Good or bad? Digitalisation and green preferences

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Abstract:
This paper explores the influence of digitalisation on green preferences based on a theoretical approach by extending Busato et al.'s (2022) model. Environmental shocks, environmental status, quality of green digitalised information, and uncertainty avoidance conditions are also taken into account.
The main results show that digitalisation can stimulate green preferences in clean environments in the presence of distortive green information. Otherwise, the green preferences are expanded in polluted environments by the digitalising of non-distortive green information. During growth expansion, digitalisation is a good incentive for green preferences in the last stages of the pre-industrial era, propagating distortive information or, in the mature post-industrial era but with non-distortive information. Green preferences can be maximised under environmental shocks but with a specific digitalisation, environmental status, green informational quality, and uncertainty-avoidance context.
The policymakers should stimulate green preferences by supporting the digitalisation process with distortive information, especially in clean economies. Otherwise, policy adjustments should be orientated to propagating digitalised green non-distortive information in polluted economies.
The model shapes green preferences in the presence of environmental shocks by taking into account the digitalisation process and the quality of green information as a novelty. It also discriminates between clean and polluted environments in different industrial stages.

Key words: digitalisation, green preferences, clean economies, polluted economies
JEL-codes: Q50, D80

1. Introduction

Digitalisation represents a contemporaneous vanguard process technically supported by the development of science and technology. Although a fast technological development characterised the progress in integrated digital electronics in the 1960s, an increased dynamic with descending rate started to proliferate since the 1980s (Moore, 1975). Spread worldwide, digitalisation strongly impacted almost all socio-economic activities, without neglecting the green sector.

The transition to a green economy can be viewed from different perspectives. One of the most famous is certainly the Environmental Kuznets Curve (EKC), which postulates an inverted U-shaped relationship between economic growth and environmental damage (e.g., Dinda, 2004; Shahbaz et al., 2013; Sarkodie and Ozturk, 2020; Burki and Tahir, 2022; Frodyma et al., 2022). More precisely, pollution increases in the first stages of growth, reaches a maximum point in the industrial economy, and falls in the post-industrial era (i.e., services sector based) as the growth continues to expand. It is noteworthy herein, that the clean environment characterises the first stages of a pre-industrial era and the mature stages of a post-industrial one. Otherwise, the polluted environment is typical for the last stages of a pre-industrial era and the debut of a post-industrial one. Although this literature is prolific, the EKC effect should be considered with caution as it is very sensitive to short- and long-run approaches as well as datasets, specifications, and functional forms (Magazzino et al., 2023).

Accordingly, a policy towards aggressive economic growth would seem to be reasonable to achieve a sustainable, green economy. However, economic growth can be achieved through various sectors and approaches, whereby technology and digitalisation are seen as a particularly useful way to a sustainable economy (Ciocoiu, 2011; Tawiah et al., 2021).

From a green perspective, Nwaiwu (2021) argues that digitalisationon has become an enabling factor for energy transitions and is transforming how energy is produced, distributed, and consumed. On the one hand, digitalisation and technological development can help to enable new and sustainable business models and optimise existing (production) processes (Ghobakhloo, 2020). For instance, interconnected computers, intelligent materials, and smart machines communicate with each other, interact with the environment, and make decisions with minimal human involvement (Gilchrist, 2016). On the other hand, digitising public institutions enables better enforceability of environmental governance and regulations (Jia et al., 2022).

The green economy is a popular trend around the world. One strand of literature focuses on the widespread awareness of the green economy related to saving energy, expanding market demand, creating new jobs, achieving sustainable economic development, and ultimately removing poverty (Huang et al., 2021; Jiang et al., 2020; Xie et al., 2019).

Feng et al. (2021) argue that green technology innovation precisely focuses on synergistic development. On the same note, Li et al. (2017) suggest that green technology aims to improve the efficiency of resource utilisation and reduces pollutant emissions in the production process, playing an essential role in the coordinated development of the economy and the environment. It has long been known that private households and their consumption patterns have a major direct influence on an economy's CO_2 emissions (Bin and Dowlatabadi, 2005; Baiocchi et al., 2010; Moran et al., 2020). Against this background, it is not surprising that the green economic preferences of households play an important role in reducing emissions economically and should have an entry in theoretical considerations of green economics (Busato et al., 2022).

