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Essays on environmental regulation and firms' performance

Ph.D. candidate**:** Enrico Botta
Thesis Supervisor: Prof. Marzio Galeotti
Ph.D. Coordinator: Prof. Alessandro Missale

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Introduction to the essays

The increasing concerns over the environmental sustainability of current development trajectories have brought numerous countries to adopt "greener growth strategies". However, given the numerous failures that hinder the well-functioning of market mechanisms in relation to the environment, environmental regulations are considered as necessary to align private and public marginal benefit (and cost) curves. This dissertation aims at contributing to the on-going debate in literature on the impact of environmental policies on economic growth.

To this end, the first essay of this thesis reviews the literature on the link between economic performance and environmental policy. The assessment underlines the different views on the effects of environmental regulations on firms' productivity proposed by the neoclassical economic theory and by the so-called Porter's hypothesis. The former considers environmental regulations as necessary to cope with market failures related to environmental externalities but as detrimental to firms' productivity. Michael Porter challenged this interpretation almost 25 years ago by arguing that "well-designed" policies do not necessarily hinder the competitiveness of firms but might actually increase it. Within this context, the essay first reviews the wide empirical literature on the Porter's hypothesis and highlights the often contrasting results. In fact, the number of studies estimating a negative effect of tighter environmental norms on firms' competitiveness appears to be almost equal to those finding a positive impact. Then, the multifaceted nature of environmental regulation is discussed as a potential explanation for the non-homogeneous results across studies. In fact, notwithstanding Porter and van de Linde (1995) underline how "well-designed" regulations may lead to higher competitiveness for firms, the vast majority of studies mainly focus on the stringency of enforced norms. Instead, a number of other aspects of regulations are likely to play a key role in determining their overall impact on economic performance. Building on the literature examining what features a "well-designed" environmental regulation should exhibit, the essay finally discusses the role that elements such as stringency, flexibility or policy-induced uncertainty may have in shaping the economic outcomes of environmental policies. The proceedings of this work constitute the backbone of an article published in the journal "Energia" (edited by Stefano Clò, published in Italian) in September 2016

The review of the first chapter underlines the presence of several gaps in the literature in relation to the impact of environmental regulation on innovation. In fact, while market-based instruments are often highlighted by scholars as providing higher dynamic incentives than non-market-based regulation, few papers have been able to empirically test such claims within the same study also given the difficulties of comparing environmental policy norms across countries. Secondly, in a resources-constrained world, environmental policy is more likely to steer the direction of technological change toward rather than increase green innovation. Nonetheless, studies on the Porter's hypothesis have often omitted to consider the impact of environmental policies on the technologies not explicitly targeted by the introduced regulation. To this end, the second essay focuses on the consequences of increasingly stringent regulation on the technologies the environmental policy aims to promote and on other innovation. Building on the discussion of what a well-designed regulation entails, the paper distinguishes between market- and non-market-based policies. In order to capture the full extent of induced innovation, we adopt a cross-sectoral approach. This is due to the assumption that innovations designed in order to comply with environmental regulation are not necessary developed in the regulated industry. In line with theoretical results, market-based instruments are shown to be the main driver of increased innovation in the technological field that environmental policy wishes to promote. At the same time, the estimations suggest that non-market-based regulations mainly decrease inventive efforts directed towards non-environmental technologies, possibly because of a negative impact on “polluting technologies”. In addition, the results show the presence of path-dependency in innovation. This work has been presented at the 2016 AIEAR Annual Conference in February 2016 and at the University College of London within the seminar series “Innovation and Technological Change Research” in April 2016.

The third essay adopts an experimental approach and focuses on a second feature often highlighted as characterizing well-designed regulation in the literature, namely (limited) uncertainty. More precisely, the paper assesses how policy-induced risk may affect investment decisions in renewable power plants. To this end, the paper first reviews the main characteristics of auction frameworks across Europe since these are being increasingly adopted by OECD and Non-OECD countries to support renewable energy deployment but are limitedly studied in the literature. The review underlines how auction designs can vary along a number of dimensions, including how planning, winner selection, construction and operation stages are regulated. Since the policy features connected to the winner selection stage are the most novel and most unique to renewable energy technologies (RET) support through auction, these are discussed in more detail. Then, a stated preference approach is leveraged to investigate how auction design and the uncertainty regarding the future arrangements between the UK and the EU contribute to determine the cost of equity for renewable energy projects. The results show that improved design can lead to a moderate decrease in the cost of equity. The largest decrease is provided by the introduction of moderate financial bid-bonds but the analysis also underlines how long-term auction programs strengthen the cost reduction effects typical of tendering competition. The adoption of “technology-specific” auctions seems also to decrease business risks. The evidence on Brexit is rather weak and, if anything, suggests the higher relevance of these negotiations for English-based investors rather than for those based in EU27.

A review of the literature on environmental policy: moving beyond policy stringency

Enrico Botta[a]
[a] Corresponding author: Università degli Studi di Milano e di Pavia,
Via Conservatorio, 7 - 20122 Milan – Italy. Tel. +39 02 503 21508.
Mail: Enrico.botta@unimi.it

Abstract
Neoclassical economic theory considers environmental regulation as necessary to address the market failures related to environmental externalities but as detrimental to firms' productivity. This interpretation has been challenged almost 25 years ago by Michael Porter by arguing that well-designed environmental policies do not necessarily hinder the competitiveness of firms but might actually increase it. In this article, we will review the main – often contrasting - results of the studies on what has become simply known as the «Porter's hypothesis». The analysis highlights how the vast majority of the literature focuses on the stringency of enforced norms omitting other aspects of environmental policy design. Building on the literature examining what should characterise a "well-designed" regulation, the role that features other than stringency may have in determining the economic outcomes of environmental regulation is discussed and potential new venues of research are highlighted.

1. A review of the literature on environmental policy: moving beyond policy stringency

1.1. Introduction

Environmental policy is introduced with main objective of protecting the quality of the environment in order to guarantee the well-being of our societies. At the same time, however, its impact on the economic growth is highly debated and, over time, several hypotheses have been formulated. Initially, the thesis of a mere compatibility between the two societal objectives of economic growth and environment protection was developed. This idea lays at the core of the concept of "sustainable development" that chiefly underlines how these two objectives can be contemporaneously pursued. A second - and more recent interpretation – has been put forward with the idea of *green growth.* This distinguishes itself from sustainable development for two main reasons. First, this underlines more clearly the crucial role that the environment plays not only for our well-being but also for the functioning of our economies since it provides the numerous ecosystem services that underpin businesses' activities (e.g. the production of fresh water, waste disposal, etc.). Therefore, the environment is not considered as simply "compatible" with economic growth but also necessary (Jacobs, 2012). Secondly, the supporters of green growth strategies underline how well-designed environmental policies can also spur economic *growth* by opening-up new markets. In this regard, the policies designed to support the deployment of renewable energy technologies are often cited. In fact, these have often been introduced with the joint objective of reducing CO_2 emissions and building a domestic industry specialized in clean electricity generation (even if the results remarkably vary from State to State).

The economic theory mainly discusses the relation between economic development and environmental protection through the concept of environmental externalities. More precisely, economists agree that it is necessary to align agents' marginal benefits and cost of production (and consumption) in order to avoid that actions undertaken by individuals generate an aggregated catastrophic effect for the society as, for instance, in the case of the ozone hole or climate change. At the same time, however, neoclassic economic theories often consider environmental protection as a hindrance to economic growth. In fact, moving from the assumption that firms are fully rational agents that operate on the efficiency frontier, environmental regulations can only be considered a factor depressing productivity since they impose an additional cost on companies.

This "traditional" interpretation of the link between environmental policies and economic outputs has been challenged by Michael Porter almost 25 years ago in an article published on the Journal of Economic Perspective. This theory, which became famous as the *Porter's hypothesis* due to its high theoretical attractiveness and lack of robust empirical evidence, underlines that there may be margins to improve economic performance without compromising the environment. This paper provides an overview of the key theoretical and empirical insights into the Porter's hypothesis and highlights gaps and potential new venues of research. Paragraph 2 describes how the Porter's hypothesis has been discussed in the literature and articulated. Next, Section 3 examines the empirical evidence on the impact of environmental regulation on economic outcomes to date. Highlighting the often-contrasting results in the literature, section 4 analyzes the role that policy features other stringency may play in shaping the economic outcomes of environmental regulations. Finally, section 5 discusses the main conclusions and highlights possible new venues of research.

1.2. The Porter's hypothesis (and its different versions).

Neoclassical economic theory considers firms as fully rational and profit optimizing agents. As such, the introduction of a new constraint to their optimization problem, namely environmental regulations, necessarily leads to lower competitiveness. This interpretation of the link between environmental regulation and productivity has been challenged by Porter almost 25 years ago. The main assumption behind the "Porter's hypothesis" is that companies are rationally-bounded agents targeting profit maximization (rather than profit optimization) and that they operate in imperfect markets. Therefore, when a new constraint – like a tax on emissions or a legal limit on maximum effluents - is introduced, they will rethink production process in order to minimize the additional costs. In turn, this redesign can potentially lead to improvement in their business performance (Porter 1991, Porter and van der Linde 1995). The underinvestment in energy efficiency is a commonly cited example of how environmental regulation can help promoting both higher economic and environmental performance. In fact, notwithstanding the adoption of fuel saving technologies can increase competitiveness and – as co-benefit- reduce pollution, companies tend to underinvest in this field due to a number of market barriers and failures (Howarth and Andersson 1993, IEA 2013).

During the past 25 years, the Porter's hypothesis has been widely discussed in the literature and, over time, has been articulated into three more precisely defined versions. The so-called "strong version" highlights how economic agents are rationally bounded and operate in incomplete markets. Within this framework, companies are naturally brought to optimize and therefore well-designed environmental regulations can lead to redesign imperfect production processes thus allowing to increase efficiency. Instead, both the weak and narrow versions of the Porter's hypothesis focus on innovation but with an important difference. In fact, both suggest that firms will react to newly introduced regulation by investing in green innovation and this, in turn, may lead to a positive knock-on effect on productivity. However, the narrow version argues that flexible regulations, defined as those that allow the regulated agents to freely choose the techniques to reduce pollution, are more likely to drive an increase in innovation. Within the current debate, this *dynamic* efficiency[1] is often attributed to market-based instruments (e.g. trading schemes), even if certain standards, like the Japanese *front-runner* scheme, can have similar properties.

