ECO-INNOVATION FOR ECONOMIC GROWTH

A panel data study with cross-sectional dependence

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Abstract

As the capacity of our planet to sustain the needs of future generations is deteriorating at an unprecedented rate, the role of innovation, research and development is becoming increasingly important. While the restrictions imposed on economic growth by the environment have been extensively examined and subject to much debate, the emerging concept of eco-innovation has not gained similar attention in the literature. With the assumption that eco-innovation provides vast opportunities to mitigate environmental impacts whilst acting as a driver for economic development, this thesis aims to depart from the methodological debate on the subject by econometrically examining its effects on GDP growth and contribute to a deeper understanding of this mechanism. Within the theoretical framework of an extended endogenous growth model to account for natural capital depletion, a regression model controlling for cross-sectional dependence was applied on panel data covering 32 OECD and BRICS countries from 1981-2014. In contrast to the initial hypothesis, the results indicate a significant negative effect of eco-innovation on economic growth. However, several methodological deficiencies, including the approximation of eco-innovation with environmental patents, suggest that further studies adopting more comprehensive measures may lead to different results. More importantly, implicit from the shortcomings of this thesis is the call for a hastened maturity of eco-innovation academia and the urge for policies promoting an accelerated empirical establishment of this concept as a vital component in green growth strategies.

Keywords: *eco-innovation, green growth, natural capital, cross-sectional dependence*

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1. Introduction

Our world is finite. The advancement of human kind is ultimately restricted by a limited amount of natural resources available on the planet and intimately connected to the deteriorating capacity of the global ecosystem and the atmosphere to nurture us. While global natural resource usage has tripled in the past four decades, recent estimates point toward an additional increase of more than 100 % by 2050 (International Resource Panel 2017; UNEP 2017). Presented in light of unequivocal evidence from the Intergovernmental Panel on Climate Change (IPCC) (2014) on global warming of up to 1 °C in the past 140 years, with two thirds of this increase occurring since 1975 and now approaching an irreversible point, together with the ever-rising levels of greenhouse gases in the atmosphere (NASA 2018), these figures paint an alarming picture of our common environmental imprint and the prospects of future sustainable development. Bearing these simple yet powerful facts in mind, continued unprecedented population growth projecting a 60 % increase of the world's inhabitants by 2100 (UN DESA 2017), the emergence of new middle- and upper middle-income economies and the remained neglect of these issues by prominent policy-makers, ensuring economic growth and sustainable development while reducing environmental impact is undoubtedly one of the greatest challenges of our civilization.

Of crucial importance to this objective is the role of innovation, research and technology development. Acting as a catalyst for economic growth through enhancing productivity and competitiveness, while mitigating environmental deterioration by improving resource efficiency and offering new adaptation technologies, the concept of eco-innovation constitutes a key mechanism in balancing the trade-off between our environment and economic growth. Although an institutional implementation of eco-innovation on the international agenda has occurred in recent years (see for instance OECD 2018, UNEP 2018 and the European Commission 2015), the empirical literature on the subject is still in its cradle. Subsequently, a vast majority of eco-innovation research is devoted to methodological concerns and not to providing policy-inducing econometric evidence.

With the ambition to depart from this theoretical tendency, motivated by the urgent need for increased efforts in mitigating environmental impacts, this study examines the effects of eco-innovation on economic growth by running a fixed effects regression model with cross-sectional dependence on a panel data set comprising of 32 OECD and BRICS countries over a period of

33 years from 1981-2014. A proposed endogenous growth model augmented to account for natural capital is adopted as a guiding theoretical framework for the analysis. In order to obtain somewhat robust and interpretable econometric results, the key independent variable of environmental technology was constructed on the basis of data availability and previous innovation literature as an approximation of eco-innovation as the share of environmental technology patents to all patents filed in total. While this measure will prove to have its drawbacks, it is perceived as a suitable estimate for eco-innovation in the absence of more comprehensive alternatives. In addition, six factors conventionally argued to have an impact on the independent variable of GDP growth rate was controlled for in the regressions; investment, population growth, human capital, the degree to which a country is open to global trade, its relative technology level and finally R&D expenditure as an approximation of other innovations. In contrast to initial expectations, the results indicate that increased eco-innovation activity has a negative significant effect on economic growth with and without an assumed delay of five years. However, while not being significant, the direction of this effect changes when allowing for a longer lag length. While the main result of this study do not directly imply increased policy-measures aimed at further inducing eco-innovation for economic growth, this latter finding cautiously urges future research to further disentangle and delve deeper into this relationship. More importantly, implicit from the shortcomings of this thesis is the call for a hastened maturity of eco-innovation academia; future research and potential evidence for the assumed growth-enhancing properties of eco-innovation are ultimately dependent on a methodological consensus, in terms of standardized measurements and definitions potentially facilitating data collection.

In order to achieve a deeper understanding of the effects of eco-innovation on economic growth, the paper is organized as follows. The second section provides an overview of the theoretical and historical foundations which the concept of eco-innovation rests upon, followed by a summary of the methodological debate on the subject and a brief account of the highly limited quantitative research on the subject. The third section guides the reader through the proposed theoretical boundaries for the analysis. The fourth section outlines the econometric method; including a detailed data and variable description, the formal specification of the regressions and an extensive discussion of potential estimation problems. The fifth section presents the results from the regressions, followed by a more elaborate discussion in the sixth section. Finally, some concluding remarks are made.

2. Background and Conceptual Framework

Before delving into the more technical matters of this study, it seems appropriate to place this paper in its proper context by examining the concepts and research on which the analysis is resting upon. In order to accentuate the importance of exploring the wide possibilities offered by innovation to mitigate climate change whilst sustaining, and in the long run possibly even enhancing economic growth, this section commences with an outline of historical and contemporary perspectives on this relationship. The context will then be successively limited towards the primary focus of the analysis by examining some of the proposed mechanisms through which economic advancements and environmental mitigation can be compatible; a linkage of the concept to research on the Environmental Kuznets curve is followed by a discussion of the role of eco-innovation in enabling decoupling towards green growth. Then, an account of the literature devoted to defining and measuring eco-innovation is presented, leading to the conceptual limitations adopted in this study. Lastly, a brief overview of the highly limited existing research on the field is provided.

2.1. The Environment and Economic Growth: Trade-off or Balance?

The notion of a trade-off between economic growth and our environment is not a novelty. Rooted in the Malthusian doctrine, the idea of limited natural resources imposing restrictions on economic expansion and development gained a renewed focus in the aftermath of the second industrial revolution through the influential report *The Limits to Growth* (Meadows et al., 1972). In her book, Meadows and her co-authors described an exponentially growing problem of unsustainable usage of natural resources and extensive pollution (p. 69), with potentially catastrophic consequences. This research contributed to a popularization of the issue, which eventually led to its presence on the international political agenda. However, as policymakers assembled to tackle the problem, it was with a newfound optimism; in the highly influential Brundtland report (1987), it was proclaimed that "[…] economic development and environmental maintenance can go along hand in hand" (p. 242). After an institutional implementation of the debate with the Rio de Janeiro Earth Summit in 1992, an academic field solely devoted to exploring this intricate, two-fold relationship both empirically and in theory began to emerge. There seems to be a consensus on the presence of vast environmental externalities in domestic and international markets, in the sense that the depletion of resources caused by economic growth in the present imposes restrictions on future generations not captured in production costs. However, the ability of the market, the role of policymaking and technological progress to internalize these externalities are disputed. Hepburn and Bowen (2012) comprehensively separate the literature on the subject into three distinguishable camps characterized by different degrees of optimism. The first camp holds the pessimistic belief that environmental restrictions will ultimately obstruct growth in the long run, while the second perspective allows for continued economic advancements but with an "environmental drag". The third viewpoint postulates that sustained economic growth in tandem with environmental improvements is indeed possible through technological development (p. 7-12). While this study seeks to empirically examine the potential positive growth effects of environmental innovation and hence implicitly leans towards the latter stances, it is of utmost importance to recognize the former ones as well.

The first perspective on the interplay between economic growth and the environment adopts the view that the restrictions put on production and consumption by the environment simply outweigh the ability of technological progress to generate long-run economic development. With its foundations in classical economics of finite resources in an era when limited emphasis was put on the environmental dimension of growth, encapsulated in Mill's (1848) notion of an imminent environmental breakdown in all scenarios except for a zero-growth state, this viewpoint as depicted by Meadows et al. may seem quite antiquated in a world where renewables as a result of continued environmental innovation account for a growing energy market share (See Eurostat 2018 and US Office of Energy Efficiency & Renewable Energy 2016). However, as Brown et al. (1973) underline in a reply to a critique of *The Limits to Growth*, the reality of Meadow's dystopia depends on the nature of resources in production and the ability to utilize these efficiently. Dasgupta and Heal (1974) argues along the same lines that progress along a balanced growth path is merely possible with a diminishing weight of non-renewable resources in the economy. Even though modern reincarnations of this perspective have been introduced through, for instance, Tim Jackson's influential book *Prosperity without Growth* (2017), the emerging focus on environmental improvement in the international policy agenda and in R&D indicates a more optimistic scenario.

