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Innovation, income, and waste disposal operations in Korea: evidence from a spectral granger causality analysis and artificial neural networks experiments

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Abstract

The aim of this paper is to assess the causal relationship among innovation in environment-related technologies, per capita income, and three major waste disposal operations (landfill, recycling, and incineration) for Korea. A time-series analysis over the frequency domain (Breitung–Candelon Spectral Granger causality) is applied, followed by Artificial Neural Networks experiments over the 1985–2016 period. Empirical results highlight that economic growth is tightly linked both to the growth of recycled waste and to the increase of environment-related innovations. Findings also highlight that waste recycling operations can spur the level of economic activity.

Keywords Municipal solid waste · Waste recycling · Waste incineration · R&D · Artificial neural networks · Korea

JEL Classification C22 · C39 · Q50 · Q53

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Abbreviations

ANN	Artificisl neural networks
ARDL	Autoregressive distributed lag
CGE	Computable general equilibrium
CO_2	Carbon dioxide
DID	Difference-in-difference
DOLS	Dynamic ordinary least squares
EKC	Environmental Kuznets curve
EPR	Extended producer responsibility
EU	European Union
FE	Fixed effects
FMOLS	Fully modified ordinary least squares
GC	Granger causality
GDP	Gross domestic product
GFCF	Gross fixed capital formation
GHG	Greenhouse gas
GMM	Generalized method of moments
HDI	Human Development Index
IRF	Impulse response function
LCU	Local currency unit
ML	Machine learning
MSW	Municipal solid waste
MW	Municipal waste
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary least squares
PCA	Principal component analysis
R&D	Research and development
RE	Random effects
RFID	Radio frequency identification
SD	Sustainable development
STIRPAT	Stochastic impacts by regression on population, affluence, and technology
TY	Toda and Yamamoto
VECM	Vector error correction model
WDI	World development indicators
WEEE	Waste electrical and electronic equipment
WML	Waste Management Law

1 Introduction

Municipal solid waste (MSW) management is at the heart of a burning and global environmental concern (Cheng et al., 2020a, b). When not treated (i.e., abandoned or deposited in open dumps), MSW is directly released into soils and generates harmful and toxic substances (Wang et al., 2019; Yu et al., 2018). When treated (i.e., collected and deposited in waste treatment facilities), MSW produces

a critical amount of polluting emissions (notably methane gas), contributing thus to global warming (Clarke et al., 2019; Xu et al., 2020). Therefore, it is crucial to investigate the waste generation-income nexus (Cheng & Hu, 2010). Using the well-known Environmental Kuznets Curve (EKC) approach (Grossman & Krueger, 1991; Kuznets, 1955), evidence of a progressive de-linking process in some advanced economies has been early noted, while other countries continue to display a positive and linear correlation among these indicators (Cole et al., 1997; Johnstone & Labonne, 2004; Magazzino, 2017; Mazzanti, 2008; Mazzanti & Zoboli, 2005). In this paper, we believe that innovation is at the heart of this de-linking process as it may substantially affect waste disposal operations (landfill, recycling, and incineration), and, ultimately, MSW generation (Hurst et al., 2005).

Looking at the waste-income literature, one striking observation is that the Research and Development (R&D) determinant has attracted a weak interest so far. It is though surprising as promoting technology innovation in the waste sector is believed to draw important local effects, playing thus a leading role along the waste treatment chain (Gardiner & Hajek, 2020). Aldieri et al. (2019) also reported strong knowledge spillovers in the waste recycling and environmental innovations areas in Europe. Innovation can help lower waste externalities by developing waste-to-energy facilities, heat recovery, and incineration capacities (AlQattan et al., 2018; Pan et al., 2015). Nevertheless, technological innovations diversify the firms' supply of goods (and thus the generation of waste), while not allowing the improvement of products' life span (Chen et al., 2018; Gardiner & Hajek, 2020). Being of central importance in growth theory, R&D expenditures lead to direct market shares and export gains for firms, but also translate into more innovative products and larger amounts of waste for municipalities (Aw et al., 2011; Szarowská, 2017). Thus, the positive role of waste-related technologies remains to be confirmed (Gardiner & Hajek, 2020; Kuehr, 2007).

This study investigates the case of Korea for three main reasons. Above all, this country is peculiar concerning its path to waste sustainability. Despite critical levels of domestic consumption, it recorded serious improvements in waste management since per capita MSW generation decreased from 514.5 kg in 1985 to 384.9 kg in 2016. Similarly, partly due to the early establishment of the Waste Management Law (WML) in the 1980s, the total MSW generation declined by 36% in the 1990–2016 period. Second, the World Atlas ranked Korea as the leading Asian country for waste recycling (with 49% of waste recycled in 2019). Later followed by Singapore and Hong Kong, Korea early employed regulatory instruments to influence and modify households' and firms' behaviours towards sustainable usages. By enforcing several waste-related acts imposing a volume-based garbage rate system built on the concept of polluter payment, waste management has become more effective for both municipal and industrial waste (Yang et al., 2015). Third, in parallel to the adoption of public acts, the Korean government has strongly fostered national research in waste management-related technologies. With the 5th highest (total) patent application in the world in 2012, the international competitiveness of Korean

research seems well-established within high-tech sectors (Nam & An, 2017). This is reflected in the booming of patents in climate change mitigation technologies related to waste management and declared to the Patent Cooperation Treaty. Between 1990 and 2016, they encountered a significant rise from 22 to 946.

Accordingly, this paper displays a competitive edge from previous studies and brings four novelty aspects to the literature. To our knowledge, this is the first empirical assessment of the relationship between MSW and income in Korea. Second, while evidence on the role of R&D intensity on waste operations is limited, this paper fills this critical gap and focuses on the relationship among patents in climate change mitigation technologies, per capita income, and solid waste. Third, this paper contrasts with previous ones as it employs a series of finer waste data, namely MSW for disposal (landfill), recovery (recycling), and incineration operations (in thousand tonnes). Finally, it proposes an innovative empirical strategy able to depict non-linear relationships amongst variables.

All in all, our research objective is to conduct an in-depth analysis on the Korean case study. Using yearly data spanning the most available period (1985–2016), we examine the relationship among innovation in environment-related technologies, per capita income, and three major waste disposal operations (landfill, recycling, and incineration). Additional production factors (Gross Fixed Capital Formation, GFCF, and labour) and urbanization have been included in the empirical analysis. Following Magazzino et al. (2020a, b, c), this study applies two independent empirical strategies: a time-series analysis over the frequency domain (the Breitung–Candelon Spectral Granger, BCSG causality), coupled with Machine Learning (ML) experiments (Artificial Neural Networks, ANNs).

Besides this Sect. 1, the remainder of the paper is organized as follows. Section 2 presents the literature. Section 3 describes the data, the econometric framework, and the ANNs model. Section 4 shows the empirical results. Section 5 provides a discussion on the results. Finally, Sect. 6 gives concluding remarks and policy recommendations.

2 Literature survey

This section first presents a concise review of the relevant literature on this topic (Sect. 2.1). Then, the role of other socio-economic factors (innovation, production factors, and urbanization) is discussed (Sect. 2.2).

2.1 The waste-income nexus

Some early studies explored the determinants of MSW generation, underlining the key role played by income in MSW generation (Johnstone & Labonne, 2004; Namlis and Komilis, 2019). Another strand of the literature employed the EKC framework

Table 1 Summary of previous panel assessments on the relationship between income and waste

Author(s)	Countries	Sample period	Methodology	Waste/GDP data	EKC
Cole et al. (1997)	13 OECD countries	1975–1990	Panel estimation model	Municipal solid waste generation/GDP per capita,	No
Johnstone and Labonne (2004)	30 OECD countries	1980–2000	Panel estimation model	Municipal solid waste generation per capita/GDP per capita	–
Mazzanti and Zoboli (2005)	18 EU countries	1995–2000	Panel estimation model	Municipal solid waste generation per capita/GDP per capita	No
Mazzanti (2008)	15 EU countries/28 EU countries	1997–2001/1995–2000	Panel estimation model	Waste generation per capita/GDP per capita	No/no
Mazzanti and Zoboli (2008)	25 EU countries	1995–2005	Panel estimation model	Municipal solid waste generation per capita/final consumption expenditure of households	No
Arbulú et al. (2015)	16 EU countries	1997–2010	Panel estimation model	Municipal solid waste generation per capita/GDP per capita	Yes
Namlis and Komilis (2019)	10 EU countries	2008–2015	PCA, OLS	Generation rates of thirteen solid waste streams/GDP/Human Development Index/Unemployment Rate/CO_2 emissions	–
Baalbaki and Marrouch (2020)	33 OECD countries	1995–2012	Panel estimation model	Municipal solid waste generation per capita/GDP per capita	No
Yılmaz (2020)	16 OECD countries	2002–2017	GMM	Municipal solid waste generation/consumption expenditure	Yes (for 8 OECD countries only)

Source: our elaborations

"–" indicates that testing the EKC hypothesis was not the explicit aim of the paper

GMM General Method of Moments, *OLS* Ordinary Least Squares, *PCA* principal component analysis

to confirm the existence of a turning point between income and waste (Arbulú et al., 2015; Yilmaz, 2020), while other studies did not (Baalbaki & Marrouch, 2020; Cole et al., 1997; Mazzanti, 2008; Mazzanti & Zoboli, 2005, 2008). Table 1 outlines the main information of this empirical literature.

Other studies conducted single-country analyses. Using various empirical strategies, the authors provided interesting results with direct country-specific implications. In general, these studies found strong inter-relations among waste generation and income, although causality directions often differ. Table 2 summarizes the main information on this literature. Nonetheless, one striking observation emerges: the Korean case has not been the subject of any empirical waste investigation so far.