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[1] The adjective "dynamic" is here used - in the same vein as De serres et al. (2011) - to describe policy instruments assumed to create incentives to "… *searching continuously for cheaper abatement options" (pag.23).*

1.3. The empirical evidence

The vast majority of studies try to assess the impact of environmental norms on the economic outcomes discussed in the different versions of the Porter's hypothesis (innovation and competitiveness) by looking at the severity of enforced norms. However, capturing the stringency of enforced process is hindered by numerous challenges, specially when cross-countries comparisons are attempted. As such, the next paragraph will review this wide body of literature leveraging two key classification elements: "how" environmental policy stringency has been measured and which impact has been studied.

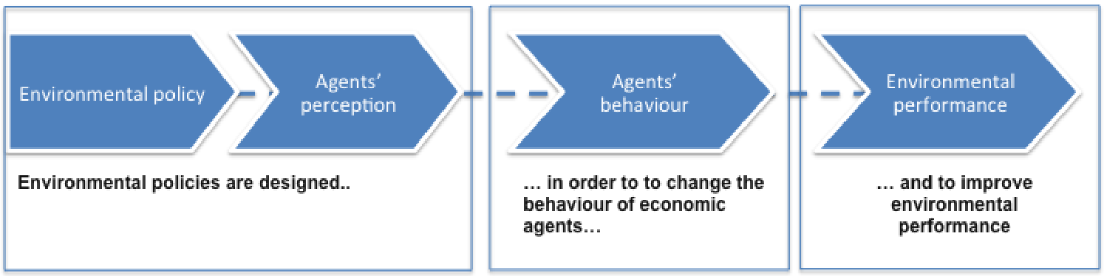
1.3.1. How (or where) environmental policy stringency is measured

Stringency of enforced environmental norms is a complex variable to capture due to numerous challenges. Multidimensionality and identification issues are probably among the most cumbersome. Multidimensionality is generated by the need to take into consideration that firms pollute different environmental media (e.g. water, air, etc.) and that different instruments can be used to regulate these negatives externalities. For instance, CO_2 emissions can be regulated through a tax, a standard, the creation of market for emissions (as the case of the EU emission trading scheme) or a combination of these instruments. At the same time, firms are likely to pollute more than one environmental media and each externality can be, as discussed, regulated by numerous instruments. As such, the overall stringency faced by a firm is given by the aggregate effect generated by the various environmental policy instruments in place for each of the environmental media polluted.

A second key challenge is represented by identification issues. In fact, numerous other factors are likely to contribute to determine the ultimate objective of environmental regulation, namely (better) environmental performance. At the firm-level, the degree of competitive pressures, access to capital, resource prices or even green marketing strategies may lead managers to adopt more or less environmental friendly techniques. On a macro level, countries characterised by a service economy are likely to exhibit lower pollution levels compared to more industry-intensive economies even if the same environmental norms are in place. Therefore, it can be particularly complex to identify a casual link between the observed environmental performance and the environmental norms in place. Other issues that further complicate these efforts include sampling problems and slack enforcement (Brunel and Levinson, 2013).

Due to these challenges, researchers leveraged different approaches in order to capture this elusive variable in econometric studies. These can be grouped according to "where" environmental policy stringency is measured. More precisely, moving from the assumption that environmental policies are designed to change the behaviour of economic agents in order to lead to a better environmental performance, it is possible to classify the various approaches according to where the stringency is measured along this cause-effect chain (Fig. 1).

Figure 1. Methodologies to measure environmental policy stringency



Source: Adapted from Botta and Kozluk, 2014.

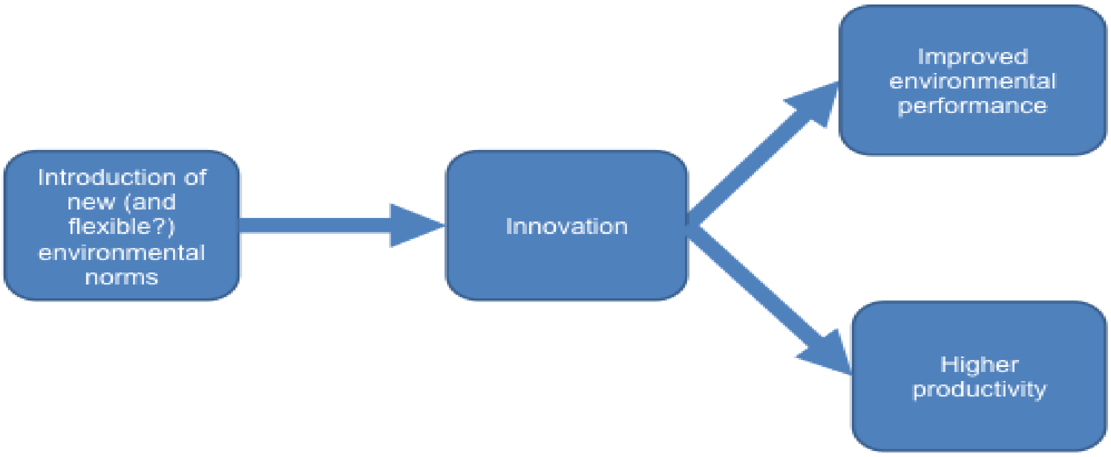
The first group is composed by those measures that are based on the direct observation of the legislation in a single country (Fig.1 , arrow 1). This includes both dummy variables introduced to account for a change in domestic legislation (e.g. a modification of national law, the signature of an international treaty) and composite indicators that are based on the aggregation of data gathered for multiple laws (Botta and Kozluk, 2014. EBRD, 2011. Sato et al. 2015. Schaffrin et al. 2015). The second group is based on questionnaires where economic agents are asked to evaluate the severity of enforced norms (e.g. WEF questionnaire). As such, these measures capture – to some extent - the stringency of environmental norms as "perceived" by the regulated entities. A third approach focuses on what can be defined as the first level consequences of environmental policies, namely the production choices of firms. Following this methodology, researchers have often tried to measure the stringency of enforced norms through surveys of firms' expenditures on pollution abatement technologies (e.g. US PACE) or, more rarely, through shadow prices estimations. Finally, several studies focused on the second level consequences of environmental policies and leveraged the variation in the environmental performance of a firm or a country as proxy for the overall stringency of enforced norms (arrow 4) (Botta and Kozluk 2014).

Each of these methodologies exhibits its own advantages and weaknesses. Broadly speaking, if stringency is measured at the begging of the above described cause-effect chain, as for instance when dummy variables or composite indicators are leveraged, then the challenges posed by multidimensionality are more severe. In fact, the risks of overlooking important aspects, omitting significant interaction effects or excessive simplifications should not be underestimated. Conversely, identification issues are relatively more easily avoided. Instead, measures based on the consequences of the enforced norms are more likely to better control the multidimensionality challenge but are exposed to identification issues. In fact, the ensemble of policy instruments in place is likely to drive firms' expenditures on pollution abatement technologies or environmental performance, thus these data should allow controlling for the multidimensionality. However, numerous other exogenous factors like green marketing, R&D with collateral improvements or regulations pertaining to other policy areas may as well play a key role in determining investment decisions or overall environmental performance. As such, identification is often a major challenge for this later type of measures.

1.3.2. ..And what is affected?

The second pair of lenses through which can be useful to reflect on the existing literature can be provided by looking at the version of the Porter's hypothesis considered. Importantly, the narrow, weak and strong versions mainly describe a cause-effect relation as well (Ambec et al. 2013). In fact, it is necessary that firms innovate (as underlined by the weak an narrow version) in order for environmental policies to improve firms' both economic and environmental performance (the strong version) (Fig. 2).

Figure 2. Cause-consequence relations in the Porter's hypothesis



Source: Ambec et al. 2013

1.3.3. The effects on innovation

The studies on the first step of the cause-effect relation suggested by Porter, namely innovation, leverages data on R&D expenditures and patents to evaluate the role that environmental regulation may play in stimulating inventing activity. Jaffe and Palmer (1997) are among the first to focus on this aspect and find a positive correlation between expenditure on pollution abatement and control equipment (US PACE data) and firms R&D expenditures. However, the results are not statistically significant when the patents in green technologies are used as innovation proxy. Instead, more recent studies often find a positive relation between PACE expenditures and innovation. Brunnermeier and Cohen (2003), who leverage as a proxy of environmental policy stringency both PACE expenditures and data on government monitoring activities, find a positive impact on USA patenting activity between 1983 and 1992. A positive impact is also found by Frondel et al. (2007) who analyse the impact of policy stringency, measured though an OECD questionnaire distributed in seven countries in 2003, on R&D expenditures. De Vries and Withagen (2005) leverage instead three different measures of stringency (ratification of international agreements, an index of environmental performance and a latent variable strategy) and identify a positive effect on firms' patenting activity only with the third methodology. An interesting approach is adopted by Wagner (2007) that focuses on the difference between process and product innovation. The results show that the implementation of environmental management systems leads to an increase on environmental process innovation while it decreases the overall inventing activity of a firm. Overall, the literature seems to depict a relatively homogenous picture pointing out to a positive impact of environmental policy stringency on innovation, specially in most recent studies. Verdolini and Galeotti (2011) study how knowledge stocks in energy-efficient and environmentally friendly technologies flow across geographical and technological space. In addition to showing that that spillovers between countries have a significant positive impact on further green innovation, some of their specifications include a policy dummy variable to account for the presence of at least one policy targeting energy efficiency in the innovating country in any year t. Also in this case, policy is shown to have a highly significant effect on domestic innovation.