This trade-off between technological development and resource usage reflects the "environmental drag" which lies at the core of the second camp of academia on the subject. Whilst adopting a more optimistic view by emphasizing the potential of innovative activities to effectively counterbalance the restrictions imposed by the environment, this literature does by no means refute the possibility of an environmental collapse if human efforts are not sufficient. As the main objective of this paper is to investigate the potential of environmental innovations to equate this trade-off, it is essential to disentangle the concept of an "environmental drag" on growth. It be divided into two components; the limitations imposed on production by our world's fixed amount of natural resources and the equally important drag from pollution (Hepburn & Bowen 2012, p. 8-10). Several attempts to estimate these components have been made, where perhaps the most influential is the work of Nordhaus (1992). He provides rough estimates of a growth drag resulting from non-renewable resources amounting to a decline of 0.184 % in the global annual growth rate, with an equivalent of 0.073 % due to pollution (p. 30-32). However, the contemporary relevance of these numbers is disputed. Jones and Vollrath (2013) argue that the dramatic increase in consumption of non-renewable resources over the last decades is offset by a parallel increase in the total stock of resources due to new discoveries of oil, gas and coal reserves (p. 236). If true, this makes their approximation of a resource drag of 0.3 percentage points in the United States, based on Nordhaus' parameter estimates in 1992, still relevant today. Other estimates depict a more alarming situation; in a widely recognized report on climate change, Nicholas Stern (2006) argues that the costs of climate change, without action, may be as large as 5 % of global GDP annually. Junbo et al. (2009) show that the growth drag from land, water and energy in China is 1.32 %, roughly six times their estimated United States equivalent, while Bruvoll et al. (1999) present an environmental drag in Norway which is more than double the global estimates of Nordhaus.

Despite these differing estimates of an environmental drag on economic growth, its presence seems rather uncontested – necessitating augmented efforts to reduce the impact of natural constraints through innovation and technological progress, as concluded in the Stern Review (p. 363). In light of this appeal, Brock and Taylor (2004) presents the less discouraging finding that the growth drag from environmental policies seems to be close to non-existent. Ultimately, it is through an effective implementation of such policy measures, targeting environment-degrading activities through for instance carbon taxes or directly promoting eco-innovation, that the combined targets of sustained economic growth and environmental improvement can be reached (Smulders 1995). An implicit assumption behind this reasoning, central to the final perspective presented below, is the notion that policy can affect the long-run growth rate of an economy. In other words, these arguments may be placed in the context of an endogenous growth framework (Jones & Vollrath 2013, p.216), which translates to the case of this analysis as evident in section three.

Moving to the third and most optimistic body of literature on the subject, its boundaries may be defined quite differently. Hepburn and Bowen (2012, p. 7-8) dismiss this notion of limitless growth even under the restrictions imposed by the environment as a somewhat naïve conclusion of neo-classical and new growth theories failing to fully account for finite resources and pollution. However, a broader and slightly more encouraging view is adopted here, primarily due to the absence of eco-innovation in these models. Although several extended neoclassical models accounting for the earth's boundaries, including Stokey (1998) and Jones and Vollrath (2013), have concluded that continuous growth is possible even under such circumstances, their relevance is contested (Mayumi et al., 1998). Similar initiatives within endogenous growth theory have also been made. In a Schumpeterian model, Aghion and Howitt (2009, p. 379-384) showed that sustained growth in the presence of exhaustible resources is achievable if the R&D labour share is sufficiently large to overcome the environmental drag. Additionally, in a comparison of different endogenous growth models, Elbasha and Roe (1995) confirm that the potential to combat environmental externalities seems to exist mainly in the models allowing for innovative activity as a driver for growth. These results accentuate the critical role of eco-innovation in this third perspective to balance the growth-environment trade-off by countervailing the diminishing returns to capital and the previously discussed environmental drag through enhanced productivity.

An alternative observation arguably also relevant in this context is the tendency of pollution levels to eventually decline as developed economies surpass a certain income level. This inverted U-shaped relationship, often referred to as the Environmental Kuznets Curve (EKC), has been subject to much debate. Despite the causality assumed in this extensive research being the reverse of the one of interest here, the inability of empirics to prove its direction may, as Carson (2009) points out, indicate a two-fold relationship and hence provide some valuable insights. In one of the most prominent studies on the EKC, Grossman and Krueger (1995) establish a relationship between economic growth and environmental impact using data from OECD countries. This correlation has since then both been confirmed (see for example Bo 2011, Managi 2011, p. 5-11; 44-46 and Selden & Song 1994) and rejected. The major criticisms as proposed by David Stern (2004) are that the relationship is merely present on a cross-sectional level in developed countries and is subject to weak econometric evidence. Despite ambiguous evidence of the EKC, its extreme advocates often appeal to an intrinsic property of economic growth to automatically improve the environment and rely on this argument to opt for economic expansion in itself as an environmental policy objective (Raymond 2004). This is not the position of this paper; rather, more emphasis is put on the role of active environmental policies spurring eco-innovation as an essential underlying catalyst in the EKC relationship. In a survey of EKC literature, Christoph Lieb (2003) concludes that the very existence of this inverted U-shape relationship for many pollutants is partly determined by policy measures. While affirming the environmental benefits of structural shifts toward a service-oriented economy, Neumayer and Van Alstine (2010, p. 6-8) also confirm the plausibility of EKC patterns as a policy response. Extending this position, Smulders and Bretschger (2000) argue that increased pollution may in fact induce policy measures promoting new technologies, generating growth as a consequence – a result reaffirmed in a similar analysis performed by Lorente and Alvarez-Herranz (2016) on energy-oriented R&D. This emergence of eco-innovation in EKC literature complements its crucial role as a growth-enabler allowing for environmental mitigation, indicating the possibility of a balance between economic growth and the environment rather than a trade-off. Bearing this in mind, the remainder of this section will, within the extended boundaries of this third position, be devoted to describing eco-innovation as a driver for green growth and providing further conceptual clarifications.

2.2. Framing Eco-innovation

This review of the different perspectives on the relationship between economic growth and the environment, with fruitful insights from the EKC literature, culminates in the concept of eco-innovation[1]. A core mechanism embedded in the hypothesis of this paper, eco-innovation may be viewed as an essential means to accomplish the target of green growth (OECD 2018). Since this

[1] Note that the labels of eco-innovation and environmental innovation are in this paper adopted as synonyms for the same concept.

idea lies at the heart of the analysis, it is appropriate to outline its multifaceted definitions and proposed ways of measuring it.

2.2.1. Eco-Innovation for Green Growth

In order to gain further understanding of the concept of eco-innovation, we may place it in a wider context of the current discourse of sustainable development – namely green growth. Essentially, this emerging objective is captured in the background above; that is, stimulating sustained economic growth while reducing the depletion of natural resources, pollution and other environmental impacts (UN DESA 2018). Important to note is that in this context, green growth is referred to with the ambition that the earth's finite resources should suffice for many generations to come, without significantly compromising contemporary economic development (Hallegatte et al., 2011). A central mechanism in the process towards this policy target is that of decoupling, or disconnecting economic goods from environmental bads (OECD 2002). This notion provides a fundamental theoretical link for investigating eco-innovation as a driver for continued economic development, captured in a 2014 report by the UNEP International Resource Panel where the potential of development in environmental technologies to "accelerate decoupling and reap the environmental and economic benefits of increased resource productivity" is emphasized (Von Weizsäcker et al., p. 12). While these possibilities find support in several other studies (see for instance Arundel & Kemp 2009 and Jänicke 2012), it is here important to distinguish the effects of eco-innovation on absolute versus relative decoupling. Defined by Jackson (2009, p. 66-72), relative decoupling occurs when environmental impact per unit of economic output declines, which implies that pollution and resource depletion may still occur in absolute terms – referred to as absolute decoupling. In a long run perspective, realizing green growth demands an increased focus on absolute decoupling.

Finally, when discussing eco-innovation for green growth in a policy perspective, a common proposition is that policies aiming to regulate environmental impacts often induce innovation and enhance productivity by increasing competitiveness. Termed the Porter Hypothesis after its initial proponent Michael Porter (1995), this idea has gained considerable attention in research and is backed by some empirical evidence (Lanoie et al. 2008; Ambec et al. 2013). Extending this suggestion to a for this study even more relevant observation, Jacobs (2012) postulates that the effect of environmental policies specifically aimed at promoting eco-innovation may result in a larger effect than anticipated due to "spillover" effects generated by these same competition-enhancing mechanisms.