Another strand of literature covers the financial and economic fields by exploring the effect of pro-environmental preferences on bond-market prices. For example, Brennan (2006) explores the possibility that the effectiveness of green preferences is a component of policy setting. The work discusses how green preferences can be used as a regulatory policy instrument to encourage more environmentally friendly behaviour. This study provides insights into the role that policy can play in shaping individual attitudes towards the environment and how these attitudes can in turn influence market outcomes.

Wichman (2016) proposes a different analysis by focusing on both private and public characteristics of private environmental goods and services in order to investigate the importance of heterogeneous green preferences. His research is grounded in the incentive-compatible Nash equilibria that ensure the provision of socially optimal public goods, the interplay between individual preferences, incentives, and the provision of public goods. More precisely, the author highlights and provides insights into how to design policies that encourage the provision of green goods and services. Particularly, Wichman (2016) shows that citizens are more likely to consider the well-being of their entire community when purchasing discrete green goods, indicating that there is a social aspect to green preferences that can be leveraged for policy purposes. From another green preference-based perspective, Zerbib (2019) considers green bonds as an instrument by analysing the yield differential between a green bond and a counterfactual conventional bond. The methodology follows a two-step regression procedure, covering July 2013 to December 2017. The main finding shows that the presence of pro-environmental preferences in the bond market can lead to a reduction in yields for green bonds.

In the green economy, digitalisation plays a crucial role in the informational area, which is the propagation of green information via digitalisation platforms that influence the consumers' environmental awareness. More and more consumers are using Information and Communication Technology (ICT) via the internet to exchange information about a wide variety of things, including topics such as ecology and sustainability. All those are relevant for shaping green preferences as social attributes. This modifies the green economy's perceptions, further modelling their green preferences. In other words, the ‘digital’ environment often filters the consumers’ green perceptions.

Unfortunately, the researchers largely ignore the diversity of household behaviour regarding possible preferences for a green economy (Busato et al., 2022). The authors offer a seminal theoretical work in the field, showing that the quality of the environment, the intensity of environmental awareness, and shocks affecting environmental concerns are crucial for green preferences. Their main results reveal that green consumption preferences mitigate gas emissions, while green shocks induce sectoral fluctuation stabilising the business cycle. A pro-cyclical sustainable consumption is registered under pollutant supply shock conditioned by households’ environmental awareness.

An important factor of consumer behaviour is the cultural background, which can be captured by means of cultural dimensions (Hofstede, 1991). It turns out that different dimensions are associated with different ecological behaviour. E.g, while masculinity and individualism tend to be negatively associated with ecological behaviour, uncertainty avoidance and indulgence generally are positively associated with sustainable behaviour (Gallén and Peraita, 2018; Zhang and Dong, 2020; Lee et al., 2022).

Individual consumer behaviour is also inevitably linked to the behaviour of other consumers, which via contact and communication exchange, are keys to determining social attributes (Zhang and Dong, 2020). This contact among different consumers and a corresponding exchange about social attributes and preferences can be mediated through the increasing use of digital communication channels (Huete-Alcocer, 2017). Furthermore, Bangsa and Schlegelmilch (2020) mainly review and summarise the impact of green product attributes on consumers' purchase decisions by splitting the product attributes into social and environmental sustainability attributes.

On this foundation, the paper examines the implications of digitalisation on green preferences by using an adjusted version of the theoretical model proposed by Busato et al. (2022).

There are two transmission channels: one is technical and the other is informational. The technical channel is related to environmental quality and supposes that both production and consumption generate environmental degradation. Their technical digitalisation adjusts the environmental quality status through the preferences for green businesses (Nwaiwu, 2021; Ghobakhloo, 2020; Gilchrist, 2016; Jia et al., 2022). The informational channel refers to the flow and quality of environmental information propagated via digitalisation that has the capacity to shape human environmental behaviour (Hofstede, 1991; Gallén and Peraita, 2018; Zhang and Dong, 2020; Lee et al., 2022; Huete-Alcocer, 2017).

The core findings show that digitalisation can stimulate green preferences in a clean environment in the presence of distortive green information and in a polluted environment dominated by non-distortive information.

