying regional or country-level macroeconomic phenomena.

Spatial Panel Models

In the spatial statistics literature, as outlined by Anselin [43], the assessment of cross-correlation involves the utilization of a "spatial matrix", denoted as W. This matrix is a nonnegative $N \times N$ matrix, where N represents the number of regions, consisting of known constants that characterize the spatial arrangement of units within the sample. Notably, the matrix's non-zero elements denote whether two areas can be deemed neighbors. Consequently, the element w_{ij} in the matrix signifies the strength or intensity of the relationship between cross-sectional units i and j.

In light of this spatial framework, a reduced model can be expressed as follows:

$$\mathbf{y} = \boldsymbol{X\beta} + \boldsymbol{B}_n\mathbf{u};\ \boldsymbol{B}_n = (\boldsymbol{I}_n - \lambda\mathbf{W}_n)^{-1}$$

With such specifications, a random shock in a specific area i (i.e., a shock in error u at any location i) does not only affect the outcome y in the *i-region* but it will be transmitted to all other locations following the multiplier expressed in $(\mathbf{I} - \lambda\mathbf{W})^{-1}$.

To exclude self-neighbors, the diagonal elements of spatial matrix **W** (w_{ii}) are set to zero by convention. This weighting spatial matrix is not symmetric and is generally used in a row-standardized form. The elements w_{ij} of **W** are obtained by calculating proximities using several algorithms according to the geospatial coordinates of the regions. There are several alternative ways to calculate the proximities. The most common are as follows:

1. Contiguity weights matrix: $\mathbf{d_{ij}}$ = 1 if regions *i* and *j* have a common boundary; otherwise, d_{ij} = 0.
2. Distance-based binary weights matrix: $\mathbf{d_{ij}}$ = 1 if the distance between regions *i* and *j* is less than a threshold cut-off distance; otherwise, $\mathbf{d_{ij}}$ = 0.
3. K-nearest neighbor: $\mathbf{d_{ij}}$ = 1 if the geographical center of region j is one of the nearest k to the center of region *i*; otherwise, $\mathbf{d_{ij}}$ = 0.

Once these distances are row-standardized, they become the w_{ij} weights of **W**.

In this study, we adopt the perspective that spillover effects, if present, in terms of RES generation, are not solely determined by geographical proximities. To account for these potential spillover effects, we utilize a spatial **W** matrix based on Euclidean distances [44]. This matrix represents an advancement from the proximity matrix previously developed in other research, e.g., [45]. The Euclidean distances matrix serves as a refined approach to capture the spillover effects between regions, emphasizing that the interdependence in RES generation is not solely contingent on spatial proximity.

This methodology allows for a better understanding and modeling of the intricate dynamics of spillover effects in the context of RES generation between Italian regions. The **W** distance matrix was computed based on the mean values from the years 2004 to 2015 for eight variables, as outlined in Table 2. These variables capture similarities (and dissimilarities) across Italian regions related to cultural, social, and economic factors. All of the variables used were sourced from various databases provided by the Italian National Statistical Institute (ISTAT); in particular, we used data on national accounts, demographic statistics, and the Health for All (HFA) database. To maintain consistency, a standardization process was applied, considering that the original data were expressed in different units of measurement. Adhering to this standardization approach, the distance between any two arbitrary regions, denoted as dij, is determined as follows:

$$d_{ij} = \sqrt[2]{\sum_{s=1}^{8} \left(z_{is} - z_{js}\right)^2}$$

Table 2. Variables of proximities matrix. Regional data, 2004–2015 mean values.

Variable	Description
Education	Share of residents with at least secondary school degree
Health expenditure	Per capita expenditure in health services
Mortality rate	Regional mortality rates (Male + Female)
Households	Average number of household components
Employment	Employment rates
Poverty	Regional poverty indexes
Research and development	Per capita regional research and development spending
Residence permits	Number of residence permits on total regional resident population

The inverse $(1/d_{ij})$ elements of the Euclidean matrix represent the w_{ij} elements of matrix **W**. The greater the strength of the Euclidean distance between region *i* and region *j*, the weaker the weight attributed to the spillover effect between the two regions (since we consider the inverse of the absolute distance as the weight). Naturally, as d_{ii} = 0 for each region, the diagonal elements of **W** are all equal to 0.

The w_{ij} weights are used to estimate an econometric model following the (spatial autoregressive (SAR)) specification. In a nutshell, SAR models are employed to analyze datasets that encompass observations pertaining to geographical areas or units with a spatial dimension. These models facilitate the fitting of linear relationships, incorporating autoregressive errors and spatial lags of both dependent and independent variables. The specification of spatial lags is accomplished through the use of spatial weighting matrices (**W**). This class of model captures the proximities' dependence in the model's residuals other than the cross-sectional correlations between regions. This specification allows for the capture of cross-sectional interactions across units and over time. Due to the small number of individuals per unit and considering that the variation in the independent variable is primarily within units (the units are relatively similar to one another, on average) [46], a fixed effects spatial lag (SAR) specification was chosen to represent the phenomenon. It can be written in stacked form as follows:

$$\mathbf{y} = \boldsymbol{\alpha} + \lambda\mathbf{W}\mathbf{y} + \boldsymbol{X\beta} + \varepsilon;$$

In structural form, the SAR model can be written as follows:

$$y_{it} = \alpha_i + \lambda\sum_{j\neq i}^{N} w_{ij}y_{jt} + x'_{it}\beta + \epsilon_{it} \quad (1)$$

where α_i is the fixed regional component, and λ is the coefficient of the spatial lagged dependent variable ($\mathbf{y}$) weighted by the w not-diagonal elements of the spatial matrix, **W**. Each w_{ij} specifies the strength of the proximities between the generic *i-region* with another *j-region*. The exogenous regressors are represented by the x vector, and the influence of each of them on the dependent variable is measured using the β coefficients. Finally, $\varepsilon_{\mathrm{it}}$ are the residuals of the model. Model 3.1 was estimated using the Elhorst [47] maximum likelihood approach.