2.2.2. Definitions and Measurement

Several definitions of eco-innovation are at hand, ranging from the simple notion of introducing new products of value to the market whilst reducing environmental impact, as stated in one of the first explorations of the idea by Fussler and James (1996), to more elaborate conceptualizations also including the entire life-cycle of the product or service as well as novel systems, production processes and procedures (Reid and Miedzinski 2008). In the final report of an OECD-initialized project titled "Measuring eco-innovation" or MEI, Kemp and Pearson (2007) extend the definition to new management and business methods, concluding that the definition of the concept critically depends on the ability to assess environmental effects and risks of new innovations. In addition, remarks have been made about the potential of eco-innovation in governance and organizational structure (Carillo-Hermosilla et al. 2009, p. 6-8). This notion that environmental innovation may occur in other forms than simple technological improvements is an important observation – overseeing this could result in an underestimation of the vast potential of eco-innovation and hence reduce its significance in policy-making.

In this context, Rennings (2000) distinguishes four different dimensions in which eco-innovation may occur; they can be of a technological, organizational, social or institutional nature. While the scope of this study lies primarily within the boundaries of the technological dimension, this does by no means make the others less relevant. Returning to the final MEI report by Kemp and Pearson (2007, p. 7), technological eco-innovation essentially refers to "the production, assimilation or exploitation of a product, production process, service or management or business method that is new to the organization (developing or adopting it) and which results, throughout its life cycle, in reductions in environmental risks, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives". There are several imperative elements in this comprehensive definition. First, many technological eco-innovations are not in fact completely new products or processes, but merely incremental alterations exploiting existing technology (Carrillo-Hermosilla et al. 2009). In fact, empirics indicate that as few as 10 % of all new innovations result in radical new changes and that this incremental bias persists in eco-innovative activities (Hellström 2006). Further, Machiba (2010) argues that incremental innovations primarily result in relative decoupling, while radical technological development is associated with absolute decoupling. In this sense, a larger share of radical systemic innovations seems desirable. Second, to ensure comparability between eco-innovations and "relevant alternatives", a standardized method of assessing environmental risks and effects over entire product life-cycles is needed. Despite several initiatives made to accomplish a generalized assessment framework (see for instance Kemp & Pearson 2007, Popp 2009, Arundel & Kemp 2009 and the Eco-Innovation Observatory Methodological Report 2012), a uniform approach in the academia is yet to be seen. A third and often overlooked element is the fact that all innovations, intentionally designed to tackle environmental problems or not, may be classified as eco-innovations if they reduce environmental impact (OECD 2010a, p. 15-17). Unfortunately, limited data availability and methodological restrictions will not allow us to account for this notion here.

Moving on, examples of organizational eco-innovation include internal structural changes, ecological business models and the implementation of eco-audits to evaluate managerial adherence to environmental objectives (Rennings 2000; Boons et al. 2013). As Motta et al. (2016) points out, the latter two are often implemented as a consequence of product-related technological eco-innovation. Social eco-innovations, in turn, may refer to more sustainable consumption patterns or increased environmental awareness.

Finally, Rennings (p. 322-324) specifies institutional eco-innovation as more general emerging regimes of environmental global governance, such as the IPCC and the United Nations Environment Programme (UNEP), as well as the increased importance of eco-innovation in domestic and international policy-making. A survey conducted on ten OECD countries reflects this trend, finding that an increased number of governments now recognize environmental restrictions not as an obstruction to economic growth but as new opportunities to enhance productivity and competitiveness (OECD 2010a, p. 19). Also, the emergence of international initiatives such as the Eco-innovation Project by the European Commission and OECD's Green Growth Forum points in the right direction. Since 2010, the former provides a scoreboard tracking EU members' efforts to induce and achieve eco-innovation, based on an index provided by the Eco-Innovation Observatory. This index is calculated from 16 different indicators including eco-innovation inputs, outputs, activities, resource efficiency and socio-economic outcomes, and was as of 2017 topped by Sweden, followed by Finland and Germany (European Comission 2018).

However, due to the novelty of the subject, data on this index and similar attempts to measure eco-innovation only exist for recent years. As more emphasis is put on achieving relevant econometric estimations, the chosen measurement in this analysis is patents filed in environment-related technologies. On top of fulfilling the econometric criteria, this measure also captures some of the most relevant aspects of eco-innovation; firstly, as patents are generally viewed as an output of the innovation process, they act as a proxy for its inputs (such as environmental policies including R&D expenditures, subsidies and regulations) and secondly, it encapsulates different innovative activities (Eco-Innovation Observatory 2012 p. 20; Oltra & de Vries 2009). To illustrate the latter property of this measurement, a graph depicting eco-innovation trends in OECD countries from 1990-2011 is shown below, based on patents filed in different environmental categories.

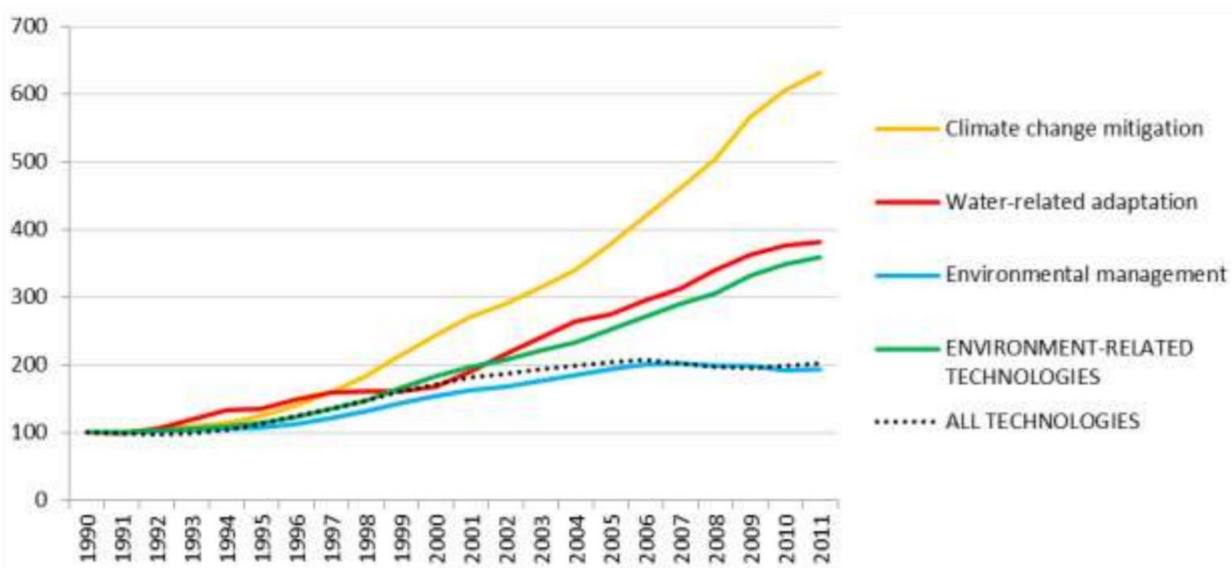

Figure 1: Eco-innovation trends by activity, measured as an index of filed environmental patents where 1990=100 (Source: OECD 2015).

Evident from figure 1 is the increased share of total environment-related patents dedicated to mitigating climate change. Also, during the period, more innovations seem to be devoted to improving the environment in general. For a further discussion on measuring eco-innovation and patents in general, see section 4.1.

Returning to the many definitions of eco-innovation, it is apparent that this choice of measurement imposes some restrictions on how the concept is specified in this study. The very bottom line, however, seems to be found in the simple distinction between "regular" innovations and eco-innovations; the latter does not only result in economic benefits in form of added value and productivity gains, but also environmental improvements resulting from for instance more resource-efficient production processes, reduced pollution and less waste. Following this notion and considering the insights of the discussion above, the definition of eco-innovation in this study is limited within the technological dimension to the aspects of the specification by Kemp and Pearson (2007) which are captured in patents.

2.2.3. A Brief Complementary Literature Review: Econometric Evidence

As the research field on eco-innovation is still in its cradle, insufficient data and the absence of a standardized definition and measurement means the econometric evidence for its potential effects on economic growth is highly limited. Instead, much of the literature, as apparent from the background outlined above, is concentrated on defining and reaching a consensus on a theoretical framework on the subject. While the underlying ambition of this section has been to provide a brief review of this academia, a brief complementary examination of the few econometric studies conducted on eco-innovation and growth is believed to efficiently wrap up this section. These studies have exclusively been performed on a firm-level, motivating the macro-perspective of this study. In a microeconometric analysis using panel data from firms in six European countries and adopting a patent-based measure for environmental innovation, Colombelli et al. (2015) show that eco-innovation tends to increase growth in firm sales. Similar, but not statistically significant, results are achieved in a study on 15 Indian regions by Mohapatra and Giri (2009). On the contrary, Marin and Lotti (2017) arrive at the conclusion that an increased focus on eco-innovations result in a lower return compared to other technological developments when examining a sample of Italian manufacturing firms. Cheng et al. (2014) show similar results in the context of technological eco-innovation in a study using panel data on 121 Taiwanese firms, although a positive effect on output growth is established when focusing on organizational eco-innovation.