1.3.4. .. and on productivity

Several studies focus on the second level consequences of environmental policies, that is, the economic performance of the regulated agents. The performance measures included in these researches vary according to whether the study is conducted at the firm, industry or country level. On a macro level, the gross domestic product or gross domestic product per capita area among the most commonly employed measures. Instead, growth productivity rates or other indicators of sectoral competitiveness are often employed in studies at the firm or plant level (Constantini and Crespi 2008, Frondel et al. 2007). Finally, also financial measures like profits and gross operating margins are leveraged, even if less common (Carbon Trust, 2004).

Few studies adopt a macro perspective, also due to the challenges of identifying norms that affect all sectors in a given country to a similar extent. A large portion of the literature opting for a macro perspective leverages the ratification of the Kyoto Protocol with contrasting results. Yörük and Zaim (2005), who focus on OECD economies, estimate a positive impact of the ratification of the Kyoto Protocol on productivity while a negative effect is found by Wu and Wang (2008) who leverage a panel of 17 APEC countries. The different results are explained by the authors underlining the diversity of studied samples but it should be also considered how the ratification of the Kyoto Protocol does not lead to the implementation of homogenous norms across countries, thus creating room for a large difference of possible impacts.

The stream of literature that leverages a sectoral approach is relatively larger and, also in this case, the results are not homogenous. Dufour et al. (1998) leverage a short time series (three years) to evaluate the impact of environmental policies on the Canadian manufacturing industry estimating a negative effect. Barbera and McConnell (1990) exploit a longer time series (almost 20 years) and focus on five American manufacturing sectors. However, the results are not conclusive since, while the direct effect appear to be mainly negative, the indirect effects are estimated to be both positive and negative, thus complicating the identification of the overall impact. Instead, a positive effect is estimated in Yang et al. (2012) for the Taiwanese manufacturing industry, by Alpay et al. (2002) for the Mexican food processing industry and by Berman and Bui (2001) who focus on the refineries located close to Los Angeles.

Finally, most studies conducted at a firm level identify a negative impact on productivity. For instance, Gollop and Roberts (1983) estimate a negative impact due to the introduction of more stringent regulations on So2 emission in the United States during ’70s. A harmful impact is also identified by Broberg et al. (2012) in the case of cellulose industry. While the initial negative impact estimated by Managi et al. (2005) for the productivity of off-shore oil & gas reserves in the United States tend to reverse and, over time, to compensate for the initial productivity lost after. Rassier and Earnhart (2010) find a negative impact of water pollution regulation, as measured by permitted wastewater discharge limits, on the profitability of 73 US chemical firms in the years 1995 to 2001. As opposed to these works, several studies however identify a positive impact on environmental regulation on productivity. This is the case, for instance, of Van der Vlist et al. (2007) for the Dutch horticulture or Jaraité and Di Maria (2012) that focus on the companies regulated through the European ETS.

Importantly, the Porter’s hypothesis envisages a dynamic mechanism that is likely to require a certain time lag between the introduction of new regulations and the potential gains for the firms due to reorganization and innovation. This dynamic dimension is often omitted and, when included, estimations are more likely to identify a positive effect. For instance, leveraging a time lag of three and four years between the introduction of environmental laws and their impact on productivity, Lanoie et al. (2008) verify the presence of an initial negative impact that gradually reverses up to the point of compensating initial losses in the case seventeen Quebecois sectors. The importance of introducing time lag is further strengthened by the results of Hamamoto (2006) who focuses on five Japanese manufacturing sectors. At the same time, regulations are often announced before they enter into force. As such, it may well be possible that firms start reacting before their date of enforcement. For instance, Nicolli and Vona (2016) leverage the a one year forward lag (i.e. time t+1) of the stringency variable in order to decrease the endogeneity risk and reverse causality, providing further evidence of a positive effect on innovation but also highlighting the difficulty in determining the correct timing for the analyses. The role played by time lag emerges also in a meta-analysis of the literature conducted by Cohen and Tubb (2017). In fact, the authors underline how studies that introduce a time lag for their policy variables are more likely to find a positive impact, thus reaffirming the dynamic nature of the Porter’s hypothesis.

Finally, some recent researches studying the impact of environmental regulation have undertaken an “integrated approach” that spans across the various versions of the Porter’s hypothesis or aggregation level with interesting insights. For instance, Lanoie et al. (2011) leverage an OECD survey on more than 4.000 firms located in seven industrialized countries. The results show a positive and significant link between (perceived) stringency and green innovation. This evidence for the weak version of the Porter 's hypothesis is however coupled with negative direct effect on productivity. As such, the results underline that innovation only partially compensates the adjustment cost to new environmental regulation and a lack of a "global miracle". Similarly, Rubashkina et al. (2015) leverage a panel of European manufacturing sectors between 1997 and 2009. By adopting an instrumental variable estimation approach, they find evidence of a positive impact of environmental regulation on innovation activity, as proxied by patents, but find that productivity appears to be unaffected by the degree of pollution control and abatement efforts. Instead, a recent OECD study attempts to evaluate the impact of environmental regulation on firm, industry and country level (Albrizio et al. 2014). The authors summarize the results underling a lack of empirical finding of a permanent negative effect on multi-factor productivity. Furthermore, the study shows how more technologically advanced firm are more likely to exhibit productivity gain when new more stringent environmental norms are introduced while firms that are more distant from the technological frontier are more likely to be negatively affected.

1.4. Moving beyond policy stringency

As it emerges from the review of this wide body of literature on the Porter' hypothesis, the conclusions of the different studies are mixed. A possible explanation for the often-contrasting results may lie in the multifaceted nature of environmental regulation. In fact, notwithstanding Porter and van de Linde (1995) underline how "well-designed" regulations may lead to higher competitiveness for firms, the vast majority of studies mainly focus on the stringency of enforced norms. Nevertheless, a number of other aspects of regulations are likely to play a key role in determining their overall impact on economic performance. Within the next pages, we will first review the (few) theoretical contributions that discuss into detail what the features that should characterise a well-designed regulation is. Then, the empirical evidence available in the literature on their impact will be reviewed.

Flexibility is among the most often cited features that should characterize well-design regulation. Porter and van der Linde (1995), when describing the features of a well-crafted regulation, underline three principles. "*First, they must create the maximum opportunity for innovation, leaving the approach to innovation to industry and not the standard-setting agency. Second, regulations should foster continuous improvement, rather than locking in any particular technology. Third, the regulatory process should leave as little room as possible for uncertainty at every stage" (Porter and van der Linde, 1995. Pag. 110).* Porter then argues that these features are more likely to be met by market-based regulation since such instruments," *including pollution taxes, deposit-refund schemes and tradable permit, [...] often allow considerable flexibility, reinforce resource productivity, and also create incentives for ongoing innovation" (Porter and van der Linde, 1995. Pag. 111).* Indeed, the idea that directly pricing externalities – in absence of market imperfection - is the most efficient approach to address environmental externalities has been widely accepted in the literature for a long time. The main underlying mechanisms, whose intuitions can be almost dated back to the work of *Pigou (1932) and Coase (1960),* lies in the equalization of public and private marginal cost and benefit curves. The direct consequence of this explicit pricing is that, given that firms are forced to pay for each additional unit of pollution, they face an ongoing incentive to reduce the tax payment. However, importantly, the term flexible regulations include also performance standards since these leave firms free to adopt the production techniques they deem as most effective. Nevertheless, in case of market imperfections - such as lack of perfect competition - the ranking of market-based and command control policies is more ambiguous (*Requate, 2005).* For instance, Montero (2002) compares the incentives to invest in environmental technologies of both tradable permits and command-and-control regulations (emissions and performance standards) considering imperfect competition on both the output and the permit market. Because of this joint market imperfection, the author shows that both emission standards and trading schemes where permits are auctioned provide higher incentives to invest in environmental technologies than a certificate market with free allocation. Furthermore, building on Montero's results, Bruneau (2004) shows that performance standards can generate higher incentives to innovate than tradable permit system also in perfectly competitive markets.

Among the few other contributions that discuss the issue of what features should characterise a well-designed regulation, there is the important contribution of De Serres et al (2010). The authors discuss five criteria that policies should meet to be considered economically efficient, namely: cost-effectiveness, adoption and compliance incentives, uncertainty and stimulus to innovation. They conclude that pricing instruments are generally the most efficient single instrument but also underline how no single instrument scores well on each of the considered criteria. Furthermore, given that environmental damage often results from several interacting market failures, a mix of complementary instruments is often likely to be required. Johnstone et al (2010) focus explicitly on innovation and suggest that rather than assessing the impacts of environmental policies in terms of broad 'types' (i.e. market-based instruments vs. "command-and-control" regulation), it may be more useful to evaluate more specific characteristics of different instruments. To this end, they identify four key features that should characterize environmental policy aiming at promoting innovation. These include: stringency, dynamic efficiency, uncertainty, flexibility (defined as the extent to which innovators are free to identify the best way to comply with the environmental regulation) and incidence (defined as the capability to target as closely as possible the externalities to be promoted/discouraged).

The importance of uncertainty in characterizing a well-designed regulatory settings emerges also in contributions exclusively dedicated to this topic. Albrizio and Costa (2013) develop a regulator's objective function including an importance parameter that reflects the weight that the regulator puts on economic growth over the reduction of CO_2 emissions. This parameter follows a mean-preserving spread process and, therefore, creates uncertainty in the investment process. Then, the authors show that the optimal investment level in clean energy decreases as the level of uncertainty increases. Devine et al. (2014) examine how different Feed-in Tariff (FiT) designs do not eliminate market price risk but rather transfer this risk to a counterparty. The policymaker's risk preferences is specified through a Constant Relative Risk Aversion (CRRA) utility function and, using Stackelberg game theory and option pricing, the authors identify the optimal feed-in tariff design. The main conclusion is that the optimal division of risk between investors and policymakers/consumers can be considered similar to risk sharing agreements in insurance contracts.