2.2 The nexus of waste with innovation and other socio-economic variables

In addition to income, the potential role of other socio-economic determinants has been empirically examined in several studies.[1] Above all, Alam et al. (2011) underlined that an increase in production function indicators is positively associated with consumption and industrial output. Subsequently, Namlis and Komilis (2019) showed that the unemployment rate is positively associated with MW generation. With data analyses conducted at various levels (panel, country, and cantonal), further evidence has been conducted, concerning the positive effect of urbanization on waste generation. Prades et al. (2015) observed that larger and more densely populated cities have higher waste generation rates in Spain. Similarly, Chen (2018) attributed the differences in the composition of MSW to urbanization differences in Taiwan. At a local scale, Jaligot and Chenal (2018) stated that urbanization is slightly negatively associated with MSW generation in the canton of Vaud (Switzerland). However, the underlying channels linking waste and co-factors are mostly unknown as the related empirical literature is sporadic. In line with Lee et al. (2016) recommendations, these variables should be considered as potential MSW drivers and added to estimation models.

Environmental economists now emphasize the need for maximizing the usage of consumption products and efficiently exploit their intrinsic values through recycling and composting. In theory, innovation should play a vital role along the process of waste treatment, starting by reusing their resource content. In practice, however, empirical research did not achieve a general consensus so far. On the one hand, it has been shown that environmental issues (and notably the land degradation caused by untreated waste) may be solved through climate change mitigation technologies (Dechezleprêtre et al., 2011; Gu et al., 2019; Norberg-Bohm, 1999). Innovation can help lower waste externalities by developing waste-to-energy facilities, heat recovery, and incineration capacities (AlQattan et al., 2018; Pan et al., 2015). Furthermore, research for more efficient recycling processes can maximize the value of the products (Daniels, 1999), with direct implications for circular models'

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[1] For instance, MSW generation has been found to be driven by waste management policy, population growth, education level as well as the nature of the consumption patterns in Albania and China (Grazhdani, 2016; Liu et al., 2019).

Table 2 Summary of previous single-country assessments on the relationship between income and waste

Author(s)	Countries	Sample period	Methodology	Results
Mazzanti et al. (2008)	Italian provinces	1995–2005	Panel estimation model	↑GDP→↓MW (EKC)
Sjöström and Östblom (2010)	Sweden	2006	CGE model	GDP→MW
Alajmi (2016)	Saudi Arabia	1980–2012	Panel estimation model	↑GDP→↓MW (EKC)
Lee et al. (2016)	US	1990–2012	GC	GDP⇔MW
Ercolano et al. (2018)	Italian municipalities	2005–2011	Panel estimation model	U-shaped link between GDP and MW
Gui et al. (2019)	China	2006–2015	Panel estimation model	↑GDP↔↑MW
Cheng et al. (2020a, b)	China	2003–2016	STIRPAT model with DID method	↑GDP→↑MW
Magazzino et al. (2020a)	Switzerland	1990–2017	GC, TY, ANNs	GDP↔MW (EKC)
Magazzino et al. (2020b)	Denmark	1994–2017	BCSG, ANNs	GDP→MW
Mazzarano et al. (2020)	Italian provinces	2001–2016	Spatial econometrics tests	GDP→MW
Agovino et al. (2021)	Italian regions	2001–2018	Panel estimation model	Three-speed country in terms of SWC

Source: our elaborations

GDP Gross Domestic Product, *MW* Municipal Waste, *CGE* Computable General Equilibrium, *GC* Granger Causality, *STIRPAT model* Stochastic Impact by Regression on Population, Affluence, and Technology, *DID* Difference-in-Difference, *TY* Toda-Yamamoto, *ANNs* Artificial Neural Networks, *BCSG* Breitung—Candelon Spectral Granger, *SWC* Separate Waste Collection

↑GDP→↓MW indicates that GDP has a negative and significant effect on municipal waste generation. GDP→MW indicates the existence of unidirectional causality from GDP to municipal waste generation. GDP⇔MW indicates no causality between GDP and municipal waste generation. ↑GDP↔↑MW indicates a bidirectional causality between GDP and municipal waste generation. ↑GDP→↑MW indicates that GDP has a negative and significant effect on municipal waste generation, and vice versa. GDP↔MW means that the related study confirmed the EKC curve among income and municipal waste generation

implementations (D'Adamo et al., 2019; Das et al., 2019; Malinauskaite et al., 2017). On the other hand, technological innovations have enriched and diversified the firms' supply, while not allowing the improvement of products' life span, and thus inducing more waste (electronical and electrical notably) (Chen et al., 2018). Although the effect of R&D on the decoupling growth-CO_2 emissions phenomenon has been demonstrated (Li & Jiang, 2020; Wang & Wang, 2019; Wang and Zhang, 2020), empirical evidence showing the positive effect of innovation on the waste-income nexus is scarce. To the best of our knowledge, the seminal contribution from Gardiner and Hajek (2020) is the only existing study that deals with that issue. The authors collected data on 284 European regions from 2000 to 2018 and assessed the causal relationship among R&D intensity, income, and MSW generation; heating energy, capital, labour, and urbanization are also included. Panel VECM and Granger causality results claimed evidence of a bidirectional causality among MSW generation and R&D intensity as well as between MSW and income. Moreover, they also considered MW landfilled and MW incinerated, and found that GDP positively drives the amount of waste incinerated, although the landfilling of waste displays a negative relationship with income.

3 Data and empirical strategy

3.1 Data collection

To implement our causality model, we derived the following data for Korea: environmental innovation, per capita GDP, municipal waste for recovery operations (recycling), municipal waste for disposal operations (landfill), municipal waste for incineration, capital, labour force, and urbanization. Environmental innovation is proxied by the number of patents in environment-related technologies (climate change mitigation technologies related to waste management) and collected by the OECD Environment Statistics.[2] Per capita GDP is expressed in constant Local Currency Unit (LCU) and taken from the World Development Indicators database.[3] Data on municipal waste for recovery operations (recycling), municipal waste for disposal operations (landfill), municipal waste for incineration are all expressed in thousand tonnes and are derived from the OECD Environment Statistics. As a proxy for urbanization, we use the urban population, expressed in percentage (%) of the total population. Similarly, capital is proxied by the GFCF and expressed in constant LCU. Employment is expressed in total numbers of employed persons, as in Sari and Soytas (2004), Shahbaz et al. (2013), Younes et al. (2015), Gardiner and Hajek (2017). All these three latter variables are taken from the World Development Indicators database. The data cover the period 1985–2016. Table 6 in Appendix summarizes the data information.[4]

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[2] Patents and municipal waste operations data are available at: https://data.oecd.org/environment.htm.

[3] Data on per capita GDP, GFCF, labour and urban population are available at: https://databank.world bank.org/source/world-development-indicators.

[4] The dataset is available upon request.

3.2 Econometric framework

To assess the inter-relationships among innovation in environment-related technologies, per capita income, and major waste disposal operations (landfill, recycling, and incineration) in Korea, we apply the BCSG causality test. This procedure brings causality inferences in a frequency domain, which is crucial for the design of policy recommendations.

If the predictability of a time series X_t can be improved by including a second-time series Y_t, it can be stated that the latter one has a causal effect on the first one (Wiener, 1956). Later, Granger (1969, 1988) modelled this idea of causality and incorporated it within linear regression models. It consists in estimating a bivariate linear model, selecting the optimal lag length, and examining the significance of the lags of the exogenous variable. This reasoning can be extended to a multivariate setting. Consider a standard bivariate Vector Auto-Regressive (VAR) model with two time-series Y_t and X_t; the theoretical framework of the Granger causality test can be expressed as follows:

$$\Delta Y_t = \alpha_{12} + \sum_{i=1}^{T_{11}} \beta_{11i} \Delta Y_{t-i} + \sum_{j=1}^{T_{12}} \beta_{12j} \Delta X_{t-j} + \mu_{12t} \tag{1}$$

$$\Delta X_t = \alpha_{22} + \sum_{i=1}^{T_{21}} \beta_{21i} \Delta X_{t-i} + \sum_{j=1}^{T_{22}} \beta_{22j} \Delta Y_{t-j} + \mu_{22t} \tag{2}$$

where Δ represents the first difference operator, T is the lag order, α and β are parameters for estimation, and μ_t a white noise error process. To determine the direction of the causality, the Granger-causality test is applied on the group of β_{12j} coefficients in Eq. (1), with $j = 1, 2, \ldots q$. It tests whether they are jointly significant or not, which is equivalent to examining whether $\beta_{121} = \beta_{122} = \cdots = \beta_{12q} = 0$, then X does not Granger cause Y. While, if the opposite is true and at least one of the β_{12j} coefficients is not equal to 0, then the past value of X has a significant predictive power on the current value of Y. In this case, X can be said to Granger cause Y. This reasoning is subsequently repeated in Eq. (2) to test for the feedback causality among variables. However, the Granger causality test displays several drawbacks. Upon them, it ignores the possibility that the existence and the direction of the causality may vary across frequencies (Lemmens et al., 2008). In addition, this test may become misleading if data are non-stationary. In response, researchers should rely on first difference-level series, causing a non-negligible loss of information (Bozoklu & Yilanci, 2013).