The contributions of this paper to literature are threefold. To the best of our knowledge, the work is one of the first investigations modelling green preferences in the presence of the digitalisation process. Inspired by Busato et al.’s (2022) contribution, our approach extends their model by controlling for digitalisation as an actual vanguard process supported by advances in science and technology. Second, as a novelty, this paper introduces psychosocial 'ingredients' and green informational characteristics by mixing them with environmental quality. Unlike Busato et al. (2022), this paper additionally controls for uncertainty-avoidance status and quality of information propagated via digitalisation, differentiating between clean and polluted environments in various industrial stages. Third, the results allow adapting the policy measures in terms of green preferences to the society’s psychological profile. These measures are based on the intensity of digitalisation and position of environmental quality to the steady-state status. Environmental shocks control the process.

The remainder of the paper is as follows: Section 2 describes the theoretical model, Section 3 presents its calibration, and Section 4 discusses the findings. Finally, Section 5 concludes and also reveals the main policy implications.

2. Model

The proposed model extends Busato et al.'s (2022) contribution on green preferences by controlling for economic digitalisation. Their core assumption is that environmental quality strongly influences the consumers' environmental awareness. Therefore, the green preferences are as follow (Busato et al., 2022, p. 11):

$$\gamma_t = \overline{\gamma}\, V_t\, \phi \tag{1}$$

where, γ_t represents the green preferences in moment t, $\overline{\gamma}$ is the initial value of clean consumption preferences, V_t denotes the shocks affecting environmental concern ($V_t > 1$), and ϕ stands for environmental awareness. In steady-state, $\phi_{ss} = 1$, with $\phi > 0$. V_t evolves as an AR(1) process (Busato et al., 2022), as follows:

$$ln(V_t) = \rho\, ln(V_{t-1}) + \varepsilon_{V,t} \tag{2}$$

where, $\rho \in (0,1)$ captures the shock persistence, and $\varepsilon_{V,t}$ stands for exogenous shock, normally distributed, having a zero mean (i.e., $V'(\cdot) < 0$ and $V''(\cdot) > 0$). The shocks follow a classical economics dynamic, convexly falling with an asymptotic shape over time.

The shocks depend on "development at the national level of information and awareness-raising policies about the environmental issues; or a natural disaster that increases concern about environmental issues; or a change in consumer sentiment, e.g., following a *Greta Thunberg* speech." (Busato et al., 2022, p. 11).

As a function of environmental quality (Delis and Iosifidi, 2020), ϕ becomes:

$$\phi = \left(\frac{Q_{ss}}{Q}\right)^{\chi} \tag{3}$$

where, Q_{ss} captures the steady-state environmental quality level ($Q_{ss} > 0$), Q is the environmental quality ($Q > 0$), and χ is the intensity of environmental awareness in changing consumption behaviour. The report spells out the environmental quality channel (Nwaiwu, 2021; Ghobakhloo, 2020; Gilchrist, 2016; Jia et al., 2022).

Corroborating (1) and (3), the ratio-effect of green preferences can be written as:

$$\Delta\gamma_t = \frac{\gamma_t}{\bar{\gamma}} = V_t\,\phi^{\chi} = V_t\left(\frac{Q_{ss}}{Q}\right)^{\chi}. \tag{4}$$

Equation (4) shows that the ratio-effect of green preferences is high when $Q_{ss} < Q$ (i.e., clean environment), while a contrary effect is observed for $Q_{ss} > Q$ (i.e., polluted environment). In both cases, χ and V_t potentiate the effects.

According to the informational channel (Hofstede, 1991; Gallén and Peraita, 2018; Zhang and Dong, 2020; Lee et al., 2022; Huete-Alcocer, 2017), we now introduce the digitalisation in a green environment by controlling χ as a function of *t* as follows:

$$\chi_t = \chi^{*}\delta_t \tag{5}$$

where, χ^{*} is the intensity of environmental awareness in the steady-state condition ($\chi^{*} > 0$), and δ captures the quality of digitalised green information in the economy. χ^{*} is supposed to be constant over a long period, being related to the psycho-social profile of people. In our approach, χ^{*} is culturally assimilated with Hofstede's (1991) uncertainty-avoidance dimension. Low uncertainty avoidance means that the members of a culture do not feel threatened by uncertain or unknown situations. In contrast, high uncertainty avoidance shows the contrary.

Further, we assume that the quality of digitalised green information in the economy (δ_t) is given by the level of digitalisation δ_t^{*} and the quality of green information propagated via the digital environment (η). In this case, δ_t can be written as follows:

$$\delta_t = \delta_t^{*}\eta \tag{6}$$

with $\delta_t^{*} > 1$, and $\eta < 0$ (distortive information / low informational quality, as η_{-}) or $\eta > 0$ (non-distortive information / high informational quality, as η_{+}).