A facet of environmental regulation that is not widely addressed in the academic literature but often discussed as a major barrier in industry-led studies is the level of red-tape generated on firms. In fact, like all other regulations, environmental norms are likely to differ in terms of the administrative burden they impose on companies. In turn, this difference may as well help to explain the variance in the empirical results on the Porter's hypothesis. However, while numerous studies analyse the negative impact of the red-tape resulting from a wide range of regulations (e.g. Nicoletti and Scarpetta, 2003; Arnold et al. 2009), few focus on the potential pitfalls of environmental laws. Kozluk (2014) reviews the environmental legislation in 30 OECD countries focusing on both regulatory characteristics that may inhibit the entry-exit process and the degree to which economic considerations are taken into account in regulation design. These two dimensions are extremely relevant since a poor design may results in position rents for incumbents due to limited market contestability, slower diffusion of innovative and more efficient technologies, slower relocation of resources to more efficient (and environmental friendly) firms and decreased inventing activity. Interestingly , the survey results show that countries widely differ in terms of the burden of their regulation. Furthermore, the author underlines how more stringent regulation is not necessarily associated to higher administrative burden to firm. Overall, this lack of correlation between stringent and burdensome regulation may offer an additional possible explanation for the often-inconclusive results in the empirical literature on the impact of stringent norms.

A relatively more limited number of studies analyse the interaction among different policy instruments and their possible synergies or misalignments. For instance, Fischer and Newell (2008) find that, while pricing is the most efficient single policy mechanism to reduce emissions, a policy portfolio composed of both emissions pricing and R&D subsidies can decrease emissions at a significantly lower cost. Nevertheless, the challenges to integrate multiple policy instruments should be carefully considered by policy-makers. For instance, Hood (2013) underlines how the interaction between quantity-based carbon pricing instruments (e.g. emissions trading) and other policies that can contribute to reduce emissions (e.g. energy efficiency standards) may undermine the properties of climate policies.

1.4.1. Flexibility

*S*tudies often do not allow to clearly identifying the type of regulations considered. This is often due to the approach used to capture environmental policy. In fact, since studies often leverage data on aggregate expenditures on pollution abatement costs (PACE) or firms environmental performance, considerations on the type of instruments enforced are omitted. Cohen and Tubb (2017) reflect upon this element and highlight how only 35% of surveyed researches allow to distinguish between flexible and "command-and-control" regulations. Notwithstanding this, the authors note that studies focusing on flexible regulations are much more likely to show positive impact. Furthermore, the evidence of whether pure market-based regulations are more effective than "command-and-control" (whether technology or performance standards) is limited due to complexity of comparing different types of regulations. In fact, while the stringency of pricing instruments (e.g. taxes) is usually measured in relation to price paid per amount of pollutant produced, the measurement of the stringency of standards is more complex and often captured by either introducing a dummy that takes value equal to 1 for newly modified standards or by observing the technologies/performance dictated by the standards. In turn, these different "measurement units" intricate the efforts to compare directly the two different types of instruments. However, some indirect evidence on the higher efficiency of market-based versus "command and control" regulation is present in the literature. Burtraw (2000) finds evidence that the switch from a technological standard with emissions caps to an allowance trading program in US environmental regulations for SO2 emissions in 1990 enhanced innovation and fostered organizational change. Lanoie et al. (2011) also provide mild indirect evidence on this issue, showing that performance standards have a significant effect on R&D expenditures while the same does not hold true for more prescriptive technological standards. However, they do not find any significant positive impact for market-based instruments and argue that "*this may be due to the fact that, in practice, such measures are frequently applied at too low a level to induce innovation" (Lanoie, et al. 2011, pag. 837).* Hoglund Isaksson (2005) looks at the impact on the abatement cost functions of 114 Swedish combustion plants during the 1990–96 period following the introduction of a charge on NO_x emission. Her results show that the technological developments occurred during the considered period allowed reducing emission reduction at very low cost. Also Andersen et al (2007) finds a neutral or slightly positive net impact of environmental taxes, whose revenues are recycled to cut other taxes, on gross domestic product. As opposed to these results, authors that studied the introduction of a permits trading mechanism to regulate SO2 emission in USA found that innovation declined compared to the previous period when command-and-control regulations were in place. For instance, Taylor (2012), who analyses patenting data for various SO_2 and NO_x technologies characterized by different costs and performances, finds that innovation dramatically decreased a few years into trading. Popp (2003) also confirms this negative trend. However, the author also argues that the innovations developed under the permit system contributed more to reduce SO2 emissions than those developed under the command and control system. More precisely, Popp leverages patent data to study innovation in flue gas desulfurization units ("scrubbers") and finds that the command-and-control regulations generated incentives to reduce the costs of operating the scrubbers while the permit system generated mainly incentives to improve the removal efficiency of scrubbers.

1.4.2. Uncertainty

Policy induced uncertainty is the design feature, other than stringency, probably most analysed in the empirical literature. Following the work of Dixit and Pindyck (1994), numerous studies adopt a real option approach (ROA) to evaluate its impact on investment decisions. Generally speaking these researches underline how increased uncertainty hinders the investment signal provided by (stringent) environmental policies even if – importantly - the direct impact on productivity is scarcely considered. Yang et al. (2008) evaluate the impact of climate policy uncertainty on private investment in power generation leveraging the market price of CO_2 as a proxy for policy stringency. Through a ROA model, they show that investors seek higher risk premia the closer an expected price shock induced by policy uncertainty is to the time of investment. In addition, they find that the process through which CO_2 price variations feed to electricity price remarkably contributes to determine the overall investment risk faced by firms. Lofgren et al. (2008) estimates the threshold condition that will trigger investment in a new abatement technology for a firm facing uncertainty on a tax on a polluting production input. The hurdle rates for abatement investments linked to an option value in case of uncertainty on the future price of the polluting fuel are estimated to range between from 2.7 to 3.6 according to the considered industry. S. Fuss et al. (2008) introduce a distinction between market uncertainty (i.e. fluctuation of allowance prices uncertainty) and uncertainty pertaining to lack of clarity on policy signals. Through a ROA approach, they show that latter uncertainty can lead to larger delays in investments in clean energy technologies while market uncertainty is shown – up a certain threshold – to have a limited impact. S. Fuss et al. (2009) reach similar conclusions comparing frequency distributions of investments in wind energy and fossil-fired generation with CCS. Interestingly, the authors also find evidence that climate change policies that are stable over a certain length of time and change abruptly lead to smaller cumulative CO_2 emissions than less abrupt but more frequently changing policy frameworks. More recently, Ritzenhofen and Spinler (2014) analyze the timing and the likelihood of investments in renewable energy generation considering three different scenarios: a fixed Feed-in tariff regime (deterministic scenario), a stochastic scenario where electricity is sold on the spot market and, thirdly, the case of regime switching where the investment is undertaken under a fixed FiT without retroactive changes. They find that regulatory uncertainty increases price thresholds required to induce investment and that, when FiTs are significantly higher than electricity market prices, investors will invest earlier in order to secure the incentive before the regulatory change. Leveraging a stated preferences approach, Luthi & Wustnhagen (2012) suggest that project developers carefully evaluate the risk/return profiles of investment evaluating the return offered by incentives against a set of policy risks. Their study, based on a panel of 63 investors, estimates that investment environment characterized by low risk of sudden policy change lead to tariff 4.10 ct/kWh higher than in case of a completely risk-free policy environment. A similar finding originates from the work of Chassot et al (2014) that leverage a choice experiments on 29 venture capital investors based in Europe and USA. Their results show that high levels of regulatory risk have a negative effect on the likelihood to invest in renewable energy. In addition, by adopting a behavioural approach, they show that this detrimental impact is lower for respondents that have a more positive attitude towards government intervention.

Other than investment decisions, the importance of a stable and predictable policy framework emerges clearly also in studies dedicated to innovation. In their previously mentioned work, Johnstone et al (2010) present empirical evidence based on a panel of countries over the period 2000-2007 that the more 'inflexible' and unpredictable a policy regime is, the less patenting activity is registered for a given level of policy stringency. Kalamova et al. (2013) assess the impact of environmental policy uncertainty on innovation, using patent data as a proxy for innovation and volatility in public green R&D expenditures as a measure of policy uncertainty. The results, based on a panel data for OECD countries over the period 1986–2007, show that a 10% increase in policy uncertainty can lead to a 1.2–2.8% decrease in environmental patent activity. Furthermore, Nicolli and Vona (2016) argues that ratification of the Kyoto Protocol, which determined a more stable and less uncertain policy framework, amplifies the inducement effect of both energy policy and market liberalization on green energy innovation.

Interestingly, also announcements of planned future modifications to market arrangement can affect uncertainty. Fagiani and Hakvoort (2013) estimate the impact of both the announcement and of the actual implementation of the integration of Swedish and Norwegian renewable energy certificate markets on certificate prices through a GARCH model. After accounting for exogenous factors, the results show an increased certificate price volatility due to the regulatory uncertainty, thus underlining how also planned policy changes can affect certificate markets. As such, the authors underline policy-makers planning to undertake major modification of enforced regulations should take steps to disclose as much information as possible about the status of the discussion, future arrangement and any other features that could help investors to form rational expectations on the novel arrangement.

1.4.3. Administrative burden

The literature on the impact of the administrative burden of environmental regulations on firms' performance is relatively limited while their anti-competitive features have received a larger attention. This is due to the presence of norms that discriminate *by design* against new entrants, also known as "vintage differentiated environmental regulations" (or VDR). These impose higher environmental performance requirements for newly established plants and are widely diffuse and common across countries. For example, the Canadian new rules for coal plants (2015) oblige new firms to install a carbon capture and storage equipment (CSS) while existing plants are exempted from this requirement until 2030. Similar norms can also be found in USA, Europe and China. While VDRs may be justified on political economy grounds, the resulting uneven playing field is likely to undermine the mechanism underlying the Porter's hypothesis. More precisely, the higher barrier to entry may undermine the entry-exit process and, more broadly, the process of creative destruction underpinning innovation as depicted by Schumpeter. In addition, the slower retirement of older vintage capital can result in lower average productivity. In this regard, Coysh et al (2017, forthcoming) shows that VDRs may be associated with a lifetime extension of older polluting firms by 8 to even 15 years. A similar analysis is carried out by Bushnell and Wolfram (2012) that analyze the effects of the USA New Source Review (NSR) environmental regulations that required new electric generating plants to install costly pollution control equipment but exempted existing plants. The authors estimate that the regulations decreased capital investment without, however, identifying any effect on other inputs or emissions. Similar results are found also in researches on other sectors. For instance, Becker and Henderson (2000) study several industries over the period 1963-1992 and find that that new regulations significantly decrease the likelihood of opening of new plants. Gruenspecht (1982) estimates that vintage differentiated car emissions standards for carbon monoxide (CO) and nitrogen oxides (NO_x), lowered sales of new cars by 2-5% over the first five years after the implementation of the new standards. One of the few contributions on the impact of burdensome administrative procedure is provided by Luthi & Prassler (2011) who leverage a survey on US and EU developers to perform a conjoint analysis. Legal security, duration of administrative process duration and grid access regulations emerge as extremely relevant driver of developers' preference. In addition, the study shows that developers may leverage non-compensatory decision-making and certain minimum "performance" level of the regulatory process can be regarded as knockout criteria.