For the above-mentioned reasons, this paper applies the Granger causality test in the frequency domain as introduced in Breitung and Candelon (2006). This procedure displays a competitive edge with respect to the traditional Granger causality test as it provides statistical predictions of causal impacts over a wide range of different frequencies. To control for heteroskedasticity, series are transformed in their logarithmic levels. Following Breitung and Candelon (2006), and Magazzino et al. (2020b), the generic log-linear specification is presented in a Vector

Auto-Regressive (VAR) equation. The predictive power of X_t can be computed by comparing the predictive component of the spectrum with the intrinsic component at each frequency. In line with Geweke (1982), the measure of causality can then be defined as:

$$M_{X \to Y}(\omega) = \log \left[1 + \frac{\left| \psi_{12}\left(e^{-i\omega}\right)\right|^2}{\left| \psi_{11}\left(e^{-i\omega}\right)\right|^2} \right] \tag{3}$$

which equals 0 if the condition $|\psi_{12}(e^{-i\omega})|^2 = 0$ holds. Thus, the null hypothesis is based on a bivariate framework technique, $[M_{X \to Y}(\omega) = 0]$, that Y_t does not predict X_t at a specific frequency ω. Thus, a rejection of this null hypothesis at P-value < 0.05 underlines that Y_t predicts X_t in the frequency domain. Finally, we refer to the Variable Importance of Projection (VIP):

$$VIP_W = \sqrt{N \sum_{w=1}^{u} \frac{S_v \frac{Z_{vw}}{Z_{vw}^2}}{\sum_{v=1}^{u} S_v}} \tag{4}$$

where N is the number of independent variables, u is the number of dimensions extracted using Partial Least Squares (PLS) algorithm, Z_{vw} represents the weight of the VIP of input variable w and the number of dimensions v explained by PLS algorithm, and S_v denotes the Explained Sum of Squares (ESS). Accordingly, the VIP_w algorithm is thought to be consistent in explaining the influence of innovation in environment-related technologies and per capita income on the efficiency of waste disposal operations in Korea.

Finally, the optimal lag-order for the frequency domain causality test is selected according to the information reported by the pre-estimation syntax for VAR models [namely, the Akaike Information Criterion (AIC), the Final Prediction Error (FPE), the Hannan and Quinn Information Criterion (HQIC), and the Schwarz Bayesian Information Criterion (SBIC)]. The resulting optimal lag selected for subsequent analysis is 3.[5]

3.3 Theoretical ANNs framework

After applying the BCSG causality test, we employ the ANNs algorithm to observe how innovation in environment-related technologies determines per capita income and accelerates the neural signal with major waste disposal operations. ANNs are mathematical/computer models of computation inspired by biological NNs' functioning mechanisms. This model consists of interconnections between computing nodes (artificial neurons) and processes that use a connectionist approach. ANNs are also adaptive systems capable of modifying their structure according to the information used to "feed" them during a defined learning phase. In practical terms, NNs are non-linear structures of statistical data organized as modeling tools. They can

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[5] The complete lag-length tests results are available upon request.

Fig. 1 A simple NN scheme.
Source: our elaborations in YeD
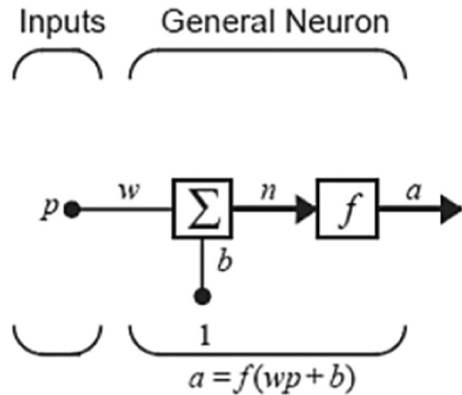
be used to simulate complex relationships between inputs and outputs that other analytical functions cannot represent, and offer effective applications in complex situations such as classification problems or non-linear regression problems. ANNs receive external signals on a layer of input nodes (processing units), each of which is connected with an intermediate layer of internal nodes, possibly even organized on several levels. Each node processes the incoming signals received and transmits the result to the nodes of the next layer (Magazzino & Mele, 2021; Magazzino et al., 2021a, b, c, d, e; Mele & Magazzino, 2020; Mele et al., 2021a, b). The fundamental element is the neuron: it is nothing more than a mathematical model that receives inputs and, through an appropriate calculation process, generates an output (Fig. 1).

The (scalar) input p is multiplied by the weight w (also scalar) to form wp. This term is added with a bias b to produce the scalar n (net input). At this point, n passes through a transfer function f, which produces the output a. Comparing the artificial neuron to the biological one, it can be stated that the weight w represents the strength of a synaptic connection, the sum point together with the transfer function is the real body neuronal, whilst the output represents the signal transmitted on the biological axon. Therefore, the output depends on the transfer function f chosen: it can be linear or nonlinear. The choice is made based on the type of problem. However, the most used transfer functions are:

1. Step transfer function. The net output a is calculated as: $\{a = 0 \text{ if } n < 0 \; a = 1 \text{ if } n \geq 0$.
2. Linear transfer function. The net output a is calculated as: $a = n$.
3. Log-sigmoidal transfer function. The net output a can then be calculated as: $a = \frac{1}{1+e^{-n}}$.

Typically, a neuron has more than one input: we speak of a neuron with multiple inputs. In this case, the net input n is calculated as a weighted sum of the inputs:

$$n = w_{1,1}p_1 + w_{1,2}p_2 + \cdots + w_{1,r}p_r + b \qquad (5)$$

Fig. 2 Neuron with multiple inputs. Source: our elaborations in YeD

Inputs Layer of S Neurons
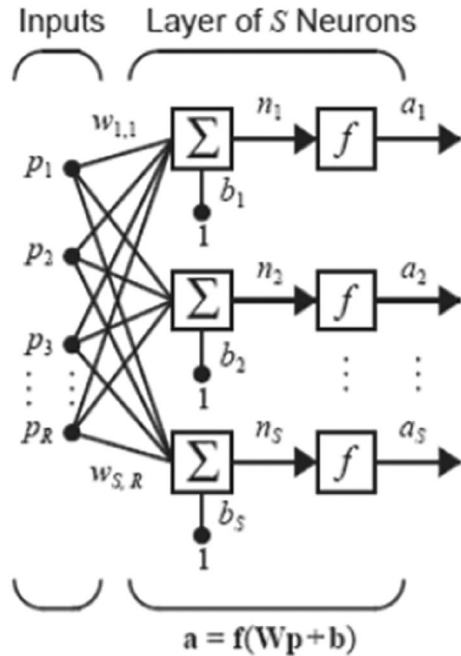
$$a = f(Wp + b)$$

which becomes in matrix form: $n = Wp + b$, where the weight matrix W has only one row in the case of a single NN. The net output then results:

$$a = f(Wp + b) \tag{6}$$

In most cases, a single neuron is not enough to achieve the desired goal. Therefore, we use several neurons operating in parallel, so we can speak of a layer of neurons. Figure 2 shows the scheme of a network with a layer of S neurons. Each of the R inputs is connected to each neuron: the weight matrix W is made up of S rows and R columns.

The layer includes the weight matrix W, the sum points, the bias vector b, and the neurons' transfer functions. Therefore, in this case, the output vector is: $a = f(Wp + b)$.

Now, we construct and analyze multivariate NN results with an input greater than 1. We use the data of the previous empirical analysis augmented by the mathematical transforms. In particular, we generate the logarithm of each variable (ln), the square (s), the first difference (d), and the first logarithmic difference ($ln.d$). This procedure is essential for the machine to operate in a broad context of data where the NN is suitable for studying the relationship between input and target. After expanding the Oryx algorithm with the Keras protocol, we follow the flow chart in Fig. 3, respecting the matrix (7).

$$W = \left[w_{1,1} w_{1,2} \ldots w_{1,r} w_{2,1} w_{2,2} \ldots w_{2,r} \vdots \ddots \vdots \ w_{s,1} w_{s,2} \ldots w_{s,r}\right];$$
$$p = \left[p_1 p_2 \vdots p_r\right]; b = \left[b_1 b_2 \vdots b_s\right]; f = \left[f_1 f_2 \vdots f_s\right]; a = \left[a_1 a_2 \vdots a_s\right] \tag{7}$$
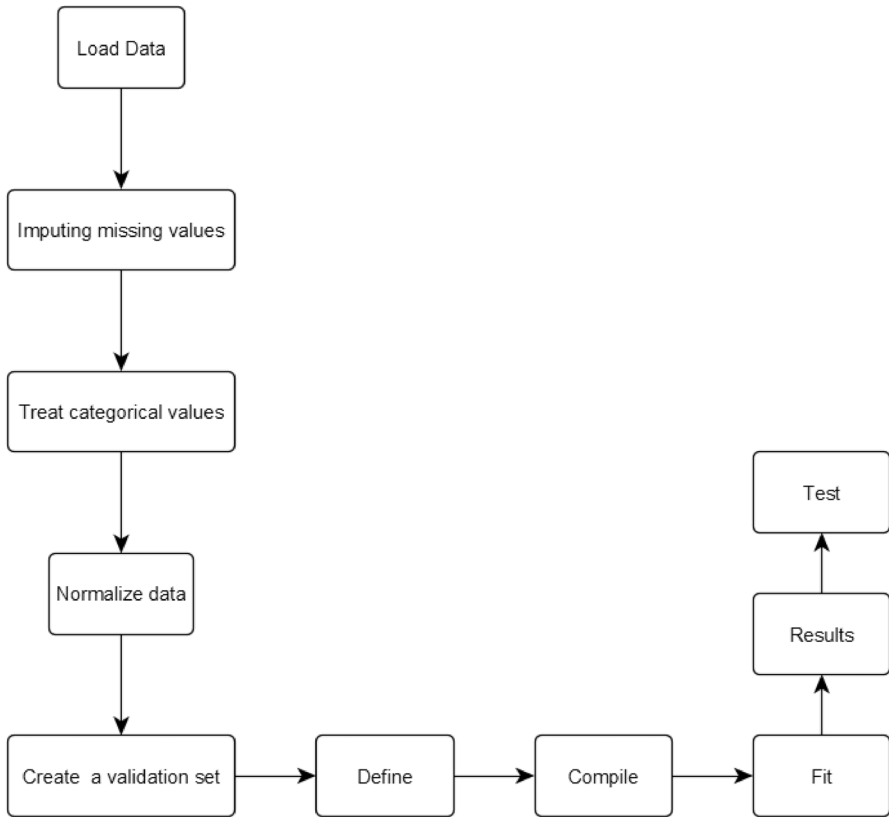
Fig. 3 ANNs flow chart. Source: our elaborations in Yed

4 Empirical results

4.1 Time-series results

As a preliminary check, descriptive statistics are provided in Appendix (Table 7). We notice that all variables have a negative value of skewness, which indicates that the tail on the left side of the distribution is longer or wider.