4. Results and Discussion

The primary objective of this paper was to examine whether the presence of COs catalyzes or deters investments in RESs. To assess the impact of various covariates on RES production, we opted for a spatial panel model, aiming to discern the magnitude and direction of these effects. This methodological choice is underpinned by the considerable heterogeneity observed among Italian regions, regarding both the investments in RESs and the control variables. The existence of cross-sectional dependencies further motivates the use of a spatial panel model.

Given the anticipation of multiple cross-sectional dependencies that may undermine the adequacy of a simple panel model, we advocated for the adoption of a spatial specification to mitigate potential bias effects. Consequently, our initial preference iwas to estimate a spatial autoregressive (SAR) model, wherein the Italian regional spatial matrix (W) encapsulates the inherent similarities between regions. This approach allows us to account for the distinctive characteristics of individual regions and the interdependence among them, thereby enhancing the precision and reliability of our empirical analysis.

As diagnostics, we tested the presence of time and individual dependences in the residual via the Baltagi method for serial correlation and Pesaran for cross-sectional correlation [48,49]. The results lead us to reject both the alternative hypothesis of time dependence and local cross-sectional dependence in the model's residual. Table 3 reports the estimates.

Table 3. Model estimates.

Variable	Estimate	*p*-Value
Λ	0.077	0.000
GDPpc	−1.861	0.001
Investments	−0.087	0.028
Epower	0.382	0.000
Qair	0.013	0.012
School	0.043	0.020
Ocrime	−0.090	0.002
SSCrime	0.014	0.122
Inter_OC SSC	0.004	0.024
	Diagnostics	
	Tests of serial correlation (alternative hypothesis: time dependences)	
Baltagi	0.294	0.588
	Tests of cross-sectional correlation (alternative hypothesis: cross dependences)	
Pesaran	0.22	0.826

All coefficients exhibit statistical significance (p-values < 0.05) and align with the expected signs, except the coefficient associated with small-scale crime (SSCrime). Notably, the sign and significance of the λ coefficient substantiate the notion of a notably positive correlation between regional characteristics and the generation of energy from renewable sources. This observation underscores the viability of employing a spatial lag model to capture these inherent spatial relationships.

Furthermore, it is noteworthy that, aside from one specific year, the residuals of the model (Equation (1)) demonstrate spatially uncorrelated patterns, as indicated by the Global Moran I-index [50]. This spatial independence in the model's residuals lends support to the robustness of the spatial lag model employed, reinforcing the credibility of the findings derived from the analysis.

The Moran I-index is a measure of spatial autocorrelation (Equation (2)). According to Anselin [43], spatial autocorrelation can be defined as a spatial cluster of similar parameter values. If similar parameter values—high or low—are spatially localized, positive spatial autocorrelation of the data is present. In contrast, the spatial proximity of dissimilar values, i.e., not spatially stable, indicates negative spatial autocorrelation (or spatial heterogeneity).

It varies from -1 to 1, and its expected value equals $-1/(N-1)$ under the assumption of the null hypothesis of no spatial autocorrelation [51].

$$I = \left(\frac{N}{\sum_i \sum_j w_{ij}}\right)\left(\frac{N\sum_i \sum_j w_{ij}(y_i - \overline{y})(y_j - \overline{y})}{\sum_i (y_i - \overline{y})^2}\right) \tag{2}$$

According to the assessment of the Elhorst [52] spatial modeling procedure to test which spatial model is technically preferred, this result leads us to reject the hypothesis of estimating more complex models of the following types: "spatial error" or "sarar" or "slx", meaning that we must also consider the spatial weights of the residual components or the explicative variables. The Moran Index statistics on the residuals for each year and relative p-values of the spatial correlation tests (under the assumption of the null hypothesis of a spatial correlation equal to 0) are reported in Table 4.

When examining investments in RESs (Investments), a positive coefficient is observed. This outcome is consistent with our expectations. Companies actively support RES generation with the hope of reducing energy expenses and electrical dependence but also in order to mitigate greenhouse emissions in accordance with rules and laws. This trend is aligned with the objective of incorporating strategies for sustainable development and CSR into their operations and activities [53].

Table 4. Moran indexes of the residual of the SAR model and *p*-values for the significance test (null hypothesis: no spatial correlation).

Year	Estimate	*p*-Value
2004	−0.048	0.824
2005	−0.020	0.266
2006	−0.089	0.307
2007	−0.087	0.339
2008	−0.048	0.810
2009	0.120	0.000
2010	−0.088	0.303
2011	−0.085	0.319
2012	−0.060	0.899
2013	−0.053	0.942
2014	−0.067	0.712
2015	−0.005	0.068

Gross domestic product per capita (GDPpc) exhibits statistical significance with a negative sign, aligning with the findings of Bandyopadhyay and Wall [54]. This result suggests that in high-income countries, such as Italy, there is a propensity to meet the escalating electricity demand using readily available fossil fuels on the market. This strategic choice by policymakers aims to uphold the citizens' perceived quality of life [30]. We cannot forget that fossil fuels represent a very important source of tax revenue for some countries, such as Italy.