By following the revised Moore's law (Moore, 1975), we assume that digitalisation increases but at a diminishing rate as:

$$ln(\delta_t^*) = \alpha\ ln(\delta_{t-1}^*) + \beta + \varepsilon_{\delta,t} \tag{7}$$

where, $\alpha \in (0,1)$ denotes the digital absorptive capacity, $\beta \in (0,1)$ stands for digital capacity, and $\varepsilon_{\delta,t}$ is the disturbance, normally distributed, with zero mean (i.e., $\delta'(\cdot) > 0$ and $\delta''(\cdot) < 0$).

By replacing all parameters, $\Delta\gamma_t$ is as follows:

$$\Delta\gamma_t = V_t \left(\frac{Q_{ss}}{Q}\right)^{\chi^*\delta_t^*\eta}. \tag{8}$$

The final equation clearly shows that the ratio-effect of green preferences depends on how the environmental quality is above or below its steady-state condition. This is controlled by the level of digitalisation and quality of green information in the economy. Not least, the psychosocial profile of people and shocks affecting environmental concerns also play a crucial role.

Now, we suppose that the individuals maximise their green preferences with respect to *t*, with the first-order condition as follows:

$$\frac{\mathrm{d}\Delta\gamma_t}{dt} = \frac{\mathrm{d}V_t}{dt}\phi^{\chi^*\delta_t^*\eta} + V_t\frac{d\left(\phi^{\chi^*\delta_t^*\eta}\right)}{dt} = 0 \tag{9}$$

$$\frac{\mathrm{d}\Delta\gamma_t}{dt} = \frac{\mathrm{d}V_t}{dt}\phi^{\chi^*\delta_t^*\eta} + V_t\,\phi^{\chi^*\delta_t^*\eta}\chi^*\,\eta\,\ln(\phi)\frac{d(\delta_t^*)}{dt} = 0 \tag{10}$$

or

$$\frac{\mathrm{d}\Delta\gamma_t}{dt} = \phi^{\chi^*\delta_t^*\eta}\left(\frac{\mathrm{d}V_t}{dt} + V_t\,\chi^*\,\eta\,\ln(\phi)\frac{d(\delta_t^*)}{dt}\right) = 0. \tag{11}$$

As $\phi^{\chi^*\delta_t^*\eta} > 0$, then $\frac{\mathrm{d}V_t}{dt} + V_t\,\chi^*\,\eta\,\ln(\phi)\frac{d(\delta_t^*)}{dt} = 0$. With $V'(\cdot) < 0$, $\delta'(\cdot) > 0$, $V_t > 1$, $\delta_t^* > 1$ and $\chi^* > 0$, this binds either when $\eta<0$, and $0<\phi< 1$ or when $\eta> 0$, and $\phi> 0$.

3. Calibration

The theoretical model is evaluated as numerical magnitude by performing a simulation based on specific dynamics of environmental shock, assumed digitalisation function, and realistic parameters inspired by literature. The model is calibrated in order to cover both clean and polluted environments.

Environmental shock V_t represents an AR(1) process with a convex decreasing shape, its effect slightly absorbing over time. The parameter ρ is set to 0.81, as in Argentiero et al. (2017). The shock function is initialised in the simplest way, from a unit plus one as a decimal to satisfy the natural logarithm-defined domain.

Environmental awareness is centred on $\phi_{ss} = 1$ as a baseline calibration (Delis and Iosifidi, 2020) by capturing the steady-state environmental awareness status. Uncertainty avoidance χ^* is 0.840 and corresponds to the median value in Hofstede's (1991) sample, being normalised to 1.

The quality of digitalised information is parametrised based on the Google Trend Index search engine as a compromise to the lack of contributions regarding the measurement of information quality. Inspired by the general approach of Askitas and Zimmermann (2015), we assume that the quality of digitalised information is high as the intensity of finding for the word combination 'true + correct + symmetric + information + green economy' is high. Alternatively, the minus sign is attributed to the intensity of the finding for the word set 'false + incorrect + asymmetric + information + green economy' in order to measure low-quality information. Google Trends Index search results generate values between 0 and 100 (0 - minimum level, and 100 - maximum one). The parameter η is alternatively calculated as a median for 2022.[1] Therefore, the distortive green information η_{-} is -0.778, while the non-distortive one η_{+} is set to 0.807, both normalised to 1.