In Table 3, we report the results of two different time-series tests on the unit root to determine the order of integration of the variables. It clearly emerges that the selected series are non-stationary at levels. Indeed, the null hypothesis (H_0) of non-stationarity is generally rejected at a 5% significance level.

In Fig. 4 the main results of the BCSG test are reported. Relationships among indicators are assessed over the time–frequency domain, and for each type of waste disposal operation (landfill, recycling, or incineration). They reveal that the null hypothesis of no predictability from innovation in environment-related technologies to each municipal waste recycling operation is not rejected at a

Table 3 Results for unit roots and stationarity tests

Variable	Unit root and stationarity tests			
	NP Intercept	NP Intercept and trend	KPSS Intercept	KPSS Intercept and trend
RPCGDP	0.5602 (−1.9800)	−0.3143 (−2.9100)	0.7405*** (0.4630)	0.1990** (0.1460)
GFCF	0.9799 (−1.9800)	−0.8056 (−2.9100)	0.6955** (0.4630)	0.1716** (0.1460)
EMP	2.0971 (−1.9800)	−1.4647 (−2.9100)	0.7825*** (0.4630)	0.1431* (0.1460)
TD	−0.3228 (−1.9800)	−1.4726 (−2.9100)	0.7051** (0.4630)	0.1760** (0.1460)
UP	0.7035 (−1.9800)	−0.9367 (−2.9100)	0.6380** (0.4630)	0.1884** (0.1460)
RMW	−0.0708 (−1.9800)	−4.0222*** (−1.9800)	0.6595** (0.4630)	0.1940** (0.1460)
LMW	−0.2200 (−1.9800)	−1.1986 (−1.9800)	0.6082** (2.9700)	0.0857 (0.1460)
IMW	−0.5648 (−1.9800)	−1.4747 (−1.9800)	0.5923** (0.4630)	0.0998** (0.1460)

NP Ng-Perron Modified test, *KPSS* Kwiatkowsk–Phillips–Schmidt–Shin test. When it is required, the lag length is chosen according to the Schwarz Bayesian Information Criterion (SBIC). For NP tests *MZt* statistics are reported; for KPSS tests *LM* statistics are reported. 5% Critical Values are given in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

5% significance level. Thus, this indicates that no causality among indicators emerges, at least in this direction. In contrast, a strong unidirectional causality from per capita GDP to waste landfills and incineration emerges. However, while the former turns insignificant when $\omega > 0.6$, the latter becomes insignificant when $\omega \in [0.7, 3.0]$ frequency range. This contrasts with the indicator of waste recycling operations that shares no significant linkage with income. Finally, the urban population is found to significantly drive waste landfills and incineration operations, but not along with the entire frequency range (i.e., signals become inconsistent when $\omega \in [0.6, 3.0]$ and $\omega \in [0.3, 3.0]$, respectively).

Inversely, recycling waste operations are found to significantly drive innovation in environment-related technologies, while no robust inferences are depicted among the other municipal waste operations (i.e., landfill and incineration) and innovation. Also, no feedback channel from the three waste disposal operations (i.e., recycling, landfill, and incineration) to per capita income can be detected. A significant causal linkage is found between GFCF and waste landfills, as well as between GFCF and incinerating operations. Finally, a significant causality emerges from recycling municipal waste operations to employment and urban population. This linkage is, however, not supported with other waste treatment operations (i.e., landfills and incinerations). Related graphs are all provided in Appendix (Fig. 9).
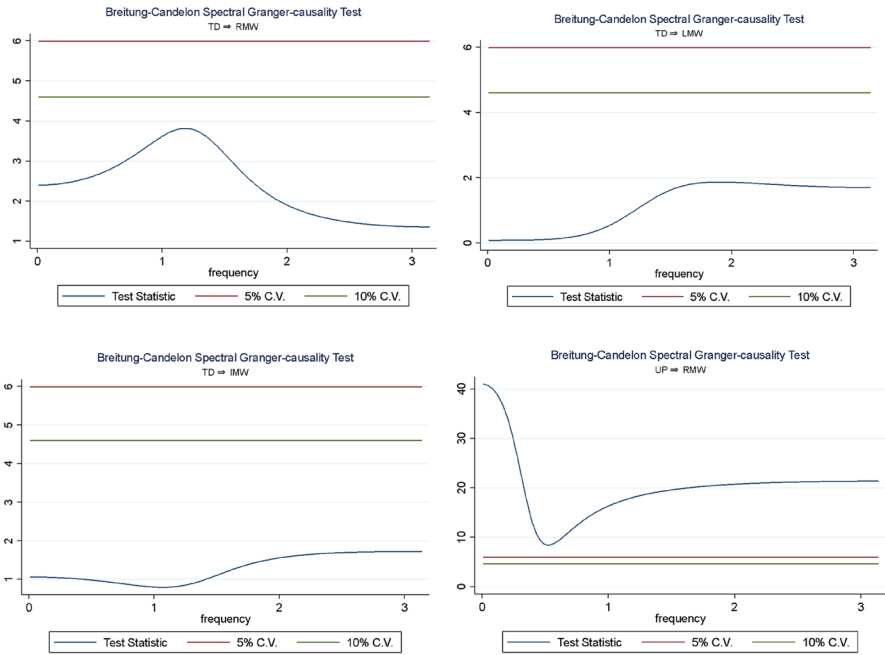
Fig. 4 Breitung–Candelon Spectral Granger-causality test results. Notes: Confidence level on *y* axis. Geweke-type conditioning used. The following relationships are empirically tested: lnTD→lnRMW: innovation in environment-related technologies→recycling waste operations. lnTD→lnLMW: innovation in environment-related technologies→waste landfilling. lnTD→IMW: innovation in environment-related technologies→waste incinerating operations. lnRPCGDP→lnRMW: per capita GDP→recycling waste operations. lnRPCGDP→lnLMW: per capita GDP→waste landfilling. lnRPCGDP→lnIMW: per capita GDP→waste incinerating operations. lnUP→lnRMW: urban population→recycling waste operations. lnUP→lnLMW: urban population→waste landfilling. lnUP→lnIMW: urban population→waste incinerating operations

4.2 ANNs results

The time-series analysis was complemented by an ANNs algorithm. In this section, we test the previous results through an experiment in ML with the use of ANNs. We use the same dataset, implementing an automatic learning algorithm developed in the Oryx 2.0.8 protocol. Table 4 shows the construction of the ANNs. It comes with a big dataset. In fact, we construct a NN characterized by 36 inputs (*GFCF*, *TD*, *RMW*, *LMW*, *IMW*, and their mathematical transformations) and three targets, which represent the variables, in terms of variation (first differences), found to be significant in the theoretical literature (*dRPCGDP*, *dEMP*, *dUP*). In total, we have a combination of 513,000 data processing. The constructed NN entirely respects the principle of a Machine Deep Learning (MDL) model capable of processing automatic information without supervision even in the face of enormous datasets.

The total number of instances is 272. The number of training instances is 164 (60.30%), the number of selection instances is 54 (19.85%), the number of testing
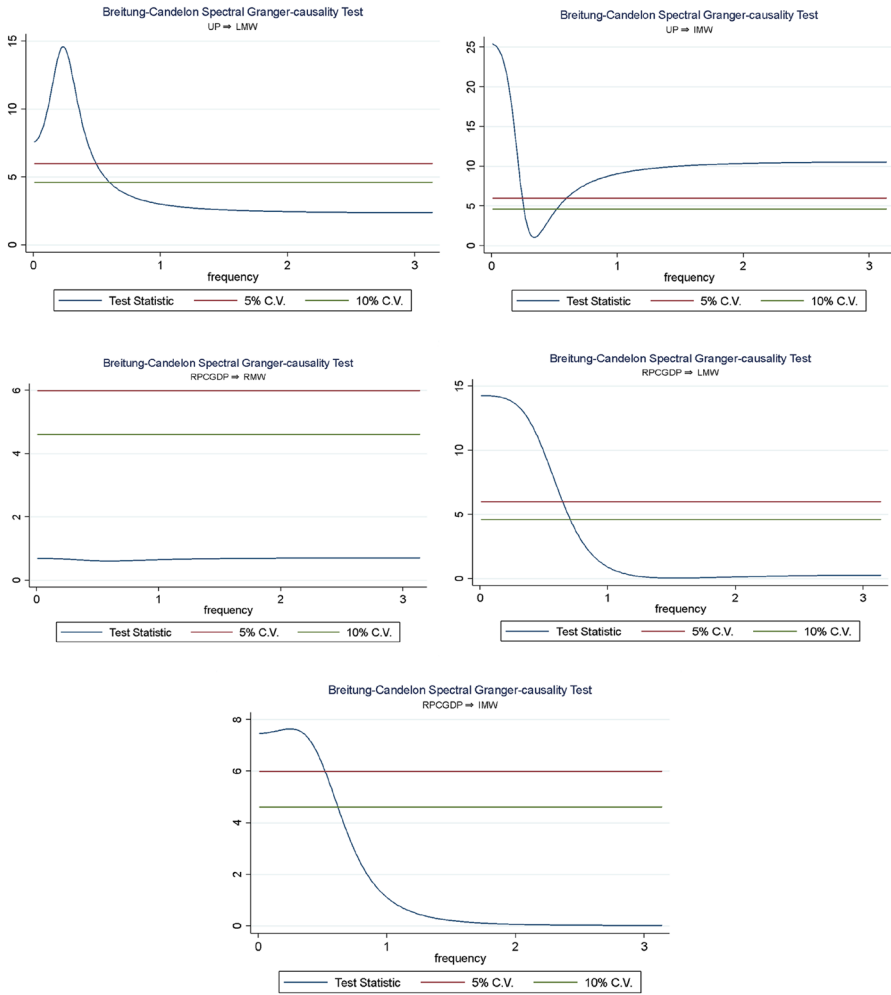
Breitung-Candelon Spectral Granger-causality Test
UP ⇒ LMW