More econometric research on the macro- as well as micro-level has been conducted with the aspiration to map the determinants of eco-innovation (see for example Horbach 2008, del Rio et al. 2016 and Demirel & Kesidou 2011). However, despite this subject being briefly discussed earlier in this section in terms of the Porter Hypothesis, a more detailed review of this literature is beyond the scope of this text. With this said, we now move on to introduce the theoretical model of the analysis.

3. Theoretical Model

In this section, the theoretical foundations of this study will be outlined. The model presented below should be moderately interpreted as a conceptualization of the insights of the previous section with the ambition to encourage the reader to connect this analysis with endogenous growth theory. Thus, less weight will be put on the technical aspects of the model and detailed calculations will not be included. Based on the Solow framework with natural resources formulated by Jones and Vollrath (2013, p. 230-232), the model proposed here extends these theories in two dimensions. First, departing from merely including natural resources, this component of the production function is redefined as "natural capital", an extremely broad concept intended to capture all aspects of the environment which may restrict economic development. At a glance, this definition may seem confusing and not narrow enough, but in order for this theoretical model to encapsulate all detrimental effects of economic development on the environment, this width is necessary. Natural capital is here referred to as the many components that make up the environment; natural resources including geological assets, energy and other biological resources such as livestock or wild animals; land, water, ecosystems, habitats and their functions and finally planetary systems and climatological properties (such as air, temperature and wind etc.) (United Nations Statistical Commission 2014; Elkins et al. 2003). In this sense, it is of utmost importance to recognize the attempt of this definition to incorporate pollution and waste generation – such deteriorating processes are reflected in a negative accumulation of natural capital. Second, technological progress is divided into two components – "general" innovation and eco-innovation aimed at augmenting the productivity of natural capital – which are subsequently endogenized in the model. Consequently, this broad definition of natural capital enables the model to account for the numerous aspects of eco-innovation discussed earlier. As such, one could view this framework as an augmented version of the model proposed by Romer (1990) to include restrictions imposed by the environment.

Moving on, the production function illustrating the combination of labour devoted to production (L_Y), the capital stock (K) and the natural capital input in each period (E), enhanced by general technological progress (A) and eco-innovation (B), to produce output (Y) can be described as

$$Y = K^{\propto}(AL_Y)^{1-\propto-\gamma}(BE)^{\gamma} \tag{3.1}$$

where $\propto$ and γ are parameters between one and zero. As evident from equation (3.1), the economy exhibits constant returns to scale in labor and capital, while the inclusion of technological development allows for increasing returns – a key assumption for sustained economic growth. Subsequently, if the total initial natural capital stock is referred to as R_0, it declines in absolute terms with

$$\dot{R} = -E \tag{3.2}$$

every period. Assuming the total natural capital stock declines with a fraction of $s_E = E/R$ over time, dividing both sides of equation (3.2) by R yields the depletion rate of natural capital, - s_E:

$$\frac{\dot{R}}{R} = -s_E \tag{3.3}$$

Ideally, the following econometric analysis would control for this depletion rate. However, the wide definition of natural capital adopted here in combination with limited data availability implies that doing so would result in a very complicated and long specification with weak results. Nonetheless, such an operation may be relevant for further research on the subject. Turning to describing the endogenized accumulation processes of environmental and other technologies, the growth rate of eco-innovation is determined by environmental research productivity (ϑ) and the number of people in the labour force devoted to environmental innovation (L_E):

$$\frac{\dot{B}}{B} = \vartheta L_E \tag{3.4}$$

This description of how eco-innovation develops is central to the analysis. As efforts in eco-innovation (B) expand according to function (3.4), the productivity of natural capital increases and presumably enables the economy to decouple environmental impacts from economic development, moving towards sustained green growth by gradually using less natural capital input per unit of economic output. Similarly, the growth rate of other innovations depends on the research productivity of these efforts (θ) and the number of researchers engaged in them (L_A):

$$\frac{\dot{A}}{A} = \theta L_A \tag{3.5}$$

Opposed to more elaborated versions of endogenous growth, but in line with the original assumptions of Romer (1990), the technological development described in equations (3.4) and (3.5) are subject to the simplifying presumption of no diminishing returns. Although this may widen the gap between the model and reality, it is in the context of this study not deemed necessary to include these parameters as it only makes matters more complicated. When it comes to the labour force, the total number of workers (L) is the sum of researchers engaged in environmental and other innovation activities and production workers;

$$L_E + L_A + L_Y = L \tag{3.6}$$

while the growth rate of the labour force is assumed to be equal to the growth rate of the population (n) according to equation (3.7):

$$\frac{\dot{L}}{L} = n \tag{3.7}$$

Finally, the accumulation of capital is, in accordance with conventional neo-classical growth theory, assumed to positively depend on the savings rate (s), in the sense that a fraction s of total GDP (Y) is reinvested in the economy, while being counterbalanced by the fact that capital depreciates at the exogenously determined depreciation rate δ:

$$\dot{K} = sY - \delta K \tag{3.4}$$

Fundamentally, it is within the theoretical framework modelled in this section that the analysis will be conducted. The long-run growth rate of the economy is presumably positively correlated with the determinants of the growth rate of eco-innovation and general technologies; namely their corresponding productivity parameters and the number of researchers engaged in each R&D domain, ultimately defined by the population growth rate. On the contrary, the share of natural capital used in production is assumed to have a negative effect on growth. While the following econometric model attempts to capture the former determinants with the approximations of environmental patents, general R&D expenditures and population growth, the latter will as previously stated not be included. With this said, we conclude by once again reaffirming that this framework should rather be viewed as a guide to place the analysis in a suitable theoretical context than a strict rationale for the hypothesis of the study.

4. Econometric Method

In order to investigate the potential effects of eco-innovation on economic growth, a multiple regression model is adopted to examine a panel data set covering 32 OECD and BRICS countries over a period of 33 years from 1981-2014.[2] This time range is determined by limited patent data availability, from which the focus variable of environmental technology was selected to provide sufficient observations for reasonable estimations. Included in the regression model is also the proxy variable of R&D expenditures to control for other, non-environmental innovation activity. The econometric specification is completed with several conventional factors known within the field of economic growth to impact this macroeconomic target.

Introducing a time dimension to cross-sectional observations to acquire a longitudinal data set enables us to conduct a more nuanced, in-depth analysis compared to data with merely one identifier. While panel data provides more observations and allows us to follow individual-specific trends over time, it may also generate additional estimation biases under the wrong assumptions with heterogeneous panels. However, its estimators are generally conceived to represent a reasonable average of the individual parameters and are hence preferential to single-dimensional data sets (Asteriou & Hall, 416-417). Bearing these aspects in mind, we shall now proceed with a more detailed investigation of the included variables, followed by an examination of the data and its sources. Subsequently, after descriptive statistics and an econometric specification are presented, we delve into an econometric discussion where potential data deficiencies are addressed.

4.1. Included Variables

Prior to providing descriptions for each variable, motivating and critically assessing their inclusion in the regression model, a couple of general remarks should be made. It is important to note that all variables are measured as percentages, with the exception of human capital. Furthermore, since the variables related to innovation suffer from numerous measurement problems due to their conceptual complexity, much of the available data is fragmented and ambiguous. However, the OECD has since the 1990s actively worked for a common

[2] The program used for processing the data is StataIC 13.

measurement agenda resulting in an extensive innovation database (OECD 2010b), which is adopted as a source for the innovation data in this study.

GDP Growth

The dependent variable of the regression is measured as the five-year annual average growth rate of real gross domestic product, calculated as follows:

$$gdpgrowth = \left(\frac{GDP\ year\ t+5}{GDP\ year\ t}\right)^{1/5} - 1 \tag{4.2}$$

The choice of using aggregate GDP and not the conventional per capita measure in the regression is mainly motivated by our ambition to examine aggregate macroeconomic performance. Since the focus variable of eco-innovation is approximated with an aggregate environmental patent count and not patents per capita, the dependent variable follows the same measure for the sake of consistency. Well aware of the potential shortcomings arising from this choice, regressions with GDP per capita as a dependent variable were conducted and yielded similar results. Hence, the aggregate measure is deemed sufficient for the analysis.