On a global scale, optimal locations for large-scale RESs have largely been exploited. The increasing adoption of renewable sources, particularly wind and solar photovoltaic systems, is underscored by the positive coefficient of the regional electric power variable (Epower) in the model. Large-scale deployments worldwide have been facilitated by the decreasing costs associated with these technologies in recent years. Numerous studies (e.g., [55]) highlight the ability of higher levels of renewable penetration to enhance grid flexibility and accommodate fluctuations in power generation. This dynamic leads to a positive correlation between the power output of individual wind and solar photovoltaic generators and significant energy production within relatively short time windows, explaining the observed positive sign for the coefficient of the regional electric power variable coefficient (Epower) in the model.

It is commonly assumed that the public is paying increasing attention to environmental issues and favors green generation. The percentage of families commenting on air pollution can be considered a proxy for regional environmental awareness. We used this variable to capture regional environmental degradation. Where this percentage is higher, a larger probability that families support the use of RESs and environmental policies emerges [56]. For this reason, the positive and significant sign of the air quality variable coefficient (Qair) may be explained as the need to satisfy the demand for greener electricity generation systems.

The coefficient of the percentage of households with at least a lower high school education (School) is positively correlated with the dependent variable. Higher levels of education can already be integrated to include appreciation for and protection of nature and the environment. Green jobs are relevant across all key sectors: agriculture, manufacturing, building, transport, tourism, and renewable energy. Skills acquisition and enhancement have great positive implications for all aspects of education and training and businesses [57]. For these reasons, RES generating plants tend to increase in regions with the highest levels of education.

High levels of public subsidies attract legitimate and illegitimate investors. For instance, concerning Italy, a strong positive connection between the distribution of wind power installed in regions and the presence of COs was discovered [5]. This result could mirror the high presence of COs in regions of southern Italy that also have greater wind energy potential. Conversely, the result could mean that COs encouraged investments in regions with weak institutions and where their power is rooted. However, other recent investigations underline the widespread presence of COs even in northern regions of Italy [58–60]. Additionally, we have to remind that RES sectors have strong interdependencies with other economic sectors, representing a driving force for many other industries, including metals, electrical and electronic equipment, IT, construction, transport, and financial services. Hence, a third hypothesis is that COs are more interested in entering high-intensive energy sectors, like manufacturing, relative to others, such as agriculture or household production [32].

As is known, RES sectors are net employment creators in Europe. Between 2007 and 2010, the number of jobs in the industry grew by nearly 30%, while EU unemployment rose by 9.6%. The virtuous circle generated by this process affects the development of legal and perfectly traceable activities that are unlikely to be infiltrated by COs. From this point of view, we can interpret the negative and significant coefficient of organized crime (OCrime) and the not significant coefficient of small-scale crime (SSCrime) (firmly considered as an indicator of the quality of the institutions in European countries [61]). Their interaction term in the model (Inter_OC SSC) leads us to consider these two coefficients in terms of conditional relationships when the other is null [62]. The coefficient of OCrime measures the link with RES investments in the absence of common crime.

As widely documented (see, e.g., [5]), the infiltration of COs into the Italian economic system, at least for southern regions, has been a barrier to the development of the sectors involving power generation from renewable sources. From this perspective, the negative and significant coefficient of this variable should be considered as interposed. Non-collusive investors preferred to relocate their investments to other areas of the country, those less infiltrated by COs. Moreover, police and judicial inquiries have discouraged investment by collusive entrepreneurs. In this way, these areas, with a strong tendency towards power generation from renewable sources (solar irradiation and presence of winds), have seen drastic reductions in investments, and this has been a further loss for the economic development of these areas, which are among the most underdeveloped in the European Union.

On the other hand, we interpret the non-significance of the SSCrime coefficient as a signal about the absence of a relationship between the quality of institutions and RES investments in the areas where the presence of COs is lower. The combined effect of the two drivers is measured by the coefficient of the interaction term (Inter_OC SSC), which is positive and significant. This result has to be jointly analyzed with previous ones. The increasing difficulty for COs to invest in the southern regions is leading to the relocation of their business interests to areas less involved in the mafia phenomenon. This leads to an increase in investment in renewable generation in more economically dynamic regions with greater innovation potential and that are richer and, consequently, more affected by phenomena linked to common crime.

The main finding of this study is the confirmation that the interested fields involved in the processes relating to RESs attract the interest of COs and that the same ones are in some way permeable to the presence and influence of COs. This situation contrasts with the expectations of private investors. While COs prefer to direct their investments to regions with weak institutions that are unable to control the territory [15], private companies prefer to invest in areas traditionally less affected by crime. The presence of COs, therefore, has a crowding-out effect on private investors. It is conceivable that in these areas, the total amount of RES investments increases due to the illicit influence of COs, but we are not able to say whether the balance resulting in lower investments from private individuals is smaller or greater. Certainly, the presence of COs implies that an important share of these resources will not turn into real investments but into a channel of illicit financing.