Breitung-Candelon Spectral Granger-causality Test
UP ⇒ IMW

Breitung-Candelon Spectral Granger-causality Test
RPCGDP ⇒ RMW

Breitung-Candelon Spectral Granger-causality Test
RPCGDP ⇒ LMW

Breitung-Candelon Spectral Granger-causality Test
RPCGDP ⇒ IMW

Fig. 4 (continued)

Table 4 ANNs report with perceptron layers		Inputs number	Perceptrons number	Activation function
	1	36	19	Hyperbolic Tangent
	2	19	15	Hyperbolic Tangent
	3	15	10	Hyperbolic Tangent
	4	10	5	Hyperbolic Tangent
	5	5	3	Linear

Source: our elaborations

Fig. 5 Instances pie chart.
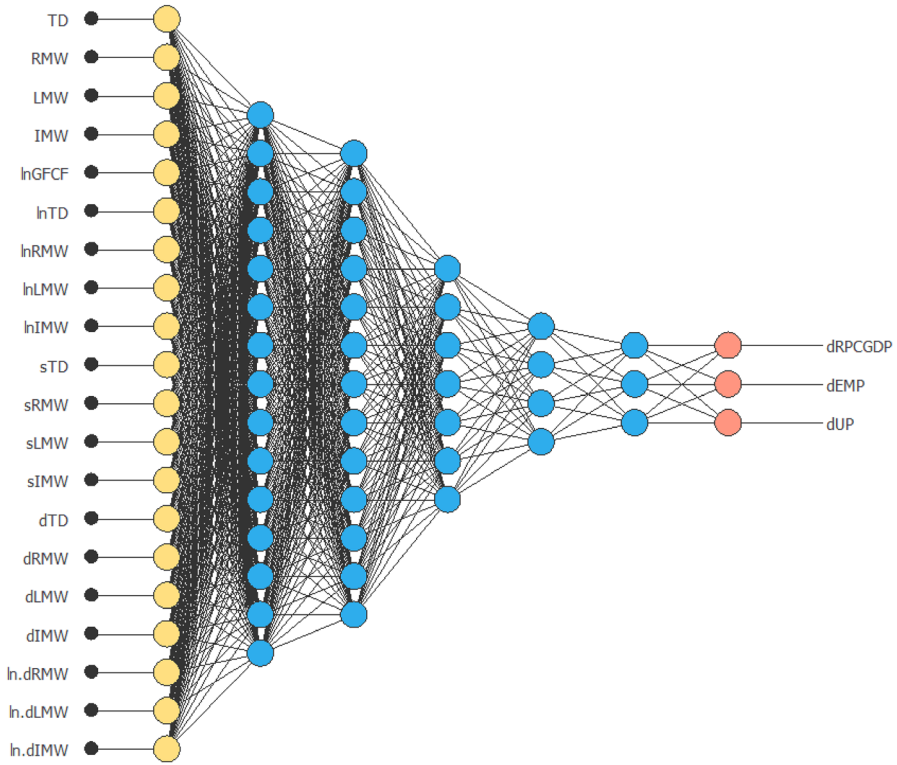Source: our elaborations in Oryx
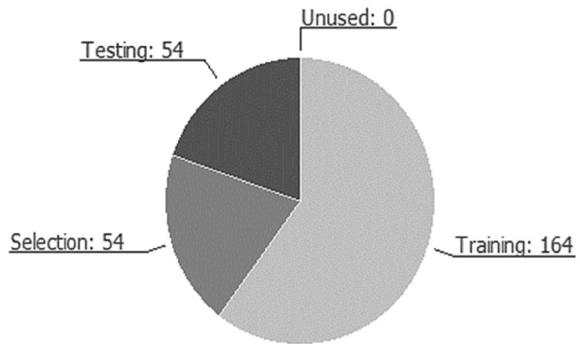
instances is 54 (19.85%), and the number of unused instances is 0 (0%). These results can be explained as follows: the training instances have designed the best process for the neural algorithm (Fig. 5).

It has a design accepted 60 times out of 100, and its value is higher than a different algorithm (selection instance), and the same value as the testing instance. Thus, the algorithm suggests the construction of the first phase of NNs. Finally, after observing the behaviour of the data concerning the processing in ML, we can analyze the results of the ANNs using the Perform Input Selection process (Fig. 6). We exploit this ML process in a big dataset where inputs can be redundant, and it affects the error of the NN. The input selection is used to find the optimal subset of inputs for the best model error.

The ANNs graph contains a scaling layer, a NN, and an unscaling layer. The yellow circles represent the scaling neurons, the blue ones the perceptron neurons, and the red circles the unscaling neurons. The number of inputs is 20, with 3 outputs. The complexity, represented by the numbers of hidden neurons, is 15:13:7:4:3. As we can see, the pre-set targets are *dRPCGDP*, *dEMP*, and *dUP*. They represent the best choice compared to 513,000 possible combinations of inputs, to generate the targets necessary for the analysis. To check for errors in the prediction process, we test our model through two different tools: the Conjugate gradient errors history and the Quasi-Newton method (Fig. 7).

Both methodologies adopt the belief that the best training strategy is one that allows the best possible loss of information as interactions or epochs grow. On the left-hand side of the figure, the Conjugate gradient is used for training. In this algorithm, the search is performed along with conjugate directions, which produces generally faster convergence than gradient descent directions. The initial value of the training error (orange line) is 16.2014, and the final value after 131 ITE is 0.097542. The initial value of the selection error (blue line) is 0.398717, and the final value after 131 ITE is 0.027509. The analysis of this test confirms how in our prediction the error decreases as the ITE increases, and this result confirms the goodness of our model. The Quasi-Newton test is based on Newton's method, although it does not require the calculation of second derivatives. Instead, the Quasi-Newton method computes an approximation of the inverse Hessian at each iteration of the algorithm, by only using the gradient information. The blue line represents the training error,

Fig. 6 ANNs graph. Source: our elaborations in Oryx
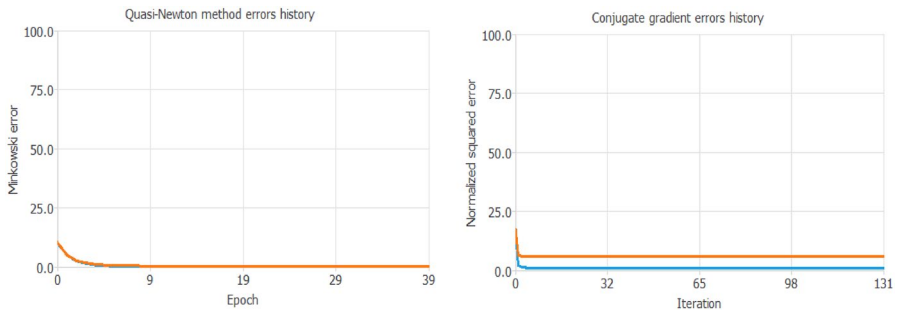
Fig. 7 Training process test.
Source: our elaborations in Oryx

and the orange line represents the selection error. The initial value of the training error is 0.120684, and the final value after 39 epochs is 0.031882. The initial value of the selection error is 0.15105, and the final value after 39 epochs is 0.030064. Again, this analysis, confirming the previous one, highlights how the whole selection and training process of our NN presents an (almost) cancellation of errors as the

Table 5 ANNs error tests

Measure	Training	Selection	Testing
Sum Squared Error	8.84325e−19	1.77222e−20	2.6506e−20
Mean Squared Error	5.39223e−17	3.28189e−18	4.90852e−18
Root Mean Squared Error	7.34318e−08	1.8116e−09	2.21552e−09
Minkowski Error	1.59822	2.02594e−15	3.43449e−15

Source: our elaborations

eras increase. Finally, we proceed with the ANNs error test, which is or is not able to confirm the goodness of this algorithm. It analyzes the result of four different errors concerning the three main instances of the NN model (Table 5).