Environmental Technology

The independent variable of interest was chosen to capture the aspects of technological eco-innovation and investments allocated to enhancing the productivity of natural capital in line with the objective of this paper**.** Defined as the percentage share of all new innovations dedicated to the development of new environmental technologies, it also allows for a more nuanced analysis as it measures the relative importance of environmental innovation compared technological development in general. As previously mentioned, innovations in this context are measured as the number of patents filed to international patent offices. Thus, the development of environment-related technologies may be translated into the share of the total number of patents dedicated to; 1) general environmental management; 2) adaptation of planetary systems (such as water-, sun- and air-related adaptation) and 3) climate change mitigation technologies (Hascic & Migotto 2015).[3] Furthermore, since previous research suggests a possible delay in the presumed

[3] A more detailed specification of what is included in these three research domains is supplied by the OECD Environment Directorate (2016).

effects of innovation on economic growth (Hausman et al. 1984), assumed to translate to the case of eco-innovation, the variable will be subjected to lags of up to two five-year periods.

This measure of environmental innovation does, however, come with possible shortcomings which are important to address. First, the validity of patents as a proxy measure for the abstract concept of innovation has been intensely debated. Additionally, the fact that it is the number of patents *filed* and not granted may imply further complications. Far from all patents filed are granted, and even fewer patent grants do in fact result in a contribution to technology development. Nonetheless, this measure is still widely used and accepted in economic growth research (Jones & Vollrath p. 92-94). More importantly, the nature of this study requires innovation activities to be broken down into sub-categories (that is, environmental innovation), which in terms of data availability is not an option with other measures of innovation such as expenditures on R&D. This alternative measure is also generally regarded as an input in innovation processes, while this study is more concerned with its outputs (Hascic & Migotto, p.14). In light of these arguments, patents are seen as the preferential measurement approach in this study. Second, the fact that the environmental technology variable is measured as a share of total innovations implies that one must be careful when interpreting the results. If eco-innovation remains stagnant while overall technology development increases, the fraction decreases and may provide a distorted picture of the effects of the variable.

In light of the limited previous research on the field, the novelty of the subject and the lack of sufficient data, our ability to predict the effects of environmental innovation on economic growth is restricted. However, since environmental innovation is a part of innovation in general, whose effects on economic growth have been extensively examined and confirmed (see for example Jones & Vollrath 2013; Grossman & Helpman 1991; Aghion & Howitt 1998 and Bilbao-Osorio & Rodriguez-Pose 2004), together with insights from previous sections, we may expect a positive effect of this variable on GDP growth. When it comes to the time required for this effect to occur, it seems probable that at least a lag length of a period of five years is necessary.

Expenditures on R&D

Introducing expenditures on R&D of all technologies as an independent variable controls for the effects on economic growth of other innovations than those related to the environment. In the absence of this variable, the model would implicitly assume that eco-innovation is the only innovative activity of importance, which seems highly unrealistic. Referring once again to the extensive literature on the subject, expenditures on R&D is included in the regression. As with the case of environmental technology, this variable will also be tested with up to two lags.

The variable is measured in GERD (Gross Expenditure on R&D) as a percentage of GDP, making it subject to a similar potential distortion as with the case of environmental technology. Furthermore, building on the discussion above regarding patents contra R&D as an approximation measure for innovation, it seems highly suitable to motivate the choice of using the latter for this variable. There are two main reasons for this; firstly, since the total number of patents is present in the denominator of the focus variable, using the same measure would lead to unnecessarily high levels of multicollinearity between the variables and thus produce unreliable results. Secondly, the fact that expenditures on R&D are often seen as an input in innovation processes adds an extra dimension to the analysis. A higher degree of multicollinearity is expected between expenditures on R&D and the focus variable as the denominator in the latter constitutes a proxy for the same phenomenon as the latter. Nevertheless, the correlation between the variables does not seem to be dangerously high (see correlation matrix in the Appendix.).

In accordance with the previous research mentioned earlier on the effect of increased R&D expenditures on economic growth, a positive coefficient is expected. This expectation does, however, depend on the lag length. Some evidence confirms the well-established trade-off between increased investments and thus reduced consumption in the present to achieve higher growth rates in the future, implying a negative effect in the presence of no lags (Ulku 2004).

Investments

Following Robert Solow's (1956) seminal paper on the crucial role of investments – defined as the share of gross physical capital accumulation of GDP – in enabling larger scales of production and hence higher GDP levels, this variable is included in the regressions. While plenty of evidence for a significant positive effect of investments exists, including the extensive work of Sala-i-Martin (1997), one should also bear in mind the possibility of a reverse causality as proposed by Barro (1996). Nevertheless, this paper aligns with conventional economic growth theory by expecting a positive effect.

Human Capital

The inclusion of human capital in the model, measured as the average years of total schooling for the population as a whole in the beginning of each five-year period, is also based upon the evidence of previous research. Mincer (1984), Barro (1992) and Wilson & Briscoe (2004) all present substantial findings in favour of a positive effect of increased investments in human capital on economic growth. Turning to theory, human capital is a well-established and commonly used input to include in the production function, especially in endogenous growth theories such as the Lucas model and technology transfer models (Jones & Vollrath 2013, p. 218-221; 140-143). In the latter family of models, the role of human capital goes beyond being a productivity booster through higher educational attainment by also acting as a crucial factor in enabling less developed countries to effectively embrace new technologies. As the supply of these new technologies is affected by the degree of openness, and the gains from learning them on the size of the technology gap, the variables complement each other. In line with these notions, the effect of this variable is expected to be positive.

Openness

Turning to openness, this variable is conventionally measured as an index in the form of a quota between the trade volumes (exports and imports) and GDP of a country, which is indeed the case in this study. The index could in one sense be viewed as an approximation with the ambition to capture the degree of which a country is intertwined with the global system, in terms of trade, capital, knowledge and technology transfer. In turn, it is the exchange and embracement of these elements which according to theory and empirics allow for higher growth rates (Jones & Vollrath 2013). Correspondingly, a higher degree of openness is predicted to result in higher growth rates.

Technology Gap

In order to control for technology transfer effects and the general technology level of economies, a variable measuring domestic total factor productivity (TFP) relative to the global technology frontier is often introduced. In this context, it is important to clarify how TFP is measured and what is meant by the technological frontier. The relative TFP measure adopted in this study is developed by Feenstra, Inklaar and Timmer (2015) and calculated as a residual from an assumed production function, where GDP and capital data identical to that used in this paper are applied as inputs (for a more detailed description, see p. 3154-55; 3191). Further, the technological frontier is assumed to be the United States, a premise which may be debated but also finds sufficient empirical support in terms of innovation output (WIPO 2017).

On the basis of theoretical evidence in the form of convergence and technology transfer mechanisms, the presumed effects of this variable are quite ambiguous. In one sense, economies far below the frontier are expected to converge towards the TFP-level of the United States and thus exhibit high growth rates – a phenomenon rooted in empirical research (Fagerberg 1987). On the other hand, countries well above the frontier would be expected to grow at significantly lower, or perhaps even negative, rates. Nevertheless, bearing in mind that the average relative TFP-level in the sample is 80 %, an overall positive effect is cautiously assumed.

Population Growth

Finally, the well-known effect of population growth on economic growth is also controlled for in the regressions. By expanding output through augmenting the labour force, a sustained increase of the population is thought to generate a higher GDP (Jones & Vollrath 2013, p. 104-105). It is also appropriate to mention that since no per capita measure is adopted in the dependent variable, the equally well-known two-fold effect of population growth is not as relevant. Also noteworthy is that this variable is calculated in the same manner as GDP growth.[4]

4.2. Data

While the innovation data was acquired from OECD, several other databases were also used. Data for the dependent variable of GDP growth as well as three control variables was gathered from Penn World Tables 9.0, a high-quality database commonly referred to in macroeconomic studies compiled by Feenstra, Inklaar and Timmer (2015). The information needed to construct the openness variables was in turn obtained from the World Bank. Furthermore, the human capital data was acquired from a dataset constructed by Barro & Lee (2016), based on information supplied by the UNESCO Institute for Statistics. All variables and sources in this study are summarized in the table on the next page, complemented with short descriptions.

[4] That is, population growth is calculated according to:

$$n = \left(\frac{Population\ year\ t+5}{Population\ year\ t}\right)^{1/5} - 1$$

Variable	Code	Description	Source
GDP growth	gdpgrowth	The five-year average annual growth rate of output-side real GDP in 2011 PPP USD	Penn World Tables 9.0
Environmental technology	envtech	Development of environment-related technologies expressed as a percentage of the total amount of domestic inventions, defined as the number of higher-value patent applications	OECD
Investments	inv	The share of output-side real GDP in 2011 PPP USD devoted to gross capital formation	Penn World Tables 9.0
Population growth	popgrowth	The five-year average annual growth rate of the population	Penn World Tables 9.0
Human capital	hcavgyears	The average years of total schooling	Barro & Lee (2016)
Technology gap	techgap	Level of TFP relative to the United States (=1)	Penn World Tables 9.0
Openness	open	The value of imports and exports of all goods and services as a share of GDP	World Bank
Expenditure on R&D	rndexp	Gross expenditure on R&D as a percentage of GDP	OECD

Table 1: Variable sources and descriptions

It should be noted that all variables are computed as five-year averages to clear the data from short-term fluctuations and macroeconomic instabilities, in accordance with the norm in the field of economic growth. Subsequently, the time dimension of the panel data is thereby reduced from 33 to 7 observations, where the last period spans over three years instead of five, resulting in a total of 224 observations.