Robustness Check

In our pursuit of robustness, we conducted a series of checks involving the estimation of alternative specification models to compare against the selected spatial autoregressive (SAR) specification. The results of these alternative models consistently yielded equivalent coefficients, as evidenced in Table 5 (columns 1–4), reinforcing the robustness of our chosen method. While the stability of coefficients was confirmed, we recognized the importance of scrutinizing the appropriateness of each model.

Table 5. Robustness checks.

Variable	PCSE		Panel Fixed		Panel Dynamic		Geo SAR	
	Estimate	***p*-Value**	**Estimate**	***p*-Value**	**Estimate**	***p*-Value**	**Estimate**	***p*-Value**
Intercept	1.089	0.542						
λ					0.741	0.000	0.328	0.000
GDPpc	−0.066	0.726	−2.682	0.000	0.313	0.461	−1.775	0.001
Investments	−0.227	0.000	−0.116	0.005	−0.085	0.017	−0.121	0.002
Epower	0.397	0.000	0.431	0.000	0.279	0.000	0.376	0.000
Qair	−0.002	0.875	0.013	0.024	−0.004	0.017	0.012	0.027
School	0.010	0.649	0.104	0.000	0.001	0.919	0.061	0.000
Ocrime	−0.014	0.872	−0.081	0.008	−0.035	0.201	−0.095	0.001
SSCrime	0.009	0.667	0.029	0.001	0.004	0.316	0.017	0.052
Inter_OC SSC	−0.003	0.514	0.003	0.044	0.002	0.229	0.004	0.010
Diagnostics								
Test for panel effects (alternative hypothesis: presence of panel effects)								
LM	487.5	0.000						
Tests for serial correlation (alternative hypothesis: time dependences								
Breush-Pagan			480.2	0.000				
AR 1 Test					−2.085	0.037		
AR 2 Test					−1.872	0.061		
Baltagi							0.294	0.588
Tests for cross-sectional correlation (alternative hypothesis: cross dependences)								
Pesaran (CD) Test			2.836	0.000	6.151	0.000	−0.21	0.833

The initial check involved subjecting the residuals of a panel-corrected standard error (PCSE) model to the Breusch–Pagan Lagrange Multiplier test (BPLM test):

$$y_{it} = x'_{it}\beta + \epsilon_{it} \tag{3}$$

The PCSE model considers both contemporaneous correlation and unit-level heteroscedasticity in deviations from spherical errors. This approach enhances the validity of inference compared to linear models estimated using the classical Ordinary Least Squares (OLS) estimator, as demonstrated by Beck and Katz [63]. The utilization of the PCSE model allows for a more robust examination of the data, addressing potential issues of correlation and heteroscedasticity that are often present in classical panel specifications.

To assess whether a pooled specification is preferable over a classical panel specification, we employed the BPLM test. This test scrutinizes the null hypothesis of no variance across units. The results of the BPLM test, as presented in Table 5, affirm the indications observed during the descriptive analyses of individual effects.

Subsequently, the analysis proceeds to estimate the panel fixed-effects model:

$$y_{it} = \alpha_i + x'_{it}\beta + \epsilon_{it} \tag{4}$$

The fixed specification, when applied, fails to produce unbiased coefficients, as indicated by our diagnostic tests. Specifically, the null hypotheses of no serial correlation in the residuals, tested through the Breusch–Pagan (BP) test, are rejected. Additionally, the cross-sectional correlation between similar regions, examined using the non-spatial Pesaran CD test [49], cannot be accepted (Table 5).

To address these limitations, we estimated a dynamic specification with the GMM estimator:

$$y_{it} = \lambda y_{it-1} + x_{it}'\beta + u_i + \epsilon_{it} \quad (5)$$

The specified model yields biased estimates for serial correlation, as evidenced by the AR1 and AR2 tests, and for cross-sectional correlation in the residuals, as indicated by the Pesaran CD test. To address this, we introduce an additional control using the spatial autoregressive (SAR) model, incorporating a geographical matrix, denoted as W^k. This approach aligns with the standard spatial literature.

In the estimation process, we calculate weights, ${w^k}_i$, for $\mathbf{W^k}$, utilizing the k-nearest neighbor algorithm (see previous section). The choice of the k-nearest method is deliberate, as it is particularly suitable when contiguity weights are not feasible due to the presence of islands without common bonds. Additionally, the distance-based binary weights method is discarded due to its inherent arbitrariness in setting thresholds.

This alternative SAR model with the Euclidean distances is favored over the geographical distance specification when assessing the Global Moran I-index (Equation (2)). The computed values of the index for the outcome variable are compared using both the weights of the geographical matrix and those of the distance spatial matrix. The findings validate the proposed theoretical framework, indicating a lack of substantial evidence for significant geographical autocorrelation in RES production. However, the autocorrelation between regions becomes significant in the last four years when proximities are measured through the matrix of Euclidean distances (Table 6).

Table 6. Moran indexes on dependent variables and *p*-values for the significance test (null hypothesis: no spatial correlation).