Four possible scenarios of prediction errors concerning training, selection, and testing can be evaluated (Table 5). For NN theory, values from training to testing should be gradually lower and lower than unity. The results obtained fully confirm the theory of this test. All the errors of the three main components of the NN are less than 1. It is clear how the training errors are lower than the selection errors, which are lower than the testing errors. This test confirms how the latest architecture of the NN respects the hypothesis of the slightest prediction error and that our generated target is correctly affected by the influence of the numerous combinations between the inputs. Now, in order to be able to understand how much the input signal can predictively influence the targets, we will operate through the implementation of our algorithm. According to Magazzino et al. (2020a), we use the so-called "shear effect". In other words, the machine—without supervision—identifies the precise value that generates the effect of each target among the thousands of combinations of neural signals. This empirical methodology, derived from Artificial Intelligence, can assess the nature and the direction of the relationships that operate among multiple variables, and independently from the econometric procedure conducted before (Fig. 8). In doing so, one is then able to confirm and extend the econometric findings and bring more robust causality evidence between innovation in environment-related technologies, per capita income, and three major waste disposal operations for Korea.

The results obtained are surprising and original. First of all, we note that the algorithm's implementation has automatically eliminated the target *dUP*, since this variable has not stored the output signal correctly (MSE 21.49). On the contrary, the remaining targets partially confirm the previous time-series results. However, the NN's computational power enriched the study with precise numerical values regarding the influence of each input on the targets. We note that consistently with the growth theory, *GFCF* generates a positive predictive variation both in economic growth (*RPCGDP* = 2.1%) and in employment (*EMP* = 0.038%). We find the same result relative to the *TD* input. The results of the waste variables are fascinating. The *RMW*, *LMW*, and *IMW* inputs generate a predictive signal on the economic growth of about 1.85% and 0.03% employment. The figures give us further information. Except for the *IMW* variable, relating to the municipal waste for recycling and
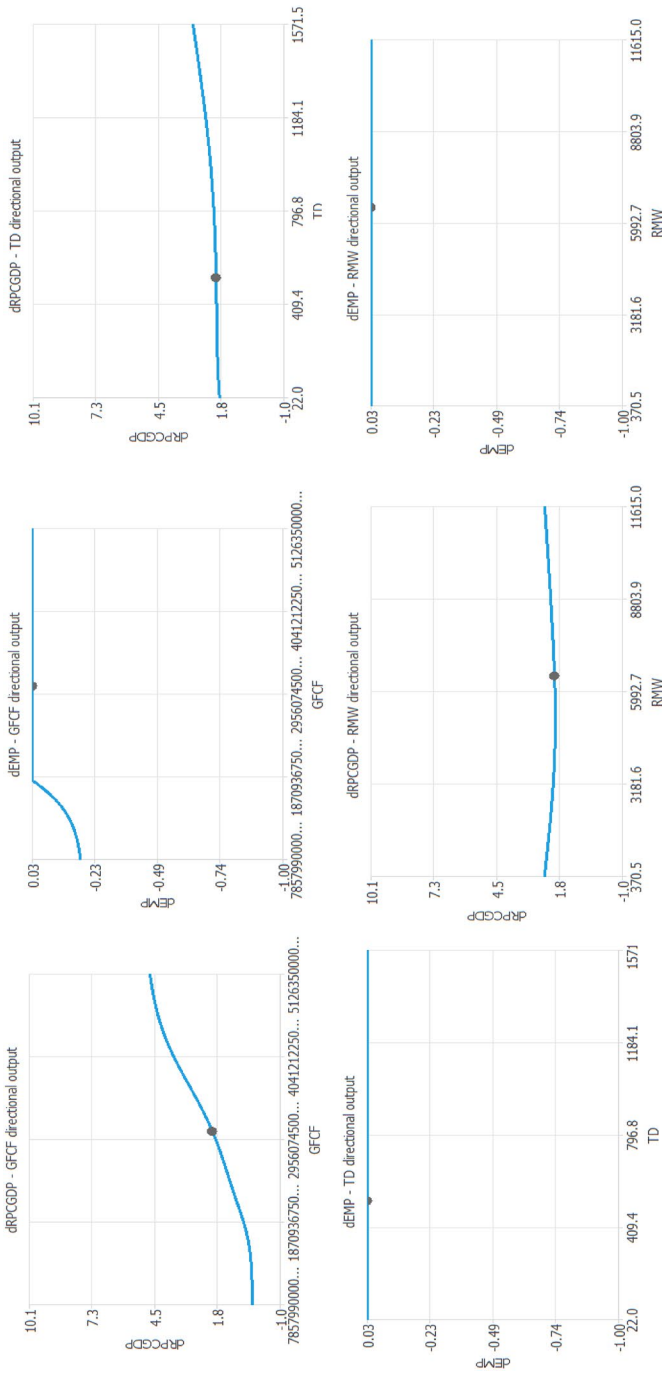
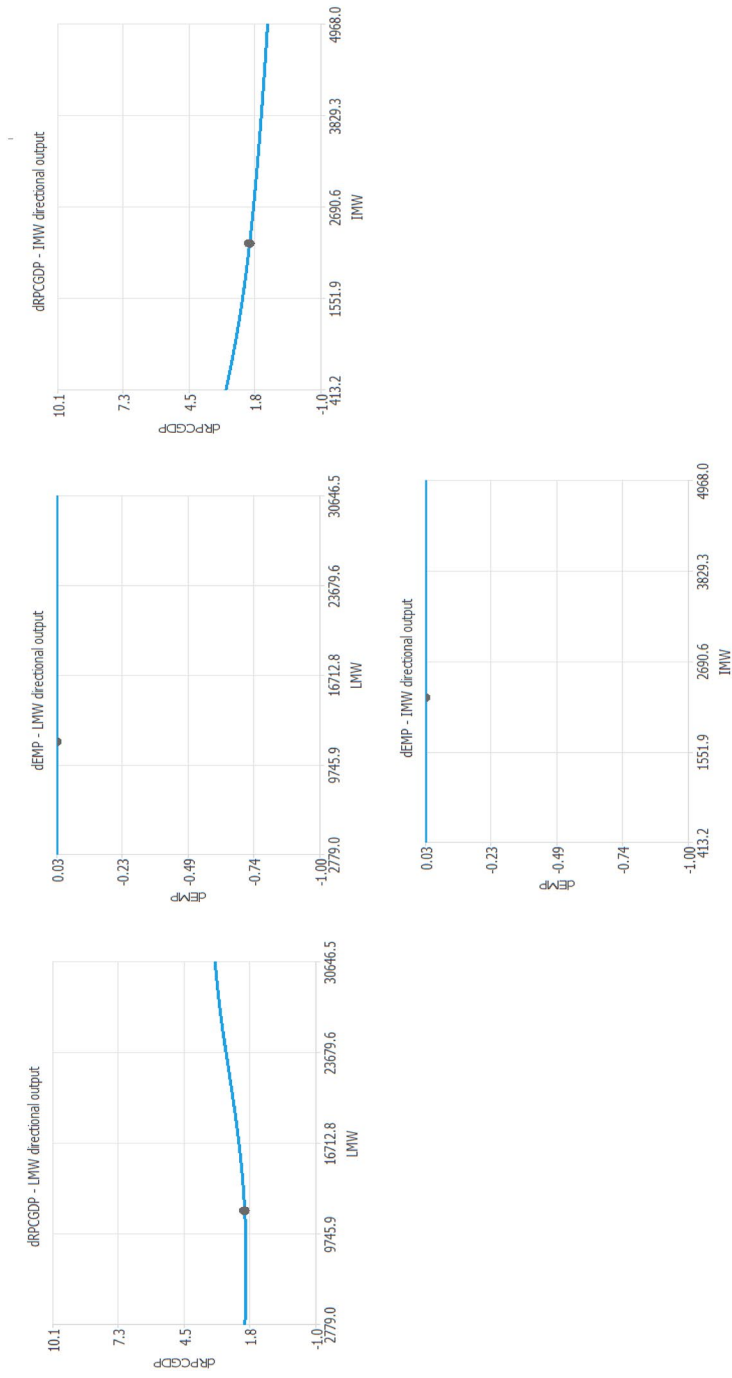**Fig. 8** Shear input-target effect. Source: our elaborations in Oryx

Fig. 8 (continued)

the municipal waste for landfill, they influence the *RPCGDP* and *EMP* targets in an increasing phase of the signal. This situation is particularly evident for the *RMW* input towards economic growth and towards *EMP* (the dot is more distant from the ordinate axis). This result can be interpreted as follows: in order to increase recycling (since ours is a predictive analysis), investments in research and development will be necessary, especially for those products for which, to date, the most significant difficulties exist.

5 Discussion

This section compares the econometrics results with the most relevant and recent literature. Subsequently, ML findings are extensively discussed.

Above all, one interesting finding of the BCSG analysis is the absence of causal linkage between innovation in environment-related technologies and the three waste disposal operations (landfill, recycling, or incineration). Instead, a one-way significant causality running from recycling municipal waste to innovation in environment-related technologies is supported. This can be consistently explained by referring to the technology-related literature. Also, in the waste recycling sector, strong knowledge spillovers can occur and result in the diffusion of technological improvements across the whole sector (Aldieri et al., 2019). In addition, when operated by private firms, recycling operations can increase the competitiveness between companies. Hence, a rational way to maximize their profitability is to upgrade technology (Agovino et al., 2020). Overall, the waste-to-energy process is now abundantly promoted. Through the well-known spillover channels, generating low-carbon electricity from waste incineration can be a non-negligible driver of R&D intensity. Thus, this partially confirms the findings from Gardiner and Hajek (2020) supporting the existence of bidirectional causality between municipal waste generation and R&D intensity in Europe. Furthermore, it turns out to be in line with Sim (2018), who developed a system dynamic model to capture the R&D investment values of renewable energy in Korea. Accordingly, our time-series result failed to depict the causal effect of innovation in environment-related technologies on the efficiency of waste disposal operations in Korea.