Turning our attention to potential deficiencies in the data, plenty of different problems inherent to the selection process and the nature of the dataset, such as missing values, unbalanced panels and outliers, may be encountered. The initial ambition was to include countries at the global technological frontier, which in terms of innovative activity is dominated by OECD members and the BRICS countries (WIPO 2017). However, due to problems with too many missing data points and the aforementioned limited availability of innovation data, several OECD countries and one BRICS country were excluded from the regressions in order to avoid distorted results. More specifically, Russia, Chile, Estonia, Slovakia, Slovenia and Iceland were not included in the analysis after comparing the results of numerous regressions with and without these states and noting severe discrepancies. This choice is further motivated by the fact that some of these countries, being former Soviet or Yugoslav member states and hence lacking data before their independence, generate a system of missing values which may be endogenous to the model, thus causing further bias (Dougherty p. 530). On the other hand, one should also be aware of the possibility of selection bias, potentially causing a misrepresentation of the population under investigation. However, due to the diversity of the sample created by the inclusion of the BRICS countries, this is not perceived as a major problem.

Furthermore, it is important to underline that even though measures were adopted to reduce the impact of missing values, there are still some observations lacking data in the final data set. Removing all countries with missing values would undoubtedly reduce the power and relevance of the results, not only by reducing the number of observations but also by reducing the diversity of the sample. Hence, it was decided that some missing values were to be allowed in the regressions. Once again, regressions were performed with and without these missing values respectively, in order to ensure that these did not skew the results. Subsequently, the data set was accepted, despite being unbalanced. While not complicating the regressions, this characteristic does narrow the spectrum of statistical tests available.

4.3. Descriptive Statistics

On the next page, descriptive statistics in terms of mean, standard deviation, number of observations, minimum and maximum values are presented for each variable. Notable numbers include the high standard deviations of openness and R&D expenditure.

Variable	Mean	Std. Dev.	Min	Max	Observations
GDP growth	3.320789	2.465434	-3.64921	11.8766	221
Environmental technology (% of total innovations)	8.763806	3.006024	3.42	23.4325	224
Investments (% of GDP)	25.97213	5.234125	14.8665	46.6443	222
Population growth	0.772775	0.691328	-0.40373	3.33193	221
Human capital	9.158661	2.317039	2.34	13.18	224
Technology gap	80.09885	22.01081	24.0649	156.112	222
Openness	68.79318	45.76173	13.1825	334.83	218
Expenditure on R&D (% of GDP)	1.663715	0.881608	0.154869	4.158	200

Table 2: Descriptive statistics for all included variables. Note that all variables except human capital are measured in percent.

Also derived from Table 2 is the fact that the number of observations differs between variables, reflecting the presence of some missing values. Seemingly, it is only the variables of environmental technology and human capital that contain a complete set of data points.

4.4. Model Specification

With the ambition to examine the effects of environmental innovation on economic growth, the standard regression model as stated below was initially considered:

$$gdpgrowth_{i,t} = \beta_1 + \beta_2 * envtech_{i,t} + \beta_3 * inv_{i,t} + \beta_4 * popgrowth_{i,t} + \beta_5 * hcavgyears_{i,t}$$

$$+ \beta_6 * techgap_{i,t} + \beta_7 * open_{i,t} + \beta_8 * rndexp_{i,t} + \varepsilon_{i,t}$$

Where i = 1 … 32; t = 1 … 7

While the above specification would suffice in the ideal situation where all cross-sectional variations are captured in the control variables, the highly probable presence of unobserved country-specific characteristics, for instance caused by historical, cultural or institutional factors, renders this model unreasonable. Hence, we allow for a time-invariant, individual-specific intercept α_i, which due to its unobserved nature is incorporated in the error term structure as follows;

$$\varepsilon_{i,t} = \alpha_i + u_{i,t}$$

which enables us to account for these unexplained variations. Note that $u_{i,t}$ is merely an additional disturbance term introduced when modelling the error component. This reasoning implies a choice between the fixed and random effects models, in which a Durbin-Wu-Hausman test was conducted in order to assist us. Under the null hypothesis, both models are consistent but the fixed effects estimation is inefficient and, correspondingly, if the null is incorrect, the random effects model generates an unnecessary heterogeneity bias (Dougherty p. 540). In this study, the p-value of the test amounted to 0.006, meaning the null was rejected in favour of the fixed effects model. Subsequently, a *T*-period lag of the innovation-related variables *envtech* and *rndexp* was also introduced in the regression model in accordance with previous research, suggesting a possible delay in the effect of these variables on economic growth. Thus, we finally land in the following dynamic fixed effects regression model:

$$gdpgrowth_{i,t} = \alpha_i + \beta_1 * envtech_{i,t-T} + \beta_2 * inv_{i,t} + \beta_3 * popgrowth_{i,t} + \beta_4 * hcavgyears_{i,t}$$

$$+ \beta_5 * techgap_{i,t} + \beta_6 * open_{i,t} + \beta_7 * rndexp_{i,t-T} + u_{i,t}$$

Where i = 1 … 32; t = 1 … 7 and T= 0 … 2

As noted in the specification, the dependent variable is GDP growth and the independent variable in focus is environmental technology, which is complemented by six control variables. The number of countries (*i)* amounts to a total of 32, with observations spanning over 7 periods (*t)* where a maximum lag of two periods or ten years is allowed. It should be mentioned that the results from the regressions where the maximum lag is included should be interpreted with great caution, as the relatively short time span of the data does not provide the ideal conditions for such a long lag length. Nevertheless, this specification is included as it is believed to reflect some interesting time-related aspects of the effects of eco-innovation and general technology development on economic growth.

4.5. Econometric Discussion

Before proceeding with a presentation of the regression results, it is of utmost importance to make certain that the data fulfils the requirements needed to produce reliable outcomes and conduct proper inference. Therefore, the data is subject to a series of tests, investigating the possible presence of non-stationarity, autocorrelation, heteroscedasticity, multicollinearity and cross-sectional dependence. Moving to our first inquiry, the time independence of the distribution mean, variance and covariance between any two data points – generally referred to as stationarity – was examined (Dougherty p. 480-482). This condition was confirmed through a Fisher-type augmented Dickey-Fuller test, which allows for unbalanced panels (Choi 2001). No unit roots were present in any of the variables, with the exception of human capital and technology gap which probed be stationary with a drift term. However, as an intercept is explicitly included in the regressions, no further manipulations of these variables were necessary.

Another potential problem is that of autocorrelation, or serial correlation of the error terms, which implies observations being dependent over time. This issue tends to cause fixed effects OLS estimators to be inefficient and render hypothesis testing invalid with biased and inconsistent estimated variances (Asteriou & Hall p. 151-152). The Wooldridge test for autocorrelation generated a p-value of 0.725, meaning the null hypothesis of no autocorrelation was not rejected.

When it comes to heteroscedasticity, a number of tests were performed to detect this common problem of differing variance across the error terms. If the variability of the disturbance terms is not the same for all observations, the parameters will, once again, suffer from inefficiency and the standard errors are likely to be biased (Dougherty p. 290-294). Initially, the Breusch-Pagan and White tests were performed, where the former accepted the null of homoscedasticity while the latter implied the opposite with a p-value close to zero. As these tests were not initially developed for unbalanced panel data, a final test more fit for the cause was executed (Greene 2002, p. 598-99). This modified Wald test rejected the null of no heteroscedasticity. Concluding that this phenomenon is indeed present in the data, an alternative to robust standard errors was adopted in all regressions to tackle the problem, as shall be seen at the end of this discussion.

Multicollinearity is another problem which is arguably present in the vast majority of econometric analyses. Arising when the explanatory variables are correlated, it is more a matter of degree than kind. Nonetheless, if too serious, multicollinearity among the variables may falsify the estimations by causing the standard errors to be larger than necessary (Asteriou & Hall, p. 98-101). While there are no conventional tests to detect the issue, common diagnostics include the variance inflation factor (VIF) and investigating the variable correlation matrix (Mansfield & Helms 1982). In this study, the mean VIF amounted to 1.20 and no variable VIF exceeded the according to O'Brien (2007, p. 673) critical level of 5 (see Appendix). Hence, after examining the correlation matrix and finding no indications of high levels of multicollinearity, no independent variables were excluded.