	Euclidean Distances SAR		**Geo SAR**	
Year	**Estimate**	***p*-Value**	**Estimate**	***p*-Value**
2004	−0.058	0.881	−0.175	0.987
2005	−0.058	0.884	−0.16	0.962
2006	−0.06	0.831	−0.142	0.92
2007	−0.06	0.823	−0.131	0.88
2008	−0.057	0.937	−0.162	0.927
2009	−0.048	0.777	−0.148	0.883
2010	−0.027	0.331	−0.096	0.672
2011	−0.017	0.212	−0.157	0.855
2012	0.007	0.048	−0.141	0.809
2013	0.01	0.039	−0.128	0.769
2014	0.007	0.051	−0.152	0.836
2015	0.003	0.065	−0.164	0.864

This finding suggests that complex factors beyond pure geography drive spatial spillover effects. Consequently, based on this empirical evidence, the Euclidean distances matrix specification is preferred.

5. Concluding Remarks

One of the pillars of sustainable development concerns investments in renewable energy sources (RESs). Not by chance, RESs are a central objective of the energy policies of the European Union.

In this view, public authorities should encourage private investors to participate and engage in renewable energy projects, as well as the use of renewable energy. From an environmental point of view, RESs represent an inexhaustible source of energy that can be used to tackle the global warming emissions associated with fossil fuels, and which also lack the negative impacts on health. From an economic perspective, RES generation represents an opportunity for the entire community. Compared to traditional energy sectors, which are typically capital-intensive, RESs are more labor-intensive. Hence, investing in RESs rather than in fossil sources tends to create more jobs, requiring a higher level of specialization. In addition to the jobs directly created in the renewable energy industry, growth in clean energy can create positive economic "ripple effects" in terms of economic development.

Not surprisingly, RESs lead to enormous flows of monetary and financial resources associated with these investments, which also stimulate the interest of criminal organizations (COs). This interest can either favor the growth of the investments, such as when COs align with corrupt politicians or provide false documents, or a reduction in investments, such as when private companies are afraid to invest and public institutions want to minimize the risk of illicit behaviors. Anyway, the share of investments by COs could only be nominal and not lead to real construction of instruments and devices.

To understand if and how COs influence investments in RESs, this study proposed a spatial econometric investigation focusing on Italy, a country characterized by a deep-rooted presence of COs, although not homogeneously spread.

This research endeavored to provide a holistic understanding of the factors influencing investment decisions in the context of organized crime and RES investments. The purpose was to provide insights that can support policymakers, investors, and stakeholders about the challenges and opportunities associated with promoting RES investments in regions grappling with organized crime.

To this aim, the study employs a comprehensive analysis that considers various factors, not limited to economic indicators, such as policy frameworks and public attitudes in the Italian regions. By leveraging data on the presence of COs and utilizing statistical indicators and proxies for illegal activities within specific territories, this study discerns patterns and correlations that shed light on the intricate dynamics between criminality and investments in RESs.

In this view, this investigation tried to show how COs can hinder or shape decision-making processes related to sustainable energy investments in Italian regions.

The first result, contrary to expectations, is that economically weaker regions in Italy have attracted more investment in RESs. This evidence could be explained by the greater involvement of the institutions that administer these regions in the search for incentives and funds made available by national or European central institutions. A second alternative is linked to the fact that COs become active parts in the process of obtaining the monetary resources available because the control of the territory in these areas is weaker.

We have also observed that citizens exert societal pressure in terms of investments in RESs in regions where there are perceived higher levels of pollution caused by traditional energy sources. However, the possibility of requesting and making investments in RESs is also linked to the level of education and specialization of people living in a certain context, as high skills are required in this sector. This is particularly true when investments in RESs are expected to also drive the development of the entire local economy.

However, the interplay between RESs and COs exhibits a nuanced dynamic. COs can act as barriers in regions with weak institutions, such as when they attract the attention of the authorities or when they intimidate uninvolved investors, but they can also be an incentive when their actions represent economic leverage in this context by attracting greater investments. Although the high profitability of RESs attracts illegitimate investors, this linkage does not seem to be the case in all the Italian regions, and this is another remarkable finding of this work.

In a nutshell, the relationship between COs and RES is complex, and the factors that foster the related investments in recent years are linked to regional features. Furthermore, the outcomes indicate that there are spillover effects that arise from a combination of elements that are not purely economic nor linked to the traditional dichotomy between the north and south of Italy.

6. Limitations and Implications

Additional research is necessary to validate the robustness of these results and overcome the limitations of this investigation. For instance, not all investments are similar in terms of impact. Investments in wind and hydropower are different from those in solar energy, as the latter are more capital-intensive and require more authorization from local institutions as they have a greater environmental impact.

A second limit is represented by the fact that the indicators employed in this study to gauge the presence of COs lack an explicit consideration for approaches of deterrence. That is, we cannot evaluate how public institutions react to the presence of COs by issuing specific regulations.

A further limit concerns the absence of comparison of these results with other countries. At the same time, it would be interesting to check if the results remain robust even at a sub-regional level. However, a panel of data for Italian provinces is not yet available. Last but not least, the inclusion of variables that are useful to gauge the effect of judicial enforcement actions would be of particular interest for policy purposes in order to find out whether an increase in competition concerning renewable investments occurred in regions where these actions have been carried out with greater effort.