Finally, following Moore (1975), digitalisation δ_t^* is assumed to follow an increasing dynamic with descending rate. The parameter of the auto-regressive term α is 0.357, capturing the capacity of the economy to assimilate the new digital innovation (i.e., absorptive digital capacity). The constant β is 0.182 and measures the ability to adapt and develop new practices with digital technology (i.e., digital capacity). Both parameters are taken from Kastelli et al. (2022).

Table 1. Parameters

Parameter	Value	Description	Source
ρ	0.81	Persistence of preference shock	Argentiero et al. (2017)
ϕ_{ss}	1	Environmental awareness in steady-state	Delis and Iosifidi (2020)
χ^*	0.840	Uncertainty avoidance (normalised to 1)	Hofstede (1991)
η_{-}	-0.778	Distortive information (normalised to 1)	Google Trend Index
η_{+}	0.807	Non-distortive information (normalised to 1)	Google Trend Index
α	0.357	Absorptive digital capacity	Kastelli et al. (2022)
β	0.182	Digital capacity	Kastelli et al. (2022)

Several scenarios are employed in Table 2 by conventionally considering different levels of environmental awareness ϕ in order to capture both clean ($0<\phi<1$) and polluted ($\phi>1$) environments. For sensitivity reasons, additional levels of χ^* and η are conventionally taken into account too.

Table 2. Calibrated scenarios

Environment awareness	ϕ scenarios	χ^*	η	Sensitivity	
Clean	$\phi_{0.90} = 0.90$	$\chi^* = 0.840$	$\eta_{-} = -0.778$	$\chi^* = 1$ $\eta_{-} = -0.778$	$\chi^* = 0.840$ $\eta_{-} = -1$
	$\phi_{0.95} = 0.95$	$\chi^* = 0.840$	$\eta_{-} = -0.778$		
Steady-state	$\phi_{ss} = 1$				
Polluted	$\phi_{1.05} = 1.05$	$\chi^* = 0.840$	$\eta_{+} = 0.807$		
	$\phi_{1.10} = 1.10$	$\chi^* = 0.840$	$\eta_{+} = 0.807$	$\chi^* = 1$ $\eta_{+} = 0.807$	$\chi^* = 0.840$ $\eta_{+} = 1$

In the neutral scenario, assuming the environmental awareness in the steady-state, the green preferences strictly follow the environmental shocks, as Figure 1 reveals.

[1] Starting with 2022, the Google Trend Index data collection system was substantially improved, any comparison with the previous period generating bias.

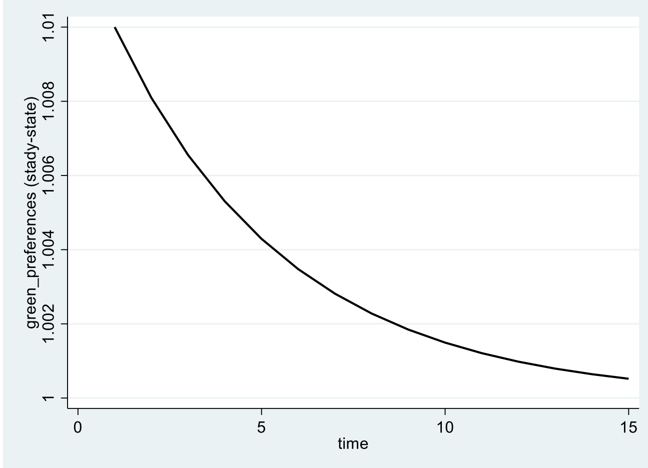

Figure 1. Green preferences in steady-state

This shows that the environmental shocks fully shape the green preferences in the environmental awareness steady-state condition, the influence of uncertainty avoidance, quality of digitalised green information, but not counting the intensity of digitalisation. More precisely, the environmental awareness status does not significantly change over time, and, in this case, the green preferences exclusively depend on environmental shocks. Herein, an environmental shock suddenly sensitises human behaviour, stimulating the green preferences that further slowly reduce over time as the concern gradually dilutes.

Figures 2 and 3 depict the dynamic reaction of green preferences in clean and polluted environments following a 1% increase in the level of digitalisation.