Finally, the less conventional, but nonetheless equally important, problem of cross-sectional dependence is addressed. In an increasingly globalized and financially integrated world, it is highly likely that domestic economic shocks and events induce spill-over effects and disturbances reaching beyond borders. As a consequence, international macroeconomic panel data sets are in contemporary econometrics often assumed to suffer from the phenomenon of cross-sectional dependence (Sarafidis & Wansbeek 2012). Essentially, this may be viewed as a cross-sectional correlation of the unobserved factors affecting individual units to different degrees, arguably making it hard to distinguish from the heteroscedasticity problem. However, the difference lies primarily in the dimension which the issue is found – the trouble discussed here concerns the correlation of the error terms between groups (Baltagi & Pesaran 2007). If left unaccounted for, cross-sectional dependence leads to inefficient parameter estimates and, more importantly, biased standard errors resulting in invalid statistical inference (Hoechle 2007). In this context, with conjectures about the presence of cross-sectional dependence in the data, a test for the phenomenon designed by Pesaran (2007) to fit fixed effects panel data with more cross-sectional than time observations was performed. A p-value of 0.000 led to a rejection of the null of no cross-sectional dependence and confirmed the suspicions. Once again, with the complex transnational interlinkages present in the world today and the extensive literature underlining the importance of this subject, this is a problem not to be underestimated. Hence, with the ambition to account for cross-sectional dependence and generate a better fit of the model, Driscoll-Kraay standard errors are used in the regressions. It should be mentioned that these standard errors are also robust to heteroscedastic disturbances (Hoechle 2007, p. 285). As apparent from the results and from the comparison between conventional robust standard errors and the Driscoll-Kaay alternative presented in the Appendix, this measure may have improved the fit of the model in terms of parameter significance.

5. Results

In this section, results from the regressions are presented. In table 3 below, the estimated coefficients for each variable are presented in rows, categorized column-wise according to the number of lags.

Variables	No lag	One period lag	Two period lag
Environmental technology (% of total innovations)	-0.10919**	-0.12309**	0.13022
	(0.03201)	(0.04027)	(0.22281)
Investments (% of GDP)	0.08176**	0.06750	0.02104
	(0.02711)	(0.03461)	(0.07224)
Population growth	0.47011	0.51894*	0.21151
	(0.36511)	(0.25237)	(0.55489)
Human capital	0.30956	0.37887**	0.92194
	(0.16036)	(0.12692)	(0.60940)
Technology gap (Technology level relative to USA)	0.01611	0.00790	-0.00414
	(0.00955)	(0.00847)	(0.01691)
Openness (Sum of exports and imports/ GDP)	0.01290	0.02334***	0.07195**
	(0.00990)	(0.00542)	(0.02361)
Expenditure on R&D (% of GDP)	-0.28209	-1.22604**	0.79157***
	(0.34822)	(0.35712)	(0.16189)
Constant	-2.94630	-1.72195	-12.85588
	(2.49726)	(1.85183)	(8.58014)
R-squared	0.09545	0.2243	0.21954
Countries	32	32	31
Observations	200	165	130

*Table 3: The regression results. Note that only environmental technology and expenditure on R&D are subjected to lags. Driscoll-Kraay standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

For each lag length, the fixed effects regression results are displayed, accounting for cross-sectional dependence with Driscoll-Kraay standard errors presented in the parentheses. Important to note is that only the key variable of environmental technology and the control for general innovation activities are lagged. For the interested reader, a comparison between the results of a fixed effects regression with conventional robust standard errors and the Discoll-Kraay alternative is found in the Appendix. The number of cross-sectional and total longitudinal observations is presented along with the coefficient of determination (R-squared), interpreted as a measure of how well the model fits the data as it indicates how much of the variance in the dependent variable that can be predicted by the independent variables. In the remainder of this section, the results from the focus variable and the control variables will be examined.

5.1. Results from the Focus Variable

In the first row of table 3, the results from the key variable in this study can be observed. As noted, the direction and significance of the impact of eco-innovation on economic growth seems to depend on the chosen lag length. When no delayed effect is assumed, a significant negative impact of environmental innovation on economic growth is apparent. At a significance level of 5 %, this result implies that if the share of environmental innovations relative to the total amount of technologies developed increases with one percentage point, a decline of 0.11 percentage points in GDP growth is to be expected. Surprisingly, this negative impact is augmented with about 0.014 percentage points when a lag length of five years is imposed, as derived from the second column. While the two-star significance is maintained when allowing for a lag of one period, introducing an additional period in the lag length seemingly yields no significance. However, the impact of the focus variable does interestingly enough change from negative to positive, arguably suggesting that the effect of environmental innovation depends on the time assumed for it to occur.

On the whole, the main result in this analysis is, in contrast to the initial hypothesis, a significant negative impact of environmental innovation on economic growth. This outcome should, however, be reflected upon in light of the apparent change of direction of the effect when allowing for a longer lag length.

5.2. Results from the Control Variables

Turning to the control variables, there are numerous aspects of the results worthy of our attention. One of the most striking features of the table is the fact that R&D expenditures have a negative significant impact on economic growth when allowing for a delayed effect of one period. With Driscoll-Kraay standard errors, the p-value amounts to 0.019, implying a decrease of about 1.23 percentage points in the growth rate if gross expenditure on R&D as a share of GDP increases by one percentage point. This is an interesting and rather unconventional result. The corresponding coefficient for the variable when no lags are present is also negative, but not significant. When allowing for a two period lag, the direction of the effect is reversed; amounting to roughly 0.8 percentage points with a two-star significance.

When it comes to the case of investments, the regression resulted in a significant positive effect of 0.082 percentage points on economic growth following a one percentage point increase in gross capital formation as a share of GDP. This effect gradually decreases as the lag length is increased, whilst only being significant in the case of no lags.

Furthermore, the direction of the effect of human capital is positive as anticipated for all regressions, while only being significant when allowing for one lag length in the innovation variables. In this case, one additional average year of schooling is expected to raise economic growth by approximately 0.38 percentage units. A somewhat more perplexing result, however, is that while the coefficient increases when introducing an additional lag, no significance is found.

When it comes to the effect of the extent to which a country is open to the global system, it is positive as expected in all regressions yet only significant when including lags of the variables related to innovation. Finally, no significant effect at the 5 % -level was found for the variables of population growth and technology gap, even though the signs of their corresponding coefficients are positive as expected.

6. Discussion

The ambition of this study was to contribute to the emerging body of research devoted to empirically examining the effects of eco-innovation on economic growth. By approximating this essential mechanism for enabling sustained green growth with data on environmental patents, the hypothesis of a positive effect of environmental innovation on eco-innovation was sought to be confirmed. As evident from table 3, the results of the regressions oppose this anticipated outcome. Despite this rejection, investigating the deficiencies and shortcomings of the adopted measure of environmental technology may provide us with several important insights in terms of future research and policy implications. Moreover, the second important result regarding the tendency of eco-innovation impact to vary depending on the lag length deserves our attention.

Referring back to the different perspectives on this relationship outlined in section 2.1, one interpretation of the estimated negative impact of environmental technology development on economic growth is simply that innovative efforts are not sufficient to counterbalance the environmental drag generated by the depletion of natural capital. The positive productivity-enhancing growth effects of eco-innovation may not outweigh the costs. While such a scenario may indeed be plausible, implying a need for enhanced research efforts, the inability of patents as a measure of eco-innovation to capture the many aspects of the concept opens up for discussion. If the deficiencies in the focus variable were to be resolved, different results may have been obtained. Firstly, as mentioned in the focus variable description, the fact that environmental technology development is measured as a fraction of total innovation may have distorted the results.

A second and central point is that measuring eco-innovation as the share of total patents filed devoted to environmental technology development only captures a fragment of the many dimensions of this mechanism. Hence, the potential effects on economic growth of eco-innovation activities on the organizational, social and institutional level are not accounted for in this analysis. While it can be argued that a joint impact across all these dimensions is necessary to achieve a prolonged change towards a better environment with sustained growth, the complications which arise when attempting to measure these concepts motivate the choice of the technological dimension as the main focus of this study. Well aware of the technology bias which this implies and its consequence for the estimated coefficients, this decision was once again grounded in the objective to depart from the theoretical domain of eco-innovation in favour of contributing to the less extensive econometric research on the subject. This goal demands a measure of eco-innovation which captures as many aspects of the concept as possible while still offering a wide data set in both the time and cross-sectional dimensions – a great challenge bearing in mind the novelty of the subject. Although the eco-innovation index described in section 2.2.2. may be viewed as a preferential choice for capturing the many facets of eco-innovation, its limited availability means that adopting it in the analysis would come at the cost of weakened econometrics, diminished relevance and robustness of the results. Hence, we are compelled to conduct the analysis within these narrow boundaries and adhere to adopting environmental patents as an approximate; there is not much we can say about the impact of the other dimensions of eco-innovation.

Implicit in the previous passage is, in the context of mankind's increased environmental impact and deterioration of natural capital, the call for a consensus on a solid theoretical ground for eco-innovation. The conclusions and ultimately the policy implications of further empirical investigations are highly dependent on this.