In terms of implications, the results of this study show that COs are inevitably attracted by the presence of investments of a public nature as they hope to appropriate a share. This is most evident in areas where the institutions responsible for monitoring the correct use of funds are somewhat weak or sensitive to external pressures by illicit organizations. Therefore, it is clear that investments in RESs must be accompanied by effective regulations but also by swift and heavy penalties. In further detail, we can claim that in regions where COs exert wide territorial control, tackling them could dismantle a crucial barrier to entry for private investors, diffusing confidence and positively impacting the economic development of these areas. This attention concerns fraud, corruption, or other illegal practices that may arise in project development, financing, or implementation. For example, cases where individuals or companies engage in fraudulent activities related to RESs only to obtain the forecasted subsidies are not rare.

These statements mean that the field of study that assesses the role of the most appropriate policies for RESs is a fruitful area for future research, as several issues remain unexplored. As renewable energy is becoming a future facet of the economy whose efficient control requires thorough analyses of all major economic incentives, evaluating the impact of COs on investments is a primary objective. This interest also reflects the effectiveness of political institutions in the regions, which are also key examples to follow in areas where the high presence of COs could slow down investments, with negative effects on the development of the local economy.

From this perspective, the most difficult objective for researchers is probably to obtain updated data on criminal influence. Therefore, legal institutions should also be involved in this process of deepening and studying their response to COs to subsequently accelerate investments in RESs and generate sustainable growth, tackling the recent slacking mentioned in the introduction; it is also imperative to assess the influence exerted by COs.

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References

1. IRENA. Global landscape of renewable energy finance. In Proceedings of the International Renewable Energy Agency, Abu Dhabi, United Arab Emirates, 13 June 2023.
2. Romano, A.A.; Scandurra, G.; Carfora, A.; Fodor, M. Renewable investments: The impact of green policies in developing and developed countries. *Renew. Sustain. Energy Rev.* **2018**, *68*, 738–747. [CrossRef]

3. Chou, C.-H.; Ngo, S.L.; Tran, P.P. Renewable Energy Integration for Sustainable Economic Growth: Insights and Challenges via Bibliometric Analysis. *Sustainability* **2023**, *15*, 15030. [CrossRef]
4. Neagu, O.; Anghelina, A.M.; Teodoru, M.C.; Boiță, M.; David, K.G. Could Globalisation and Renewable Energy Contribute to a Decarbonised Economy in the European Union? *Sustainability* **2023**, *15*, 15795. [CrossRef]
5. Ruggiero, V. Sustainability and Financial Crime. *Int. Criminol.* **2022**, *2*, 143–151. [CrossRef]
6. Checchi, V.V.; Polo, M. Blowing in the Wind: The Infiltration of Sicilian Mafia in the Wind Power Business. *Ital. Econ. J.* **2020**, *6*, 325–353. [CrossRef]
7. Deiana, C.; Geraci, A. Are wind turbines a mafia windfall? The unintended consequences of green incentives. *Reg. Sci. Urban Econ.* **2021**, *89*, 103691. [CrossRef]
8. D'amore, R. Why Is the Mafia Investing so Much in Renewable Energy? Bocconi University Newspaper. 2021. Available online: https://traileoni.it/2021/04/why-is-the-mafia-investing-so-much-in-renewable-energy/ (accessed on 15 June 2023).
9. Rahman, S. The Energy and Natural Resources Sector: Business Crime Risks and Remedies. Financiaer Worldwide. 2021. Available online: https://www.financierworldwide.com/the-energy-and-natural-resources-sector-business-crime-risks-and-remedies (accessed on 16 June 2023).
10. Ikejemba, E.C.X.; Schuur, P.C. Analyzing the Impact of Theft and Vandalism in Relation to the Sustainability of Renewable Energy Development Projects in Sub-Saharan Africa. *Sustainability* **2018**, *10*, 814. [CrossRef]