1.4.4. "Complementary" regulations

Finally, a growing body of literature underlines how environmental regulations are not introduced in vacuum but in a context characterised by several other norms often geared towards more polluting production process. As such, the interaction of environmental regulations with pre-existing norms should be considered when evaluating their impact on firms' productivity or innovation. Nesta et al (2014) is among the first contributions that empirically assesses the complementarity between environmental policies and competition in energy production. To this end, the authors build a dataset on renewable energy policies and product market regulation (PMR) for OECD countries since the late 1970s. The results show that renewable energy policies are more effective in fostering green innovation in countries with liberalized energy markets. In particular, the combination of environmental policies and market deregulation is the most effective method of inducing innovation in renewable energy, particularly near the technological frontier. Nicolli and Vona (2016) further develop the idea proposed in Nesta et al. (2014) by assembling a database on EU countries for the years 1980 to 2007. Their estimations suggest that, compared to privatization and unbundling, lowering entry barriers has a significant positive impact on renewable energy technologies. In addition, the authors are able to evaluate the impact on eight different renewable technologies and find that the aggregate effect of market liberalization found in the previous literature is driven by technologies where both patenting activity is less concentrated activity across firms and the entry of independent power producers is more likely, such as wind and solar thermal energy. Benatia and Kozluk (2016) show that both the likelihood and the volume of entry of renewable power generators are significantly influenced by industry regulation, local structural industry characteristics, such as concentration, sectoral expansion jointly with renewable support policies and installed base. However, notably, also environmental regulation shapes can promote or decrease competition in a sector. Cretì and Sanin (2017) highlight the potential trade-off between promoting a high CO_2 price through emission trading schemes and promoting competition in energy markets, specially in sectors where firms are vertically integrated (e.g. the power sector). Ang et al (2017) show that both innovation and investment flows in renewable power are driven by both incentives in place and the broader investment environment, including investment policy (e.g. policies on registering property; regulatory quality); investment facilitation (e.g. licenses and permit systems) and competition policy (e.g. direct control of the state over enterprises).

1.5. Conclusions

While the theoretical arguments for the Porter's Hypothesis appear to be solid, the empirical evidence is - at least – mixed. The literature review confirms the presence of a still divided community, specially in relation to the strong version of the Porter's hypothesis. Overall, the number of studies estimating a negative effect of tighter environmental norms on firms' competitiveness appears to be almost equal to those finding a positive impact. However, we should note that studies conducted at a plant, firm or sectoral level seems to be more likely to yield negative estimations of environmental policy impact on productivity. Regarding innovation, the literature - and specially most recent studies – often identify a positive impact, thus validating the weak version of the Porter's hypothesis. As such, overall, the literature seems to suggest that firms react to new regulation through an increase in innovation but does not allow to clearly discerning the overall impact on economic performance.

What rationale can be identified behind these mixed results? Through a review of the literature on environmental policy design, we argue that a possible explanation for the lack of homogenous results across studies may lie in the multifaceted nature of environmental regulations. In fact, while the vast majority of studies focus on the stringency of enforced norms, environmental policy instruments enforced in different countries vary along numerous dimensions. In turn, these features affect to a various extent different economic outcomes. For instance, vintage-differentiated regulations seems to result in slower capital turn-over and higher barrier to entries, thus possibly undermining the process of creation destruction that underpins Schumpeterian innovation. Uncertainty delays investment decision and rises investment costs while environmental red-tape, which is found to vary considerably across countries and to be uncorrelated with environmental policy stringency, can lead to sensibly higher compliance cost for firms. Finally, the role of flexibility, which is one of the few features characterizing well-designed regulations discussed in the original Porter's work, is limitedly assessed in the literature as well.

As such, while the existing literature provides interesting insights on the Porter 's hypothesis, it also underlines new interesting venues of research. First of all, the need to sharpen our understanding of the role played by different "types" of policy instruments seems to emerge clearly. Cohen and Tubb (2017) reflect upon this element and highlight how only 35% of surveyed studies allow to distinguish between flexible and "command-and-control" regulations. This scarcity of analyses seems even more pronounced – and surprising – in the case of innovation since the higher dynamic efficiency of flexible regulation is one of the main reason behind its adoption. Therefore, the study of how the impact of regulation on innovation varies according to the type of policy implemented appears to be an important area for further research.

The role that other features of environmental regulations can play in determining their overall impact on economic activity is another unexplored and promising areas of research. To this end, further studies may help to reconcile the contrasting results in the empirical literature adopting a fine-grained approach to environmental policy design. In this regard, policy-induced uncertainty, vintage differentiation and the red-tape that policy instruments generate on firms constitute potentially fruitful areas of research. An important challenge in this regard for researchers, however, may lie in the difficulty of identifying data with enough variation across countries.

Thirdly, even if economics is often labelled as the "sad science" because it focuses on how to allocate scarce resource, the vast majority of the research on innovation considers only the impact of environmental regulation on green innovation omitting to examine possible consequences on other technological areas. Nevertheless, environmental regulation is more likely to redirect innovation efforts towards green technologies rather than increasing innovation tout-court. While this is often underlined in models on technological change (e.g. Acemoglu 1998 and 2007), only one study seems to deal with this question in the literature. Aghion et al. (2016) research the impact that higher taxes on fuels have on the type of innovation patented by automotive industry. Their results show the presence of a directional effect, that is, a positive impact on green innovation coupled with a decrease in the patenting activity for polluting technologies.

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Does environmental regulation drive the direction of technological change?

Enrico Botta[a]
[a]Corresponding author: Università degli Studi di Milano e di Pavia,
Via Conservatorio, 7 - 20122 Milan – Italy. Tel. +39 02 503 21508.
Mail: Enrico.botta@unimi.it

Abstract
In resource-constrained world, environmental regulation is more likely to *steer the direction of technological change* than simply to increase green innovation. Nonetheless, studies on the Porter's hypothesis have often omitted the impact of environmental policy on "not-green" technologies. Furthermore, although there are compelling arguments in favour of the higher dynamic efficiency of market-based policy instruments, only few papers empirically tested such claim within the same study also because of the difficulties of comparing environmental policy norms across countries. Within this context, the paper empirically assesses the consequences of increasingly stringent market- and non-market-based regulations on the technologies the environmental policy aims to promote and on competing innovation. The estimations suggest that different types of regulatory instruments have distinct influences on the direction of technological efforts but reveal also the presence of path dependency. Market-based instruments are shown to be the main driver of increased innovation in the technological field that environmental policy wishes to promote while non-market-based measures principally shift private innovation efforts away from polluting technologies.

2. Does environmental regulation drive the direction of technological change?

2.1. Introduction

The increasing concerns over the environmental sustainability of current development trajectories have brought numerous countries to adopt "greener growth strategies" (OECD, 2015). These can be generally defined as a path of economic development that not only recognizes the role that environmental assets have in sustaining our wellbeing but also considers the environment as tool to promote economic growth (OECD, 2011). However, greener growth trajectories are constrained by market failures in relation to the environment and therefore environmental regulations are considered necessary to align private and public marginal benefits (and cost) curves. Nevertheless, their impact on economic activity is debated. In fact, the traditional view on environmental policies sees them as a cost to economic growth since firms have to invest into pollution prevention and abatement technologies or to curb production in order to comply with regulation (Jaffe *et al.* 1995). More recently, Porter introduced an alternative view arguing that well-designed environmental regulation might set dynamic incentives to innovate and therefore could increase both the level and the growth rate of productivity while ensuring an higher level of environmental protection (Porter, 1991. Zipper and Kuzlok, 2014).

This paper focuses on the first step of this virtuous chain delineated by Porter, namely innovation. In fact, our main working hypothesis is that that the level of stringency of environmental regulation affects innovation decision of firms. Numerous scholars investigated this channel through which environmental regulation could be beneficial to economic performance. While these studies provide excellent insights they are also affected by some limitations. First of all, although there are compelling arguments in favour of the higher dynamic efficiency of market-based policy instruments, only few researchers have been able to empirically test such claims within the same study (Cohen and Tubb, 2015). Secondly, there is a limited usage of panel data given the difficulties of comparing environmental policy norms across countries. Thirdly, and maybe most surprisingly, the vast majority of studies - with few exceptions (Rubashkina et al., 2015. Aghion et al. 2016) - consider the impact of environmental regulation only in relation to green innovation. However, technological change is not neutral: it benefits some production factors and agents more than others (Acemoglu, 1998 and 2007. Aghion et al. 2016). Underlining this concept, theoretical models on directed technological change highlight the shift between two competing activities. Otherwise said, given our resource-constrained world, environmental regulation is more likely to *steer the direction of technological change* towards, rather than simply increasing, green innovation. Nonetheless, studies on the Porter's hypothesis have often omitted the impact of environmental policy on "not-green" technologies.

In this context, the paper aims at empirically testing the impact of different types of environmental regulations on the direction of technological change. Under this light, its impact on both green and not green innovation is assessed. To this end, the paper leverages a novel OECD composite indicator of environmental regulation - being this an additional innovation to the literature since, while often employed in several other economic areas, such measures have never been applied to the field of environmental economics and innovation – to test the dynamic impact of both market and not market-based regulations on a panel dataset. The only similar contribution we are aware of is by Verdolini and Bosetti (2017) who use this indicator to study technology diffusion. While the paper is not about innovation, diffusion is however part of the technological change process which is often studied in this field.