In addition, our results support the existence of a unidirectional causality flow from per capita GDP to waste landfills and incineration operations, but not vice versa. This is congruent with the hypothesis that the growth of income boosts the emergence of consumption habits, which, in turn, linearly increases the amount of waste generated and deposited in landfills (Cheng et al., 2020a, b; Gui et al., 2019; Magazzino et al., 2020a). Specifically, the urban population is found to significantly sustain that momentum and drive waste landfills and incineration operations. This, again, corroborates Chen (2018), who demonstrated that the generation of MSW is related to the various features of urbanization. As a global threat to sustainability, this dynamic is particularly alarming in urban areas located in developing and booming economies. Thus, knowing that the income-MSW relationship presents only a few de-linking evidence in the literature (Arbulú et al., 2015 for 16 EU countries; Lee et al., 2016 for the US; Yılmaz, 2020 for 16 OECD countries), further

recycling and waste-to-energy operations are expected to turn cities towards a sustainable path. Moreover, empirical findings highlighted a significant effect of municipal waste recycling on employment and urban population indicators but not vice versa. Although a few studies provided evidence on the feedback channel (Cheng et al., 2020a, b; Prades et al., 2015), seminal recent works confirmed that recycling performance has non-negligible employment impacts, which is not negligible (Kaseva et al., 2002 for Tanzania; Liu et al., 2020 for Florida).

Furthermore, stimulating results have been reached thanks to ANNs experiments. First, capital stock and innovation are found to significantly drive per capita GDP and employment, which is congruent with the growth theory. Second, each of the three waste disposal operations generates a substantial predictive signal on employment and per capita GDP indicators. More precisely, such a signal appears even stronger when looking at the relationship between municipal waste recycling and per capita GDP. Similarly, the amount of municipal waste for recovery operations (i.e., recycling) is found to powerfully determine the employment level. Hence, these findings confirm the econometric outcomes obtained over the frequency domain. Moreover, our study corroborates the contributions by Gardiner and Hajek (2020), and Liu et al. (2020), since promoting waste treatment operations boost "green" jobs creation and are consistent with a sustainable path. At the EU scale, if 70% of the waste generated is recycled, this would create 322,000 direct jobs, 160,000 indirect jobs, and 80,000 induced jobs (Pauli, 2017). On a global scale, it has been estimated that turning waste to heat and renewable energy under a circular model should create about twenty million jobs worldwide by 2030 (Pauli, 2017; International Labour Organisation, ILO, 2015). Therefore, further investments in R&D activity might avoid down-cycling risks and induce employment effects. However, this requires extensive resources and cooperation between companies, research centres, and universities. On the demand side, Green Public Procurement might allow exploitation of the level of public procurement to encourage the development of products, technologies, and services with reduced environmental impacts. Promoting the development of green products can lead to a network of companies engaged in eco-innovative production, with both environmental and employment benefits. Overall, our ML experiments successfully complement the time-series results as they empirically link waste recycling performance, innovation diffusion, and economic growth in the case of Korea. For too long regarded as relatively incompatible, the linkages amongst these three variables may represent a fruitful research direction since it turns to play a decisive role in the future green growth (i.e., with low environmental impact).

6 Concluding remarks and policy implications

The aim of this paper was to investigate the causal relationships operating among innovation in environment-related technologies, per capita income, and three major waste disposal operations (landfill, recycling, and incineration) for Korea, a country characterized by a singular system of waste management and a declining trend of MSW. To do so, we collected data spanning the period 1985–2016 and incorporated urbanization and production factors (GFCF and employment) within our

multivariate framework. Following Magazzino et al., (2021a, b, c, d, e), we applied two independent empirical methodologies: a time-series Granger causality procedure on the frequency domain together with ANNs experiments.

Above all, econometric results revealed no significant causal linkage amongst innovation in environment-related technologies and the three types of waste disposal operations in Korea. Instead, recycling waste operations are found to significantly drive innovation in environment-related technologies, while no significant causal flow emerged among the other municipal waste operations (i.e., landfill and incineration) and innovation. A strong unidirectional causality running from per capita GDP and GFCF to waste landfills and incineration is established, whereas the urban population is found. Furthermore, recycling waste operations cause employment growth in Korea, while landfills and incineration do not. This finding is roughly confirmed by ANNs experiments. More specifically, the ML process shows how innovation affects per capita income, which, in turn, generates, in a target objective, variations in the amount of recycled waste. Moreover, the amount of municipal waste for recycling operations is found to determine the employment level. Therefore, ML experiments successfully complement the time-series results as they empirically link waste recycling performance, innovation diffusion, and economic growth in Korea. Far from being outdated, these results provide new country-level evidence for Korea, thus enlarging the geographical scope of econometric research on waste management, which has been so far largely focused on European economies.

Taken together, these findings clearly highlight how the growth of income is tightly linked to the growth of recycling waste operations on the one side, and the increase of innovations in environment-related technologies on the other side. Furthermore, the present results emphasize the existence of a feedback linkage, indicating that waste recycling can also result in income generation and employment creation (Kaseva et al., 2002). Based on this valuable information, 5 policy implications can be proposed for Korea, and extended to countries in search of waste management improvements with similar income characteristics.

First, improving the treatment and recycling of MSW remains highly dependent to the state of innovations in environment-related technologies in Korea. This is, in turn, substantially determined by the volume of investment flows allocated to R&D in this sector. Thus, in accordance with our empirical findings, a virtuous phenomenon may emerge as promoting innovation along the waste treatment chain may not only increase the value embedded in consumption products through recycling applications, but also positively drive employment and income per capita in the long-run. Even its limitations, this paper demonstrates that economic and environmental strategies may be simultaneously achievable, once eco-innovation and recycling targets are adequately set for a given economy.

Second, an important take-away of this study is that municipal waste is a resource itself. When not treated (i.e., abandoned or deposited in open dumps), it generates harmful and toxic substances contaminating soils and groundwater (Wang et al., 2019; Yu et al., 2018). However, when collected, treated, and recycled in adequate facilities, MSW may directly profit the whole economy because it shares spillovers connections with innovation, employment, and income in Korea (Al-Hamamre et al., 2017; Gardiner & Hajek, 2020). Therefore, policymakers ought to encourage

the development of a labour force, adequately skilled for the processing waste, by investing in human capital formation, as achieved in standard industrial sectors in the past (Cervellati & Sunde, 2005). Meanwhile, adequate incentives should be provided by governments to enhance the technological innovations along the waste operations chain (site selection, waste collection, and treatment, route optimization) (Akhtar et al., 2017). It can be done through market-based solutions such as subsidies, fiscal incentives, and deposit-refund systems (Zhang, 2013). Such proposition is congruent with the main conclusions drawn by Castellacci and Lie (2017) who stressed that R&D policies are the most relevant ones to enhance innovation in waste-reducing firms in Korea whereas environmental taxes are more effective to drive technological change in atmospheric pollution-reducing firms.

Third, the municipal waste incineration and recycling capacity should be deployed across the whole territory. It would limit the landfill's dependency of Korea and encourage innovation diffusion across the firms present in the waste sector. According to Nam and An (2017), short patent duration leads to large spillovers effects, indicating that proper patent duration policy such as renewal and grace period can help diffusing innovative applications within the industry. Furthermore, developing waste treatment processes should be conducted in the most homogeneous manner to limit the emergence of waste treatment disparities across locations and social groups.

Fourth, special policy funding should be allocated to facilities collecting electrical, thermal, and gaseous energy from waste (Waste-To-Energy (WTE) process); with incineration being located near the point of waste deposit in order to avoid transporting waste over long distances (Cucchiella et al., 2014). It is worthy to remind that waste shipment also contributes substantially to global carbon emissions worldwide, thus highlighting that a closed-loop supply chain management strategy does matter too (Mishra et al., 2020). Additionally, because Korea depends on imports for 97% of its energy needs, it is imperative to strengthen its energy security by producing power through alternative sources, including waste incineration. A remarkable fact is that waste covered 67% of new and low-carbon energies in 2014 in Korea while displaying cheaper average energy generation costs: 10% and 66% lower than solar and wind power, respectively. Recently, the Ministry of Environment granted a subsidy to local governments for the installation of waste disposal facilities. However, further supports should be provided to resolve the shortage issue of financial resources (Inter-American Development Bank, 2020).

Fifth and finally, because Korea has very limited carrying capacity (its population density is 481 people per km^2: the third highest in the world), specific attention should be paid to lowering the waste generation on the demand side. This can be achieved by extending the individual-incentive-based Radio Frequency Identification (RFID) waste pricing systems, like those implemented by the Korean Ministry of Environment on apartment complexes in 2013 (Lee & Jung, 2018). Similarly, environmental propositions rooted around the adoption of a volume-based waste fee system requiring every household to purchase certified plastic bags for waste disposal, as initiated in 1995, should be extended to additional products [especially to Waste Electrical and Electronic Equipment (WEEE)]. On the supply side, the Extended Producer Responsibility (EPR) scheme should be further deployed, strengthened, and extended to multinationals (Lee, 2013; Lee & Paik, 2011). These elements emerge as unavoidable prerequisites before reaching the circular model

minimizing resource inputs, maximizing reuse and recycling of materials, and eliminating waste disposal: a mandatory step to turn economies towards a sustainable path (Inter-American Development Bank, 2020).