11. Dugato, M.; Calderoni, F.; Campedelli, G.M. Measuring Organised Crime Presence at the Municipal Level. *Soc. Indic. Res.* **2019**, *147*, 237–261. [CrossRef]
12. EUROPOL. Organised Crime & Energy Supply. Available online: www.europol.europa.eu/sites/default/files/documents/organised-crime-in-energy-supply.pdf (accessed on 24 October 2023).
13. Daniele, G.; Geys, B. Organised Crime, Institutions and Political Quality: Empirical Evidence from Italian Municipalities. *Econ. J.* **2015**, *125*, 233–255. [CrossRef]
14. Rahman, K. Overview of Anti-Corruption in the Renewable Energy Sector. The U4 Anti-Corruption Resource Centre. 2020. Available online: https://knowledgehub.transparency.org/helpdesk/overview-of-anti-corruption-in-the-renewable-energy-sector (accessed on 24 October 2023).
15. ISTAT. *Shadow Economy in National Accountability, Years 2018–2021*; ISTAT: Rome, Italy, 2022.
16. Blaustein, J.; Fitz-Gibbon, K.; Pino, N.W.; White, R. The Nexus between Crime, Justice and Sustainable Development. In *The Emerald Handbook of Crime, Justice and Sustainable Development*; Blaustein, J., Fitz-Gibbon, K., Pino, N.W., White, R., Eds.; Emerald Publishing Limited: Leeds, UK, 2020; pp. 3–24. [CrossRef]
17. Gennaioli, C.; Tavoni, M. Clean or dirty energy: Evidence of corruption in the renewable energy sector. *Public Choice* **2016**, *166*, 261–290. [CrossRef]
18. Arminen, H.; Menegaki, A.N. Corruption, climate and the energy-environment-growth nexus. *Energy Econ.* **2019**, *80*, 621–640. [CrossRef]
19. Di Pillo, F.; Levialdi, N.; Marzano, R. Organized crime and waste management costs. *Reg. Stud.* **2023**, *57*, 168–180. [CrossRef]
20. Andreatta, D.; Favarin, S.; Lisciandra, M.; Millemaci, E. Digging into waste: An analysis of waste crime in the Italian provinces. *Reg. Stud.* **2023**, *57*, 1367–1379. [CrossRef]
21. Sadorski, P. Wind energy for sustainable development: Driving factors and future outlook. *J. Clean. Prod.* **2021**, *289*, 125779. [CrossRef]
22. Darghouth, N.R.; Barbose, G.; Zuboy, J.; Gagnon, P.J.; Mills, A.D.; Bird, L. Demand charge savings from solar PV and energy storage. *Energy Policy* **2020**, *146*, 111766. [CrossRef]
23. Bernardo, G.; Brunetti, I.; Pinar, M.; Stengos, T. Measuring the presence of organized crime across Italian provinces: A sensitivity analysis. *Eur. J. Law Econ.* **2021**, *51*, 31–95. [CrossRef]
24. Zeiler, I.; Sallusti, F.; Kamprad, A.; Bisogno, E. Measuring illegal economic activities and illicit financial flows: Challenges and possible solutions. *Indicator* **2019**, *16*, 1.
25. Riccardi, M.; Soriani, C.; Giampietri, V. Mafia infiltration in legitimate companies in Italy: From traditional sectors to emerging businesses. In *Organised Crime in European Businesses*; Savona, E., Riccardi, M., Berlusconi, G., Eds.; Routledge, Taylor & Francis Group: Abingdon, UK, 2016; pp. 119–140. [CrossRef]
26. Gamba, A.; Immordino, G.; Piccolo, S. Corruption, Organized Crime and the Bright Side of Subversion of Law. Centre for Studies in Economics and Finance, 446. 2016. Available online: https://www.csef.it/WP/wp446.pdf (accessed on 16 June 2023).
27. Lavezzi, A.M. Organised crime and the economy: A framework for policy prescriptions. *Glob. Crime* **2014**, *15*, 164–190. [CrossRef]
28. Li, Q.; Cherian, J.; Shabbir, M.S.; Sial, M.S.; Li, J.; Mester, I.; Badulescu, A. Exploring the Relationship between Renewable Energy Sources and Economic Growth. The Case of SAARC Countries. *Energies* **2021**, *14*, 520. [CrossRef]
29. Ergun, S.J.; Rivas, M.F. Does higher income lead to more renewable energy consumption? Evidence from emerging-Asian countries. *Heliyon* **2023**, *9*, e13049. [CrossRef]
30. Marques, A.C.; Fuinhas, J.A.; Pires Manso, J.R. A quantile approach to identify factors promoting renewable energy in European Countries. *Environ. Resour. Econ.* **2011**, *49*, 351–366. [CrossRef]
31. Romano, A.A.; Scandurra, G.; Carfora, A. Probabilities to adopt feed in tariff conditioned to economic transition: A scenario analysis. *Renew. Energy* **2015**, *83*, 988–997. [CrossRef]
32. Pinotti, P. The Economic Costs of Organised Crime: Evidence from Southern Italy. *Econ. J.* **2015**, *125*, 203–232. [CrossRef]