The empirical results provide evidence that market-based regulations are the main driver of increased innovation in the technological field that environmental policy wishes to promote while non-market-based measures principally shifts private innovation efforts away from polluting technologies. At the same time, the estimations underline how innovation builds on the cumulated knowledge stock in the same technological area.

The paper is organized as follows. Section 2 provides a brief literature review on environmental regulation and innovation highlighting existing gaps. Section 3 describes our main working hypothesis and the empirical strategy to test them. Section 4 provides the main empirical results while section 5 discusses their robustness. The final paragraph concludes and presents the principal policy implications.

2.2. Literature Review

The traditional view on environmental policies sees them as a cost to economic activities since firms have to invest into pollution prevention and abatement technologies or to curb production in order to comply with regulation (Jaffe *et al.* 1995, Ambec *et al.*, 2013). A second "view", also known as the Porter's Hypothesis, suggests that "well-designed" environmental policies might not only yield environmental benefits but also boost productivity (Porter, 1991. Porter and van der Linde, 1995). Extensively discussed in the literature, the Porter's Hypothesis has been articulated into three more narrowly defined "forms" nowadays known as the weak, strong and narrow version of the Hypothesis (Jaffe and Palmer, 1997).

The strong version of the Porter's Hypothesis rejects the assumption of perfect markets with fully rational agents and assumes instead that firms are not operating at the maximum possible efficiency. In this context, well-designed environmental policies might induce firms to rethink their production process and lead to extra profits. The most often cited example is energy efficiency, where numerous market failures impede firms to pursuit cost-effective opportunities (Howarth and Andersson, 1993. IEA, 2013).

The weak and narrow version implies that environmental regulation will lead to an increase *in environmental* innovation with an important distinction. As Jaffe and Palmer (1997) describe, firms subject to the environmental regulation face an additional environmental constraint next to their financial ones. As firms are assumed to be profit-maximizing agents, they will innovate in order to comply with the new regulation in the most cost effective manner. Thus, innovation in the field of environmental technologies will increase. The narrow version of the Porter's Hypothesis asserts that *flexible* environmental policy regimes are more likely to increase innovation and improve company performance. Flexibility is usually characterized as key property of market-based (or explicitly externalities- pricing) regulations. In fact, in a first-best world addressing externalities entails essentially closing the gaps between the social and private costs (and/or benefits) of polluting activities. By setting an explicit opportunity cost on emissions, market-based regulations generate an incentive to continuously search for cheaper abatement solutions. Therefore they are likely to provide higher dynamic incentives compared to non-market-based regulation (de Serres et al., 2010).

The first empirical study on the weak version was probably carried out by Jaffe and Palmer (1997) and points to a significant positive link between pollution control expenditures (PACE) – used as a proxy of environmental policy stringency - and R&D expenditures, whereas patents are shown to not be affected by more stringent regulation. Instead, positive links between PACE expenditure and environmental patents counts are often found by more recent studies (Lanoie et al., 2011). Similar results are found by Brunnermeier and Cohen (2003) who use USA patent data between 1983 and 1992 and, as an indicator for environmental policy stringency, both pollution abatement expenditures and government monitoring activities. de Vries and Withagen (2005) exploit data on EU environmentally related patents and measure policy stringency according to three different indicators: Compliance with international agreements by individual signatories; an index of environmental sensitivity performance combining different pollutants, and stringency modelled as a latent variable. Only the third stringency indicator is found to have a strong positive relationship with environmental innovation. Wagner (2007) finds "…that the implementation level of environmental management systems has a positive effect exclusively on environmental process innovation, whereas it is negatively associated with the level of a firm's general patenting activities." Econometric results leveraging a 2003 OECD survey covering seven countries (Canada, France, Germany, Hungary, Japan, Norway, and the USA) finds that R&D expenditures increase following an increase in the perceived policy stringency of the questioned firm (Frondel et al. 2007). Again leveraging the 2003 OECD survey, Lanoie et al. (2007) find strong support for the weak version and qualified support for the two other versions of the Porter's hypothesis. Using a panel data set of Italian firms in 2002 and 2004, Mazzanti and Zoboli (2006) find that environmental policies and environmental voluntary auditing schemes exert some relevant direct and indirect effects on innovation although *"… evidence is mixed and further research is particularly needed."*

From the above literature review, some limitations emerge. First of all, there is scarce evidence of the ability of environmental policies to direct technological change. Technological change is not neutral: it benefits some production factors and agents more than others. These distributional impacts imply that some groups will embrace new technologies and others will oppose them. Underlining this concept, theoretical models on directed technological change highlight the shift between two competing activities. Initially conceived by Hicks (1932) and Habakkuk (1962) and later on perfectioned by Acemoglu (1998, 2002; 2007), these models have only recently been extended to the field of environmental innovation and regulation (Aghion et al. 2016). These recent contributions help to understand that, in a constrained resource world, environmental regulation is likely to steer innovation efforts towards green knowledge and away from other technological areas. As such, both changes should be empirically measured to properly assess the soundness of the underpinning theoretical arguments. Nevertheless, since most of the empirical studies focus only on green technologies and omit the competing effects on other innovation, there is limited evidence on the capability of environmental regulation of directing innovation efforts away from other technologies (whether "polluting" or not) towards green innovation. The main contribution in this regard is Aghion et al. (2016) who develop a one-period model of an economy of directed technical change and empirically test their conclusions. They show that firms tend to innovate relatively more in clean technologies when they face higher tax-inclusive fuel prices though firm-level panel data on auto industry patents across 80 countries over several decades. Rubashkina et al. (2015) also test the weak version of the Porter's hypothesis not focusing only on green innovation but on total innovation in order to account for possible opportunity cost (e.g. firms may decrease innovation in other fields to develop new technologies to comply with environmental regulation). Their results show that more stringent environmental regulation leads to higher overall patenting activity.

Secondly, while the narrow version of the Porter's hypothesis is a theoretical compelling argument, surprisingly there are few studies assessing jointly the impact of both market and non-market-based regulation (Cohen and Tubb, 2015). In fact, the vast majority of articles focus either on market or non-market-based regulation and therefore do not provide a fully homogenous framework for testing the narrow version of the Porter's hypothesis. An important exception is Johnstone et al. (2010) who consider seven policy instruments including: Research and Development, Feed-in Tariffs Taxes, Investment Incentives, Voluntary Programmes, Obligations, Tradable Permits. However, as the authors underline, they lack continuous stringency variables for several policies under consideration and therefore they are forced to code many as dummies (Binary variables are constructed for tax measures, investment incentives, bidding systems, voluntary programs, and quantity obligations) limiting the explicative power of their research.

Thirdly, composite indicators of environmental policy have never been applied to the field of environmental economics and innovation. In order to estimate impact of environmental regulation it is necessary to leverage an adequate proxy of implemented policies. Nevertheless, the identification of a suitable candidate is hindered by several challenges (Brunel and Levison, 2013). In order to cope with these issues, most of the empirical studies try to capture the level of stringency of the implemented policies focusing on the first-level consequences of regulation, namely firms' environmental related expenditures. However, these measures suffer from identification and sampling issues. In fact, overall expenditure in pollution abetment technologies might be due to other policies (e.g. labour policies, capital regulation, etc.), to firms' decisions (e.g. "green" marketing, efficiency/profit seeking investments in capital, etc.) and are intrinsically difficult to use in cross-country studies since economies characterized by a larger presence of heavy industries are more likely to register higher level of pollution and therefore higher expenditures in abatement technologies (Brunel and Levinson, 2013. Galeotti et al. 2015). Few studies leverage policy-based measures of environmental policy stringency like the introduction or change of a certain policy. Compared to "ex-post measures" of stringency, their key advantage is that they do not suffer from the identification issues but are heavily exposed to multidimensionality. In this regards, the main assumption is that it is possible to proxy for the overall policy stringency in a country for a given sector by aggregating selected instruments. In addition, the usage of such measures is further complicated by the difficulty of comparing the enforced environmental norms across countries. For this reason, most of the studies leveraging policy – based stringency measures either focus on a single country or, when panel studies are considered, often introduce a dummy variable (usually for the date of signature of an international treaty) and therefore rarely allow for testing the influence of particular aspects of the policy change (e.g. phase in, accompanying measures, design characteristics, policy interactions) (Van der Vlist et al. 2007; Curtis, 2012). The few panel studies leveraging policy variables that are not based on dummies can be classified in two groups according to the type of regulation analyzed: either market-based or non-market-based. Regarding market-based regulations, scholars often use total taxes on fuels as a proxy for environmental policy stringency implicitly assuming that fuel taxation steams mainly from environmental concerns. Leveraging this method, both Popp (2002) and Aghion et al (2016) find a significant impact from both energy prices and past knowledge stocks on patents. The evidence regarding non-market-based regulations is even more limited. One of the most interesting panel studies is provided by Popp (2006) who shows that inventors respond to environmental regulatory pressure in their own country but not to foreign environmental regulations focusing on the case of NO_X and SO_2 regulation in the US, Japan, and Germany. Composite policy based indicators, which are a specific kind of policy based proxy of policies, are commonly leveraged to test the impact of regulation in several economic fields but have never been applied in the area of environmental economics and innovation. This is specially due to the lack of a sufficient time-series dimension of the handful available (Dasgupta et al. 1995. EBRD, 2011).

We build on this literature and we contribute to it in two main ways. First, we test empirically the narrow version of the Porter's Hypothesis in panel setting. To our knowledge, very few panel data studies include both market and not-market-based regulation and therefore are able to provide a fully homogenous framework for testing such hypothesis. To this end, the paper leverages an OECD composite indicator of environmental policy stringency to disentangle the impact that different kind of environmental regulations have on innovation. Secondly, we provide some further evidence that environmental regulation is able to drive the direction of the technological efforts. The closest contribution is Aghion et al (2016) who show that stricter environmental norms for the automotive sector increase *green* innovation and decrease *grey* innovation using firm level patent data. However, since they leverage firm level data our concern is that they might not capture the full extent of the induced innovation impact. In fact, innovations are increasingly achieved through the convergence of different scientific fields and technologies. This interdisciplinary nature is specially evident for green technologies. A review of the literature cited in patents, a technique used to assess science and industry linkages, shows that green innovations frequently draw on material science, chemistry and engineering and therefore go beyond the narrow categories of environmental science (Igami, 2007. OECD, 2010). In a less formal way, this means that the scrubber that allows a power plant to meet certain emission levels are not necessary developed within the energy sector but most probably by firms operating in the machinery industry. For this reason, we leverage aggregate patent data in order to avoid overlooking induced innovation taking place outside the directly regulated industry.