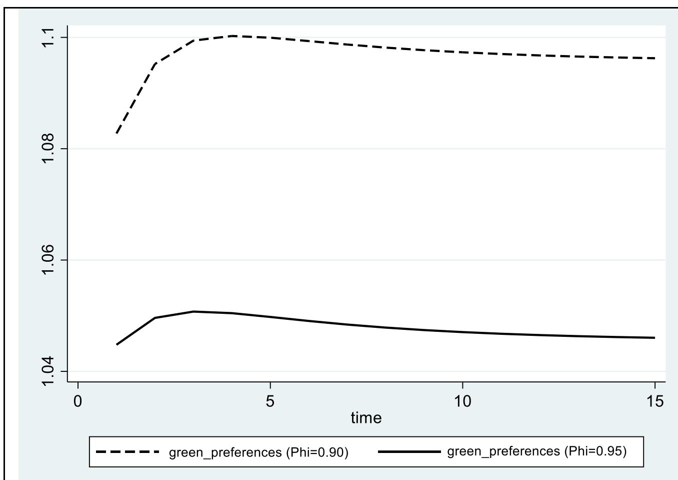

Figure 2. Green preferences in clean environment (dynamic adjustment following an increase in δ_t^* and change of ϕ status)

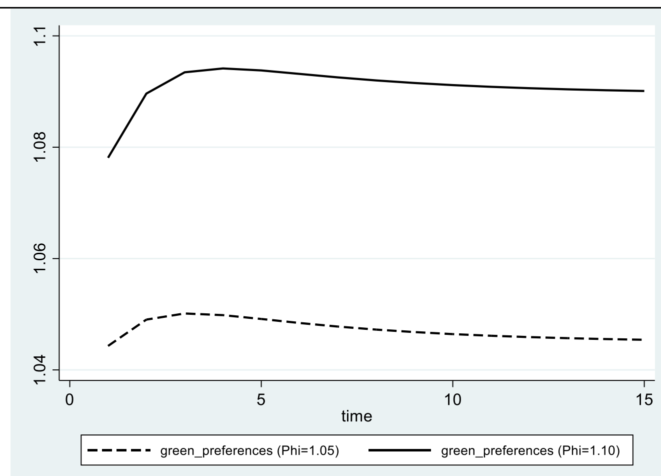

Figure 3. Green preferences in polluted environment (dynamic adjustment following an increase in δ_t^* and change of ϕ status)

The green preferences are maximised in the clean environment under distortive digitalised green information (0<ϕ< 1 and $\eta_t < 0$). Their level seems to be higher as the environmental quality Q is improved, but the level of Q delays the green preferences in reaching their maximum. Otherwise, the green preferences are maximised in the polluted environment under non-distortive digitalised green information ($\phi > 1$ and $\eta_t > 0$). Noteworthy is that their magnitude improves for lower levels of environmental quality Q, also delaying reaching the maximum.

Figures 4 and 5 reveal the dynamic of green preferences in clean and polluted environments following a 1% increase in the level of digitalisation but alternatively assuming higher uncertainty avoidance or informational quality levels.

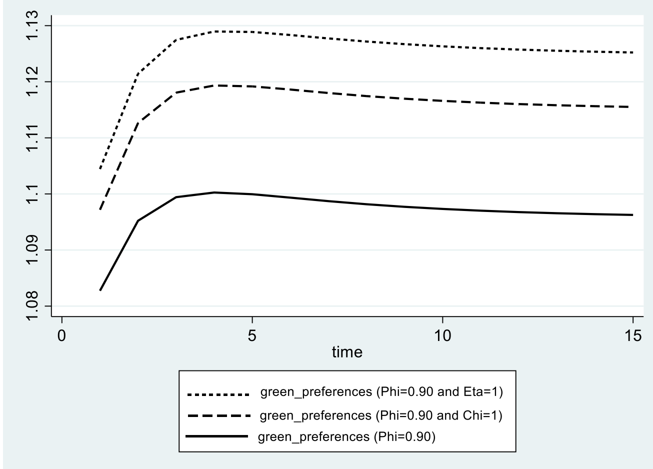

Figure 4. Green preferences in clean environment (dynamic adjustment following an increase in δ_t^* and change of χ^* and η status)