A well-known drawback of macroeconomic analysis is that it may provide broad impact estimations. For this reason, future studies should rely on finer datasets. If data availability allows that, one should identify which type of environment-related innovation allows for the performance of recycling operations at the firm level. Inversely, exploring the feedback channel may draw crucial insights since the R&D progress in the recycling sector is also driven by technological spillovers across firms. This would validate our findings and bring a better understanding of the innovation-environment puzzle.

Appendix

See Tables 6, 7 and Fig. 9.

Table 6 Data information

| Domain	Variable	Acronym	Source
Environmental innovation	Patents in environment-related technologies (climate change mitigation technologies related to waste management) (total)	TD	OECD Environment Statistics
Income	Per capita GDP (constant LCU)	RPCGDP	World Development Indicators
Waste disposal methods	Municipal waste for recovery operations (recycling) (thousand tonnes)	RMW	OECD Environment Statistics
	Municipal waste for disposal operations (landfill) (thousand tonnes)	LMW	OECD Environment Statistics
	Municipal waste for incineration operations (thousand tonnes)	IMW	OECD Environment Statistics
Production factors	Gross Fixed Capital Formation (constant LCU)	GFCF	World Development Indicators
	Employment (total number of employed persons)	EMP	World Development Indicators
Urbanization	Urban population (% of total population)	UP	World Development Indicators

Source: our elaborations

Table 7 Descriptive statistics

Variable	Mean	Median	SD	Skewness	Kurtosis	Range	IQR
RPCGDP	16.7084	16.7914	0.4731	− 0.5030	2.1105	1.5996	0.7671
GFCF	33.2548	33.3735	0.5060	− 1.0605	3.1701	1.8755	0.6341
EMP	16.9711	16.9794	0.1041	− 0.2305	2.1422	0.3715	0.1474
TD	5.8650	6.4151	1.2795	− 0.6550	2.1859	4.2687	2.2159
UP	4.3554	4.3793	0.0644	− 1.5008	4.2468	0.2335	0.0685
RMW	8.4136	8.8969	1.0751	− 1.1110	2.9086	3.4453	1.4062
LMW	9.0345	8.9638	0.8382	0.1007	1.5838	2.4004	1.6903
IMW	7.4114	7.6887	0.8688	− 0.2501	1.4730	2.4869	1.7120

SD standard deviation, *IQR* inter-quartile range, *10-Trim* 10% trimmed mean

Source: our calculations on OECD and WDI data
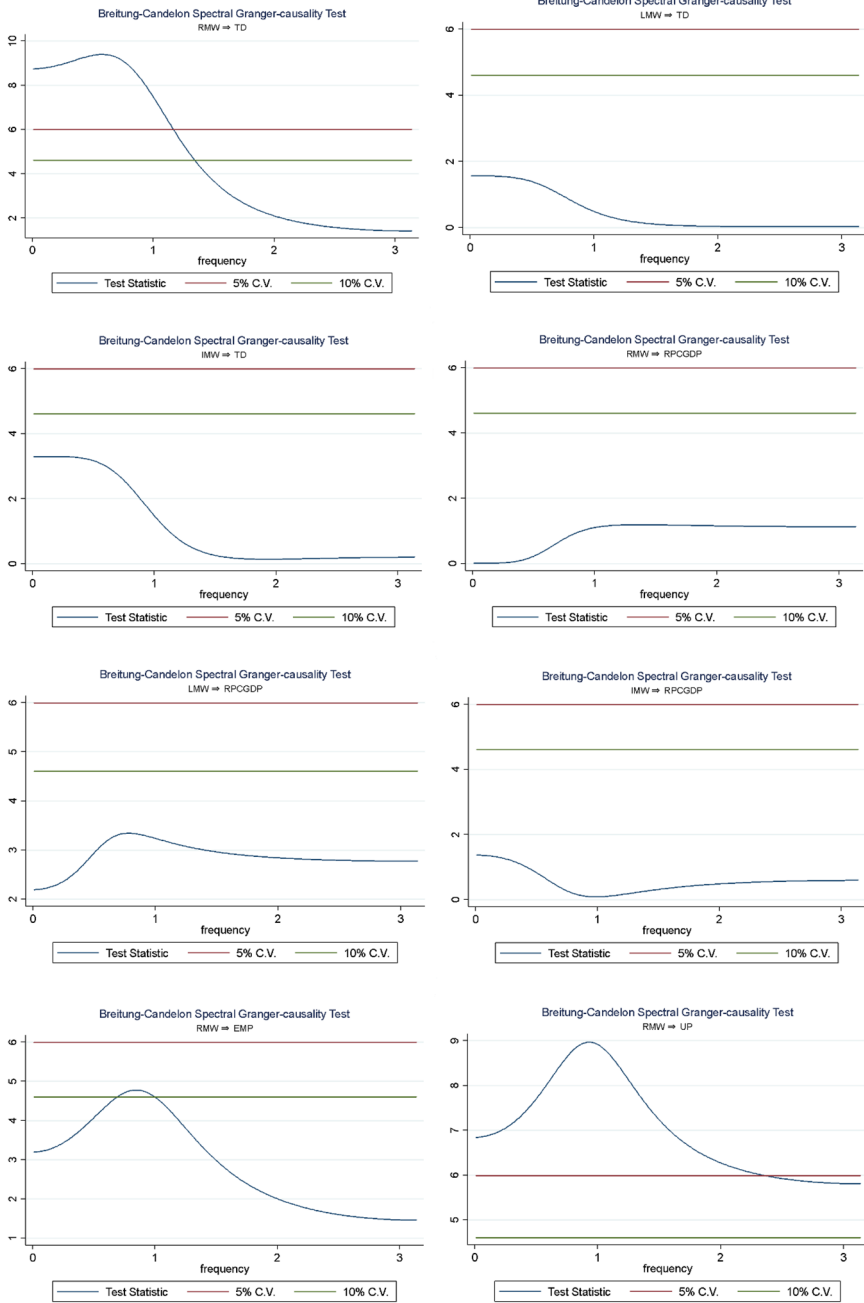
Fig. 9 Breitung–Candelon Spectral Granger-causality test results (additional results). Note: Confidence level on *y* axis. Geweke-type conditioning used.
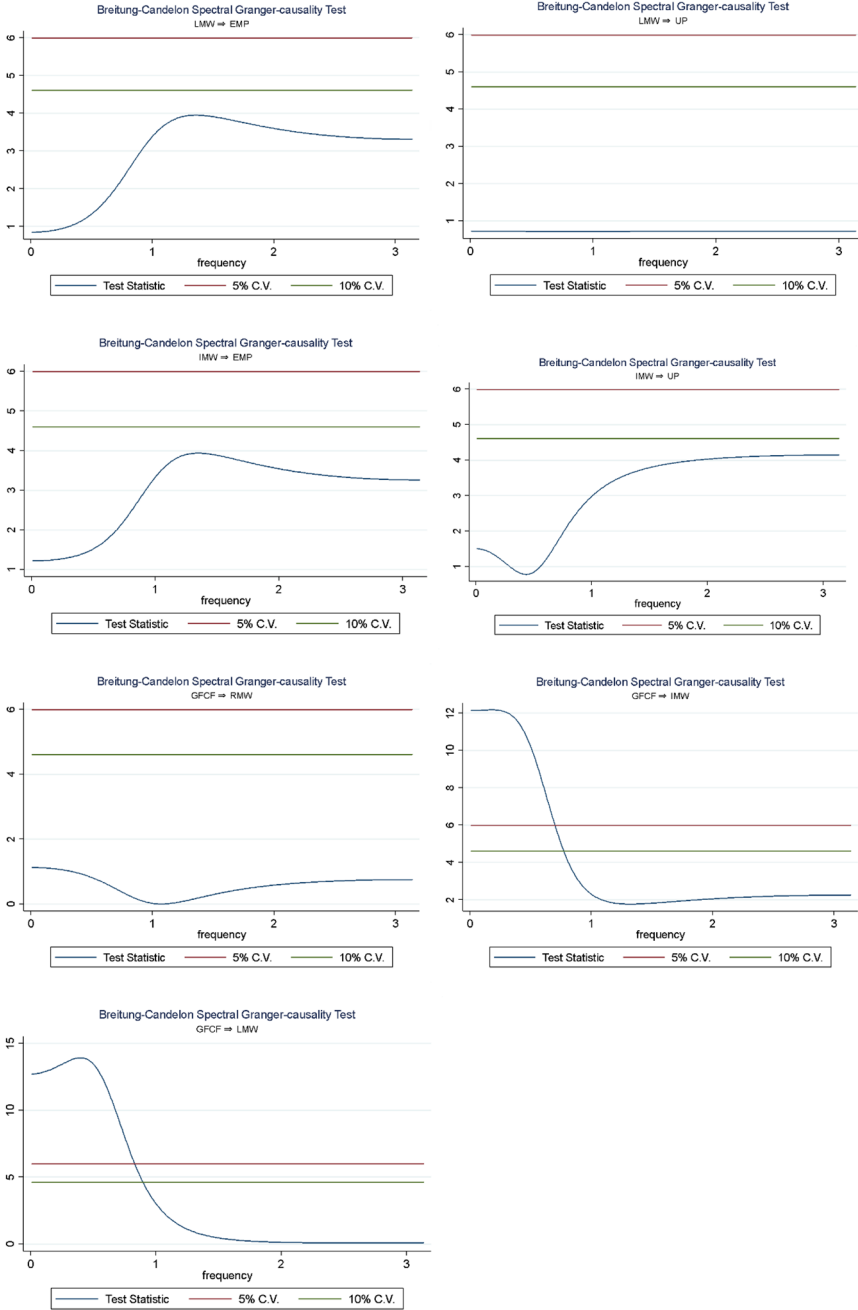
Fig. 9 (continued)

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