2.3. Main hypothesis

Our main working hypothesis is that the direction of technological change is driven by two key factors: the level of stringency of environmental regulation and available knowledge stock. Furthermore, we assume that different types of regulations provide different dynamic incentives. More in detail we put forward three hypotheses:

I. *Market-based regulation provides dynamic incentives and therefore stimulates higher rates of green innovation than non-market-based regulations*
II. *A more stringent environmental regulation may steer innovation away from other technologies towards green technologies. This crowding-out effect should take place chiefly in polluting technologies but a-priori cannot be excluded to be present in other fields.*
III. *The direction of technological change is affected by the cumulated knowledge stock*

Our first research hypothesis is that market-based regulations provide higher dynamics incentives than non-market based regulations. In a first-best world addressing externalities entails essentially closing the gaps between the social and private costs (and/or benefits) of polluting activities. By setting an opportunity cost on the emissions, market-based regulation is supposed to close this gap while providing polluters with incentives to continuously search for cheaper abatement solutions in order to keep the marginal cost of abatement below the emission price set by the tax or the permit market (de Serres et al. 2010). Under command-and-control regulations, which usually set a maximum level of allowed pollution, polluters have little incentives to search for abatement options once they have complied with the standard (Jaffe et al. 2001). In this sense, market-based instruments outperform the non-market based regulation under a dynamic efficiency criterion.

Importantly, we leverage aggregated patent data in order to capture the full extent of induced innovation. This is due to the assumption that innovations designed in order to comply with environmental regulation are not necessary developed in the regulated industry. More generally, we assume that technologies leveraged in an industry are not always developed within the same sector. A common example could be the converter or the microfilm used for solar panels. These are being developed in response to increasing environmental concern and ensuing stricter regulation for the energy sector but large incumbent electricity producers are not the main innovators. For this reason, we leverage a measure of stringency of regulation affecting energy generation and we estimate its impact on "green energy generation" patents regardless of the applicant's industry of specialization.

Our second objective is to investigate the presence of a crowding-out effect. Tighter environmental regulations are assumed to lead to an increase of environmental innovation under both the weak and narrow version of the Porter's hypothesis. However, in a resource-constrained world higher innovation efforts in a specific field are likely to come at cost of innovation efforts in other fields. More formally, in a resource-constrained world environmental regulation is likely to steer innovation efforts towards green technologies and away from other technological areas. It is important to underline that while polluting technologies are the most likely to suffers from increasing environmental policy stringency, the crowding out effect might be taking place also in other "segments" of human knowledge as firms change the focus of their innovation efforts in order to profit for a growing market for environmental technologies. It should be noted that this phenomenon does not imply that environmental regulation is detrimental for growth. As in the case of energy efficiency, green innovation might well be environmental friendly and profit enhancing.

Our third main working hypothesis relates to the arguments of path dependency. In fact, the stock of cumulated knowledge is a key explanatory factor of innovation performance but it might also drive the direction of technological change. The capability of innovating depends on the currently available knowledge, a well - know phenomenon called with different names in the various literature: "inter-temporal knowledge spill-overs" in growth theory, "Cumulated knowledge" in evolutionary economics or "Standing on the shoulders of giants" in philosophical studies (Keller, 2002. Verdolini and Galeotti, 2011. Aghion et al, 2016). Overall, actors (being these countries, firms or industries) who exhibited greater investment in technological development are also more likely to engage in innovative practices in the future (Baumol, 2002). Nevertheless, as underlined by Acemoglu et al (2012), knowledge accumulation can be a double-edged sword. In fact, increasing specialization in a given technological field might decrease the relative cost of continuing innovating along the same technological trajectory compared to others. If this is true, then we might face a vicious path dependency in polluting technologies against green technologies. At the same time, however, as the stock of cumulated green knowledge grows, a virtuous path dependent process might be started where green innovation becomes progressively more convenient. For this reason, the stock of cumulated knowledge can be a substantive factor in explaining the direction of innovation. Notably, the rate of technological change can also be influenced by the stock of foreign cumulated knowledge as often underlined in the catch-up literature. However, these international flows are hindered by numerous barriers. For instance geographical distance, different language and technological specialization are often found to be inversely correlated with knowledge spill-overs (Jaffe et al. 1993, Jaffe and Trajtenberg, 1996. Keller, 2002. Peri, 2005).

2.3.1. The econometric model and data

The following empirical model is developed to test the hypotheses set out above:

$$\boldsymbol{eq.1}: INN_{tech,it+1} = ENVPOL_{it} + DOMESTIC\_KS_{it} + L1.FOREIGN\_KS_{it} + CONTROL_{it} + \eta_i + \tau_t + \varepsilon_{it}$$

$$where\ i = 1 \dots N,$$
$$t = 1 \dots T,$$
$$tech = green\_energy, general\_purpose\_ environ\_tech. and\ grey\_tech$$

where $INN_{tech,it}$ is our proxy of innovation for a given type of technology (either green energy, other green or grey technologies) in country i and in year t; $ENVPOL_{it}$ is the measure of environmental policy stringency; $DOMESTIC\_KS_{it}$ and $FOREIGN\_KS_{it}$ are respectively the country's available domestic and foreign knowledge stock; $Control_{it}$ is a matrix of control variables and ε_{it} is an error term.

The innovation performance of an agent (being this a country, a firm or other) is usually captured in empirically studies using data either/both on R&D expenditures or/and on number of patents application/granted. Compared to R&D expenditures, which are a measure of the inputs in the innovation process, patents data focus on the outputs of the inventive process (Griliches 1990; OECD 2009) and have several advantages: they have a close link to invention; patent documents are a rich source of information (on the applicant, inventor, technology category, claims, etc.) and data are often readily available from patent offices (Dernis et al. 2001). This richness of information also asks further questions to the meticulous researcher. For instance, the distinction between residence of applicant and inventor is important to consider since these do not always match and leads to wonder which country a given innovation should be attributed to. However, patents have also major weaknesses. First of all, they are designed to only protect technological innovations and therefore other kinds of innovation (like organisational, managerial and non-technological innovations) are not captured. Secondly, much knowledge is tacit and therefore not protectable through legal means. Thirdly, since patenting requires disclosing all information regarding an innovation, inventors might prefer to protect their knowledge through secrecy. Fourthly, not all patented inventions are of the same quality. In fact some patents might represent a small progress for the scientific community while others might be of higher importance. The problem of difference in quality of patented inventions is further exacerbated by tactical approaches to patenting by firms which include requesting patents for minor modification of a previous invention in order to increase protection, strategies to enter patent pools, etc. Finally, a patent application is a lengthy process. For instance, the European patent grant procedure takes between three to five years from the date the application is filed[2]. This issue is exacerbated by the presence of "grace periods" (several countries, including USA, have a grace period of twelve or six months during which an invention, even if it has been disclosed, it is still patentable) and the Paris convention which allows to use the filling date of the first patent application as priority date in following patent applications in other countries. These features of the patenting system make data for most recent years less reliable.

In order to mitigate these issues, we capture innovation by the number of patents granted annually in a country leveraging patent families. A patent family is a set of individual patents covering different geographical regions, that is, all the equivalent patent applications deposited at various patent offices corresponding to a single invention (Haščič and Migotto, 2015). They are often used in empirical analysis since they provide numerous advantages over simple patents counts. First, they provide a common measure of innovation across countries. For example, if the same invention is covered by two different patents in US and in Japan, this will be counted as a single invention (Hascic and Migotto, 2015). Secondly, as with citations, they are extensively used to mitigate issues with the quality of inventions (Lanjouw and Schankerman, 2004. Guellec and van Pottelsberghe de la Potterie, 2000. Harhoff et al. 2002. OECD, 2009[3]). While the lack of data on citations is a weakness of our analysis, we claim that this is not a major drawback for our research questions that aim at shedding light on the ability of regulation to drive the direction of innovation efforts, regardless of the quality of the resulting invention. The most commonly used patent family is the so-called triadic patent family (TPF) which is a specific family composed by inventions that have been patented in all three world's major patents offices (USPTO in the US, EPO in Europe and JPO in Japan). Unfortunately, this family class is not very suited for econometric analysis in case of environmental technologies given the high number of zero that risk to bias the results. For this reason, we leverage a novel dataset elaborated the by OECD Environment and Innovation Department. This database offers information on national innovation performance through patents families but providing two additional key benefits. First, it offers a more fine-grained breakdown of patents in different environmental classes (e.g. the OECD triadic database offers data on overall patents in renewable energy technologies while this novel dataset drills down to single technologies like solar, wind, hydro, etc.). Secondly, the database offers multiple definitions of patents families: all patents that have been registered at least one (PF1), at least two (PF2), at least three (PF3) and four patent offices (PF4). Through this increasingly stringent definition of patent families, lower quality innovations are filtered out without losing as many observations as when three patent offices in three different continents, as in the case of the triadic patent family, are considered. Given these elements, we focus our analysis on the highest quality inventions and therefore on the category PF4. Finally, since we suspect that firms need time to innovate in response to a change in the regulation, as common in the literature, we introduce a one-year lag to reflect