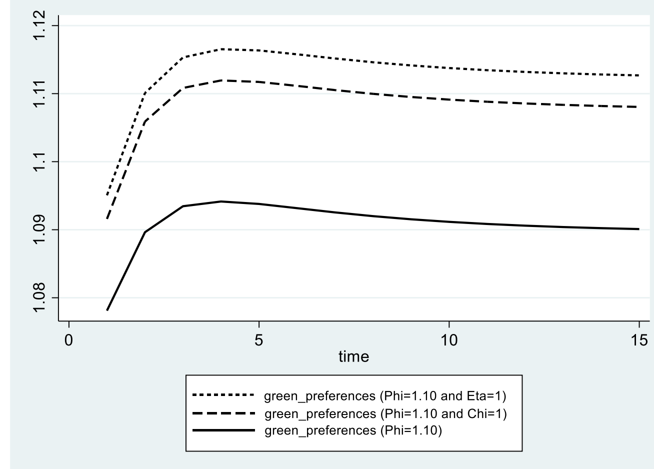

Figure 5. Green preferences in polluted environment (dynamic adjustment following an increase in δ_t^* and change of χ^* and η status)

In both cases, green preferences tend to be higher under a worsening of uncertainty-avoidance status or an alteration of green informational quality in a clean environment, and improvement in the polluted one. Moreover, the amplitude seems to be more pronounced in the case of informational quality compared with uncertainty avoidance, both delaying the reach of the maximum level of green preferences.

The findings suggest that digitalisation plays a key role in shaping green preferences, neutralising the contrary-induced effect caused by descending tendency of environmental shocks.

4. Discussions

Two main implications derive from equation (8), conditioned by the position of Q_{ss} with respect to Q initially assuming no environmental shocks. Herein, $Q_{ss} < Q$ suggests a clean economy ($0 < \phi < 1$), while $Q_{ss} > Q$ indicates a polluted one ($\phi > 1$).

(i) Under the $Q_{ss} < Q$ (i.e., clean environment) assumption, the green preferences increase ($\Delta\gamma_t\{\uparrow\}$) if the level of digitalisation accelerates ($\delta_t^*\{\uparrow\}$) but in the presence of distortive information ($\eta_t < 0$). Otherwise, the green preferences register a contrary effect in the presence of non-distortive information ($\eta_t > 0$) despite digitalisation rising.

(ii) Under the $Q_{ss} > Q$ (i.e., polluted environment) assumption, the green preferences expand ($\Delta\gamma_t\{\uparrow\}$) if the level of digitalisation accelerates ($\delta_t^*\{\uparrow\}$) but in the presence of non-distortive information ($\eta_t > 0$). Conversely, the green preferences reduce in the presence of distortive information ($\eta_t < 0$), although digitalisation increases.

The shocks affecting environmental concern play a key role as they influence human behaviour by offering a better perception regarding the environmental consequences. Therefore, they have the propensity to shape green preferences because societies are sensitive to environmental issues, natural disasters or changes in consumer sentiment due to influencers. In parallel, the magnitude of the green preferences ratio-effect is multiplied in societies characterised by high uncertainty avoidance, and attenuated otherwise.

Therefore, the green preferences are maximised in the presence of shocks with respect to time, as equation (11) shows. Our findings do not align with Busato et al. (2022, p.11), as the green preferences do not follow the environmental shock in our approach. Unlike in that study, the influence of environmental turbulences is counteracted by digitalisation under specific environmental and informational conditions.

If $Q_{ss} < Q$ (clean environment), the green preferences maximise for a given combination $\{\phi \in (0{,}1)|\chi^*|\eta\}$, with $Q_{ss} > 0$, $Q > 0$, $\chi^* > 0$, $\delta_t^* > 1$, and $\eta_t < 0$. Moreover, the magnitude of green preferences tends to be higher as the environmental quality Q is improved but delays reaching the maximum. By assuming the EKC effect (i.e., environmental quality increases as the economy expands and vice-versa), this situation characterises the first-stage of the pre-industrial era or the last-stage of the post-industrial one.

Such a healthy environmental climate can induce a normality status, often the environmental well-being feeding both lethargy and fatigue (MacDonald, 2020) and scepticism (Kumar, 2016; Syadzwina and Astuti, 2021) in terms of green preferences. In order to awaken any latent green perceptions to support the maximisation process, the information have to be 'manipulatively' propagated to alter the perception related to the excellent factual environmental status. Such adjustments are appropriate to the mature post-industrial stage, where environmental quality improves under economic expansion (i.e., the economy is dominated by services).