33. Horlings, L.G.; Marsden, T.K. Exploring the New Rural Paradigm in Europe: Eco-economic Strategies as a Counterforce to the Global Competitiveness Agenda. *Eur. Urban Reg. Stud.* **2014**, *21*, 4–20. [CrossRef]
34. Sen, S.; Ganguly, S.; Das, A.; Sen, J.; Dey, S. Renewable energy scenario in India: Opportunities and challenges. *J. Afr. Earth Sci.* **2016**, *122*, 25–31. [CrossRef]
35. van Vliet, M.; Wiberg, D.; Leduc, S.; Riahi, K. Power-generation system vulnerability and adaptation to changes in climate and water resources. *Nat. Clim Chang.* **2016**, *6*, 375–380. [CrossRef]
36. Alvarez, A.; Lorente, D.B.; Shahbaz, M.; Cantos, J.M. Energy innovation and renewable energy consumption in the correction of air pollution levels. *Energy Policy* **2017**, *105*, 386–397. [CrossRef]
37. Yusupova, G.F.; Podgorecki, J.; Markova, N.G. Educating Young People in Multicultural Educational Environment of Higher Education Institution. *Int. J. Environ. Sci. Educ.* **2015**, *10*, 561–570. [CrossRef]
38. Cipollone, P.; Montanaro, P.; Sestito, P. Value-Added Measures in Italian High Schools: Problems and Findings. *G. Degli Econ. Ann. Econ.* **2010**, *69*, 81–114. [CrossRef]
39. Lévay, P.Z.; Vanhille, J.; Goedemé, T.; Verbist, G. The Association between the Carbon Footprint and the Socio-Economic Characteristics of Belgian Households. *Ecol. Econ.* **2021**, *186*, 107065. [CrossRef]
40. Phillips, P.C.B.; Sul, D. Dynamic panel estimation and homogeneity testing under cross section dependence. *Econom. J.* **2003**, *6*, 217–259. [CrossRef]
41. Coakley, J.; Fuertes, A.M.; Smith, R. Unobserved heterogeneity in panel time series models. *Comput. Stat. Data Anal.* **2006**, *50*, 2361–2380. [CrossRef]
42. Eberhardt, M.; Teal, F. A common factor approach to spatial heterogeneity in agricultural productivity analysis. In *CSAE Working Paper*; WPS/2009-05; University of Oxford: Oxford, UK, 2009.
43. Anselin, L. Spatial Econometrics: Methods and Models. In *IBIDEM, Spatial Econometrics Chapter Fourteen*; Kluwer Academic Publisher: Dordrecht, The Netherlands, 1988; pp. 310–325. ISBN 978-1-4200-6424-7.
44. Borg, I.; Groenen, P. Modern Multidimensional Scaling. In *Theory and Applications*; Springer: Berlin/Heidelberg, Germany, 1997; ISBN 978-1-4757-2711-1.
45. Carfora, A.; Romano, A.A.; Ronghi, M.; Scandurra, G. Renewable generation across Italian regions: Spillover effects and effectiveness of European Regional Fund. *Energy Policy* **2017**, *102*, 132–141. [CrossRef]
46. Clark, T.; Linzer, D. Should I Use Fixed or Random Effects? *Political Sci. Res. Methods* **2015**, *3*, 399–408. [CrossRef]
47. Elhorst, J.P. Spatial Panel Data Models. In *Handbook of Applied Spatial Analysis*; Fischer, M.M., Getis, A., Eds.; Springer: Berlin/Heidelberg, Germany, 2009. [CrossRef]
48. Baltagi, B.H.; Song, S.H.; Jung, B.; Koh, W. Testing panel data regression models with spatial and serial error correlation. *J. Econom.* **2007**, *140*, 5–51. [CrossRef]
49. Millo, G. Narrow Replication of a Spatio-temporal Model of House Prices in the USA Using R. *J. Appl. Econom.* **2014**, *30*, 703–704. [CrossRef]
50. Moran, P.A.P. Notes on Continuous Stochastic Phenomena. *Biometrika* **1950**, *37*, 17–23. [CrossRef] [PubMed]
51. Gittleman, J.L.; Kot, M. Adaptation: Statistics and a null model for estimating phylogenetic effects. *Syst. Zool.* **1990**, *39*, 227–241. [CrossRef]
52. Elhorst, J.P. Matlab software for spatial panels. *Int. Reg. Sci. Rev.* **2014**, *37*, 389–405. [CrossRef]
53. Bandyopadhyay, S.; Wall, H. The Determinants of Aid in the Post-Cold War Era. *Fed. Reserve Bank St. Louis Rev.* **2007**, *89*, 533–547. [CrossRef]
54. Wirth, H.; Kulczycka, J.; Hausner, J.; Koński, M. Corporate Social Responsibility: Communication about social and environmental disclosure by large and small copper mining companies. *Resour. Policy* **2016**, *49*, 53–60. [CrossRef]
55. Mohammed, Y.S.; Mustafa, M.W.; Bashir, N. Hybrid renewable energy systems for off-grid electric power: Review of substantial issues. *Renew. Sustain. Energy Rev.* **2014**, *35*, 527–539. [CrossRef]
56. Noblet, C.L.; Teisl, M.F.; Evans, K.; Anderson, M.W.; Mccoy, S.; Cervone, E. Public Preferences for Investments in Renewable Energy Production and Energy Efficiency. *Energy Policy* **2015**, *87*, 177–186. [CrossRef]
57. Maclean, R.; Jagannathan, S.; Panth, B. Overview. In *Education and Skills for Inclusive Growth, Green Jobs and the Greening of Economies in Asia*; Technical and Vocational Education and Training: Issues, Concerns and Prospects Series 27; Springer: Singapore, 2018.
58. Chiodelli, F. The Dark Side of Urban Informality in the Global North: Housing Illegality and Organized Crime in Northern Italy. *Int. J. Urban Reg. Res.* **2019**, *43*, 497–516. [CrossRef]
59. Lavogna, A.; Sergi, A. Different manifestations of organised crime and corruption in Italy: A socio-legal analysis. In *Corruption, Greed and Crime Moneyin*; van Duyne, P.C., Harvey, J., Antonopoulos, G.A., Maljević, A., Markovska, A., Eds.; Wolf Legal Publishers: Oisterwijk, The Netherlands, 2014. [CrossRef]
60. Sergi, A. Conclusion: A Socio-behavioural Approach in Policing the Mafia–Organised Crime Spectrum. In *From Mafia to Organised Crime. Critical Criminological Perspectives*; Palgrave Macmillan: London, UK, 2017; ISBN 978-3-319-53567-8.
61. Bartlett, W.; Čučković, N.; Jurlin, K. A comparative perspective on institutional quality in countries at different stages of European integration. Tijdschrift Voor Economische En Sociale Geografie. *J. Econ. Soc. Geogr.* **2016**, *108*, 92–108.

62. Jaccard, J.; Wan, C.W.; Turrisi, R. The Detection and Interpretation of Interaction Effects Between Continuous Variables in Multiple Regression. *Multivar. Behav. Res.* **1990**, *25*, 467–478. [CrossRef] [PubMed]
63. Beck, N.; Katz, J.N. What to do (and not to do) with Times-Series Cross-Section Data in Comparative Politics. *Am. Political Sci. Rev.* **1995**, *89*, 634–647. [CrossRef]