Moving to our third and final note on the shortcomings of the chosen approximation of eco-innovation, the consequences of estimating innovation with patents are reemphasized. Thus, even within the technological dimension, our ability to interpret the results is restricted by the absence of established links between environmental patents as an output of the eco-innovation process and its inputs. Not only do patents blur the lines between incremental and radical innovations – two different aspects which as aforementioned may have significantly different impacts on the prospects of sustained growth – but are also unable to capture the entire value, in terms of diffusion and implementation, of the innovation to the economy. Without additional information of the full potential of all the filed patents used in the data, their estimated negative effect on growth is of little relevance; for instance, if merely 10% of annual patent applications actually resulted in increased productivity of natural capital, the investments funding these research activities may deemed as sunk costs. While this note links to a wider debate on the validity of patents as innovation indicators, which will not be further investigated here, it also once again underline the importance of a more comprehensive measure of eco-innovation.

As touched upon when presenting the theoretical framework of this paper, the exclusion of natural capital in the analysis may also have an impact on the relevance of its conclusions. Under certain assumptions, treating natural capital depletion as an omitted variable may even, to some extent, suggest an overestimation of the derived negative effect of eco-innovation. If presuming that natural capital usage in production results in reduced economic growth, which appears to be realistic at least in the short run (see Jones & Vollrath 2013, p. 234), and at least some degree of positive correlation between this input and the focus variable, econometric theory tells us that the direction of the omitted variable bias resulting from this exclusion is downward (Dougherty p. 252-257). While this argument demands great caution, especially in the latter assumption, it may still be relevant. More importantly, it sheds light on a structural problem with significantly larger implications – the failure to properly acknowledge the role of natural capital in the aggregate economy. If national accounts and conventional economic growth indicators would incorporate natural capital as a determinant, the fact that resources are finite and the earth suffers from widespread pollution would be recognized on an institutional plane and gain renewed focus in policy-making. However, such a measure presupposes the first step of achieving methodological consensus on the subject.

In contrast to the first main result of the regressions – the significant negative effect of eco-innovation on economic growth – our second major finding, as evident from table 3 when allowing for a two-period lag, carefully suggests that the direction of this impact may in fact reverse in the longer run. Obviously, the room for drawing any relevant conclusions from this observation is reduced by 1) the questionability of the relatively short time span of the data to allow for lag lengths longer than one period, 2) the lack of significance of the estimated coefficient for eco-innovation when allowing for a two-period lag length and 3) the methodological limitations described above. Nevertheless, the mere fact that the direction of the effect of eco-innovation changes direction if assuming a 10 year delay insinuates new opportunities for future research when more data is available. An interesting complementary note in this context is that this effect actually seems to be significantly positive with two lags when not controlling for cross-sectional dependence (see the comparison table in the Appendix). In addition, the equivalent sign change of the coefficient for R&D expenditure, which actually is supported by statistical significance, suggests that the impact of innovations in general is subject to a delay. The time taken for an idea to be developed, tested and eventually diffused in the economy accentuates the need for more patience when exploring the potential of innovation processes. This tendency could translate to eco-innovation. Even though these results may not provide sufficient evidence for an increased focus on eco-innovation in the contemporary policy agenda, they indicate that many aspects of the long-run potential of this concept are yet to be revealed.

Finally, a few notes on the result from the other control variables are appropriate. When it comes to the investment variable, the fact that its positive effect on growth is only significant when adjusting for cross-sectional dependence seems to confirm the econometric complications arising from a highly integrated and internationally intertwined financial system. Furthermore, the effect of openness is only significantly positive when allowing for a delay impact of innovation. One might cautiously suggest that this could reflect the time needed to accumulate the innovative capability and technological capacity required to gain from technology transfers enabled from an increased openness to the world. Lastly, the quite surprising result of a strong negative coefficient for R&D expenditure with one lag is subject to a similar reasoning as performed above; a distortionary effect related to the variable being measured as a fraction of GDP may be present, while other underlying methodological issues are also likely. Alternatively, five years may not suffice for the gains related to technological development to outweigh the costs – when more resources are devoted to R&D, less are available to invest in production.

Rounding up, it is apparent from the results and the subsequent discussion in this section that the evidence for eco-innovation as a driver for economic growth is highly limited. Instead, the outcome of the analysis indicates an incapability of eco-innovation processes to generate enough value for the economy, both in terms of increased productivity and reduced environmental impact, to outweigh the costs. Nevertheless, we remain confined to the boundaries imposed by the approximate measures adopted in an attempt to capture the many facets of the mechanism. This notion calls for further research to expand these boundaries by developing more comprehensive measurements. Undoubtedly, the full potential of eco-innovation remains to be discovered when more data is available.

7. Conclusion

The capacity of our planet to sustain further generations deteriorates an alarming rate, making the role of environmental innovation and R&D as a driver for economic growth while providing solutions to these global problems more important than ever. This thesis has aspired to shed light upon the potential of the emerging concept of eco-innovation to balance the widely recognized trade-off between our environment and economic development. The ability of eco-innovation to enable sustained growth seems, within the narrow boundaries of this study, quite limited. Yet there are some aspects, such as the directional change of the effect of eco-innovation when allowing for a longer lag length, which suggest a less discouraging picture.

As evident from the methodological nature of existing literature on eco-innovation, the obtained results and their implications are ultimately subject to the ever-present dilemma of emerging research topics; a lack of uniformity in definitions, ambiguous measurement approaches and data availability limited to recent years. Hence, policy implications are limited to those ensuring an accelerated empirical establishment of eco-innovation as a vital component in green growth strategies. Correspondingly, the methodological shortcomings of this study emphasize the need for future research to fill these gaps in order to obtain a deeper understanding of eco-innovation.

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Appendix

Comparative table of results with Driscoll-Kraay versus robust standard errors

Variables	No lag		Lag of one period		Lag of two periods	
	Standard errors		Standard errors		Standard errors	
	Robust	Driscoll-Kraay	Robust	Driscoll-Kraay	Robust	Driscoll-Kraay
Environmental technology	-0.10919*	-0.10919**	-0.12309	-0.12309**	0.13022	0.13022
	(0.06285)	(0.03201)	(0.11147)	(0.04027)	(0.08047)	(0.22281)
Investments	0.08176	0.08176**	0.06750	0.06750	0.02104	0.02104
	(0.05131)	(0.02711)	(0.05571)	(0.03461)	(0.09003)	(0.07224)
Population growth	0.47011	0.47011	0.51894	0.51894*	0.21151	0.21151
	(0.59125)	(0.36511)	(0.66228)	(0.25237)	(0.84623)	(0.55489)
Human capital	0.30956*	0.30956	0.37887*	0.37887**	0.92194***	0.92194
	(0.16341)	(0.16036)	(0.19151)	(0.12692)	(0.27123)	(0.60940)
Technology gap	0.01611	0.01611	0.00790	0.00790	-0.00414	-0.00414
	(0.01422)	(0.00955)	(0.02007)	(0.00847)	(0.03272)	(0.01691)
Openness	0.01290	0.01290	0.02334***	0.02334***	0.07195**	0.07195**
	(0.00970)	(0.00990)	(0.00758)	(0.00542)	(0.03267)	(0.02361)
Expenditure on R&D	-0.28209	-0.28209	-1.22604**	-1.22604**	0.79157**	0.79157***
	(0.39399)	(0.34822)	(0.46913)	(0.35712)	(0.37066)	(0.16189)
Constant	-2.94630	-2.94630	-1.72195	-1.72195	-12.85588***	-12.85588
	(2.35525)	(2.49726)	(3.62612)	(1.85183)	(3.65545)	(8.58014)
R-squared	0.09545	0.09545	0.2243	0.2243	0.21954	0.21954
Countries	32	32	32	32	31	31
Observations	200	200	165	165	130	130

Correlation Matrix

e(V)	envtec~g	inv	popgro~h	hcavgy~s	techgap	open	rndexp~g	_cons
envtech_lag	1.0000							
inv	0.0277	1.0000						
popgrowth	0.1649	-0.0093	1.0000					
hcavgyears	0.2141	0.0956	0.1995	1.0000				
techgap	0.1149	0.0625	-0.0267	-0.1982	1.0000			
open	-0.0717	-0.1620	0.0437	-0.0891	-0.2491	1.0000		
rndexp_lag	-0.0028	-0.3129	0.0035	-0.2537	-0.1988	0.1212	1.0000	
_cons	-0.5580	-0.5686	-0.2773	-0.5218	-0.3804	0.0738	0.1631	1.0000

Variance Inflation Factor (VIF) Table

Variable	VIF	1/VIF
hcavgyears	1.29	0.773898
rndexp_lag	1.27	0.787891
techgap	1.24	0.808229
inv	1.13	0.885088
open	1.12	0.896293
envtech_lag	1.11	0.904132
popgrowth	1.07	0.937507
Mean VIF	1.17	