Otherwise, if $Q_{ss} > Q$ (polluted environment), the green preferences maximise for a specific set $\{\phi > 1|\chi^*|\eta\}$, with $Q_{ss} > 0$, $Q > 0$, $\chi^* > 0$, $\delta_t^* > 1$, and $\eta_t > 0$. In this case, reduced environmental quality is assimilated with an improvement in the level of green preferences. In light of the EKC effect, this is typical for the last-stage of the pre-industrial era or the first-stage of the post-industrial one. Herein, non-distortive information are crucial to depict the factual altered environmental reality. This stimulates green preferences, supporting their maximisation process. Moreover, the environmental factual damages are easily observed, often determining generalised fatalistic environmental resignation (Simonet and Fatorić, 2015). To reactivate such latent perceptions, non-distortive green information can also be more than welcome. Under the economic expansion, such a process characterises the last stage of the pre-industrial era, where growth continues to alter the environmental quality before reaching the industrial stage.

Noteworthy is that the endogenous change of environmental awareness, because of environmental quality status during economic expansion, induces a delay in reaching the maximum green preferences under the digitalisation process. A worsening of uncertainty avoidance stimulates green preferences as well as an alteration of green informational quality in a clean environment or an improvement in a polluted one. Moreover, green preferences are more sensitive to the green quality of information than uncertainty-avoidance status. This is because people have a sudden responsive reaction validating the main characteristics of emotional shocks in terms of effects.

The research has several limits given by the restrictive factors used to control human behaviour in the green environmental area, scarcity regarding the variables quantifying the quality of information, lack of empirical support, and non-adaptation of the theoretical model to other specific contexts. Additionally, no other types of shocks than environmental ones are considered (e.g., pandemic disease, geo-political turbulences, economic-financial shocks, etc.).

5. Conclusions

This paper explores the influence of digitalisation on green preferences based on a theoretical model as an extension of Busato et al.'s (2022) approach. Quality of green digitalised information, environmental awareness status, and uncertainty-avoidance characteristics are also considered.

The main results show that digitalisation can stimulate green preferences in a **clean environment** under environmental shocks and distortive green information, with growth stimulating the clean environment. Such environments are generally mature post-industrial economies dominated by services and high welfare status, with a high propensity for environmental fatigue and scepticism. That is why green preferences can be revitalised by propagating altered green information to counteract the perception related to the excellent factual environmental status. In other words, the green 'lethargy' cannot be awakened without using alarming signals to induce an altered perception status of environmental quality despite the positive factual reality.

Conversly, a **polluted environment** can boost green preferences via digitalisation under environmental shocks and assumed growth but only in the presence of high green informational quality. In this case, the economies are in the last stage of the pre-industrial era, still characterised by low growth, with consumption of dirty goods, pollutant technologies, and lack of alternative energies. Herein, the green preferences seem to be stimulated by propagating digitalised high-quality green information. These have the propensity to reinforce the factual image of the damaged environment and additionally counteract the fatalistic environmental resignation.

Digitalisation can maximize green preferences under environmental shocks by counteracting the alarming environmental signals as the shocks and digitalisation follow contrary dynamics. The maximum level can be reached either in a clean environment in the presence of distortive information or in a polluted environment but with non-distortive information. Moreover, the maximization process is delayed in a clean environment when the environmental quality improves or in polluted environment when environmental quality is altered. This suggests that green preferences are very sensitive to environmental quality status and elastic to the digitalisation process. Uncertainty avoidance status and magnitude of green informational quality can mediate the process, shaping the effects.

Two main policy implications are identified. On the one hand, policymakers in clean economies should encourage green preferences by stimulating the digitalisation and propagation of distortive green information. These measures allow for counteracting the green lethargy, and also represent a strong antidote for environmental fatigue and scepticism. On the other hand, policymakers should support the digitalisation process to boost green preferences in polluted economies by ensuring high green informational quality. Such measures have the capacity to raise awareness of degraded environmental reality and reduce fatalistic environmental resignation.

The green preferences maximisation target should follow dynamic adaptive informational policies by carefully monitoring the shocks and environmental quality status given the elasticity of green preferences to digitalisation (i.e., generates time delay). To compress the time reaction, environmental quality change should be compensated by the strong use of digitalisation and adequate quality of propagated green information (i.e., distortive in a clean environment and non-distortive in a polluted one). Uncertainty avoidance should be considered only in the long-term.

As for further research, the proposed theoretical model can be supported by an empirical approach covering both polluted and clean economies, based on panel model estimations, with an extension of considered types of shocks. Such quantitative analysis allows policy makers to tailor their informational measures according to country's environmental and psycho-behavioural specificity.

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