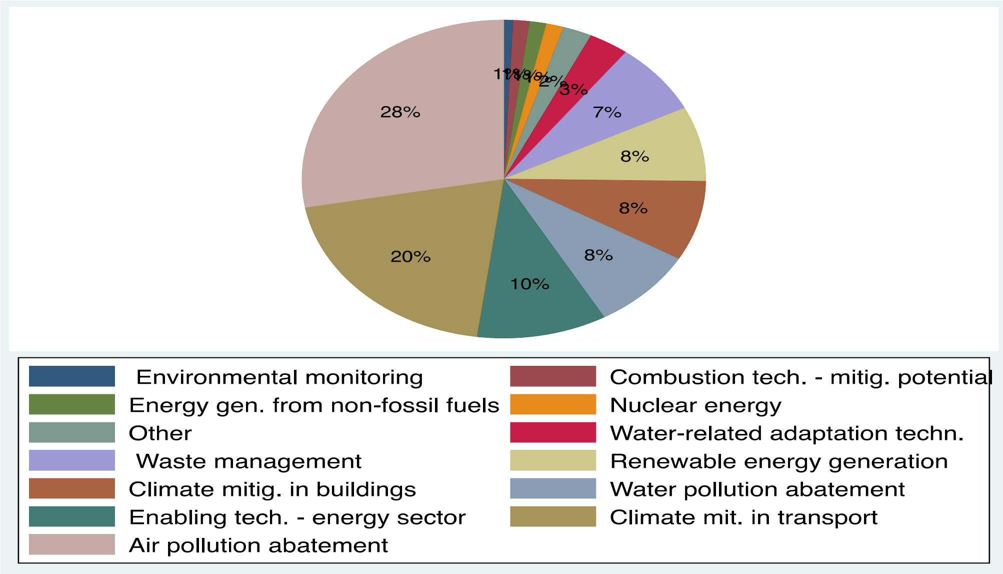
[2] EPO website. Accessed on the 9th March 2016.
[3] OECD, 2009. OECD Patent Statistics Manual

this delayed response. Importantly, our patent data are fractional (non-negative continuous variables) since – as usually for patent statistics – patents are assigned to countries according to the inventor's (or applicant's) residence, using fractional counting if there are multiple inventors to avoid double counting.

The OECD PATSTAT provides information on yearly environment-related patents grouped into several sub-categories (Appendix B provides a detailed break-down of the different technologies). Importantly, these patents are not assigned to a given sub-category according to the industry where the applicant operates but according to the purpose of the developed technology (e.g. solar energy or effluent control). We aggregate these data into three main groups. The first group is composed by all patents in green energy technologies identified as patents related to Solar thermal and photovoltaic (PV) energy, Solar thermal-PV hybrids, Geothermal energy, Marine energy (excluding tidal), Hydro energy - tidal, stream or damless, Hydro energy – conventional, biofuels and fuels from waste, combustion technologies with mitigation potential (ex. Combined heat and power (CHP), Combined cycles (incl. CCPP, CCGT, IGCC, IGCC+CCS), and Heat utilisation in combustion or incineration of waste), Technologies for an efficient electrical power generation, transmission or distribution, Enabling technologies in the energy sector (e.g. energy storage) and technologies for the Capture, storage, sequestration or disposal of greenhouse gases. We collect all the other green patents into a second group called "other green". This group includes patents in the following areas: General Environmental Management (air, water, waste and soil remediation); Water-related adaptation technologies (e.g. Indoor water conservation or Irrigation water conservation), Nuclear energy, Fuel efficiency in transportation (road, marine and train) and Energy efficiency in buildings and lighting. Finally, we consider all remaining patents as not-environmental related innovation and therefore we label them as "grey". This group is equal to the difference between "total patents" and sum of the patents in the two groups above mentioned for each country in a given year. It is important to underline that this group is composed of all patents that are not deemed to have an environmental impact and therefore comprises a large set of technologies ranging from traditional (polluting) combustion technologies to health technologies and others. As shown in figure 1, air pollution abatement, hovering at around 30% of the green knowledge stock cumulated in OECD countries, is the largest category among all environmental technologies. The second largest category is environmental technologies in transportation. Overall, patents belonging to the group labelled as "green energy generation" weight for 22% of environmental knowledge stocks in OECD countries. Finally, environmental patents count for small portion of portion of the national stocks of countries (on average 11% of total patents).

Figure 3. Environmental Patents by category

OECD Countries, 1980 - 2012



Our main explanatory variable is a novel composite indicator of environmental policy stringency developed by the OECD. The index covers 26 OECD countries combining information on 15 environmental policy instruments (both market-based and not-market-based) over the years 1990-2012. This indicator ranges from 0 to 6 where 0 is associated with lax regulation while 6 with more stringent policies. Furthermore, it is composed of two main components, one capturing market-based regulation and one capturing non-market-based regulation. Among the two indicators proposed by the OECD, one focusing on the energy sector and another that includes additional information to obtain a proxy for the whole economy, we leverage the first measure due to several factors. First, we are interested in studying the impact of environmental regulation in directing technological change. For this reason, we need a variable that is as close as possible to the type of technological efforts we are interested in. From this standpoint the first indicator, being built as a measure of environmental norms regulating the negative externalities deriving from the generation of electricity, eliminates spurious impact from regulation of other activities. Secondly, this indicator also better matches our first group of patent data that focus on green energy generation. As such, given our hypothesis of direction of technological change, we expect a positive impact of our indicator of environmental policy stringency on green energy generation innovation and negative impact on grey technologies. The effect on other green innovation cannot be defined a-priori as it might be negative, if firms change the focus of their innovation efforts in order to sell products to meet the increasingly stringent regulation in the energy sector, or positive, if the environmental policies applicable to other economic activities increase simultaneously with the stringency of norms regulating electricity generation.

Finally, we assume that firms are forward-looking and/or alternatively that environmental policies are announced before their implementation. As such, we expect that companies may react to new regulation before this enters into force. However, at the same time, the argument in favour of market-based instruments is rooted in their dynamic efficiency after their introduction (since firms, the theory predicts, will continue to innovate in order to minimize the cost of the environmental externalities). Otherwise said, this means that we expect the lagged structure of market-based instruments to be chiefly positive and to outperform non-market-based regulation. In fact, in the case of performance standards, the inventing steps should be visible before the introduction of these instruments since the inability to comply with them once these enter into force will simply mean that the firm is in violation of the law and therefore subject to fines. From this standpoint, market-based instruments offer a wait-and-see approach that non-market-based instruments lack. Given these competing suggestions to focus either on a forwards and lagged structure, our main explicative models leverage both a contemporaneous and forward/lagged structure for the environmental policy stringency indicators.

As common in the empirical literature, we capture the available knowledge stock in a country at time t by accumulated patents (Klaassen et al. 2005. Kobos et al. 2006). However, since we are interested in verifying the presence of any path-dependence in the innovation process, that is, if previous experience in a given technology fields is likely to drive innovation in the same technological area, we include separate variables for the knowledge stock of the green technology that is supposedly promoted by the environmental regulation captured by the indicator (green generation), for other green technologies and for "not-environmental related" (or "*grey*") technologies.

Furthermore, since knowledge is often assumed to be subject to obsolescence and to become less valuable over time, a depreciation rate δ describing the annual loss is considered when computing the knowledge stock. There have been different estimates of this rate in literature and generally it is assumed to range between 10% (Keller, 2002. Verdolini and Galeotti, 2011) and 20% (Aghion et al, 2016). Often, it is also argued that the appropriate discount factor varies according to the technology considered (Bointer, 2014). For instance, Grubler et al. (2012) in their literature review find typical depreciation rates of 10–40% in the energy sector. Watanabe et al. (2000) consider a 20.3% obsolescence for PV while Miketa and Schrattenholzer (2004) and Kahouli-Brahmi (2009) used a depreciation rate of 3% for several energy technologies. Kobos et al. (2006) indicates 2.5% for wind and suggests 10% for PV. Klaassen et al. (2005) used 5% depreciation for wind energy. We use a conservative approach and consider a depreciation rate equal to 10% for both types of environmental technologies while 20% for not-environmental related technologies. The knowledge stock in country i at time zero (1990 in our analysis) is set equal to $know\_stock_{tech,i,1990} = \frac{inno_{tech,it}}{\delta}$. To summarize, the resulting law of motion of knowledge, calculated using the perpetual inventory method (Verdolini and Galeotti, 2011), is:

$$\boldsymbol{eq.2}: know\_stock_{tech,it} = inno_{tech,it} + (1-\delta) * knowstock_{tech,it-1}$$

Given that for two countries in our sample (Australia and Spain), the knowledge stock for green energy patents is equal to zero in 1990 and that we use the logarithm of this variable in our econometric model, we add a small constant (0.0001) to all knowledge stocks to avoid the problem of the logarithm being undefined in zero.

As discussed, we believe that path dependency might work also across national boundaries. To this end, a measure of foreign knowledge available for domestic innovation is constructed using country specific weights. This approach relies on the idea that only a portion of knowledge stock of country A is available for domestic innovation in country B because of the barriers to international flows. Furthermore, these barriers are considered to be specific to each country pair (e.g. residents in USA are likely to more easily access knowledge generated in UK than in France). In the literature, two main methods have been used to estimate the intensity of foreign knowledge spill-overs. Following Coe and Helpman (1995), several articles leverage trade data either in the form of bilateral import shares (Keller, 2002. Madden et all. 2001) or foreign direct investments to proxy for knowledge flows (Conley & Ligon, 2002; Keller, 2002b). More recently, patents citations have been used since they provide a trail of the flow between the cited and citing document (Jaffe, et all. 1992 . Adams, 2002. Jaffe and Trajtenberg, 2002. Jozefowicz, 2002. Peri, 2005). An innovative contribution underlines that knowledge flows could differ also according to the type of technology considered and provide an estimation of flows specific to renewable energy and energy efficiency related technologies (Verdolini and Galeotti, 2011). Given our focus on different types of technologies, we would ideally leverage such kind of technology and country specific coefficients to determine the level of foreign knowledge available to each country. Unfortunately, the only analysis with this level of detail is provided by Verdolini and Galeotti (2011) for renewable energy and energy efficiency related technologies. For this reason, we leverage their estimated coefficients to compute the foreign knowledge stock available to each country in relation to green energy generation and we recour to bilateral trade import data for the other two types of technology groups considered in our analysis. More in detail, the weighted foreign knowledge stock available to country i at time t is defined as

$$\boldsymbol{eq.3}: Foreign\_KS_{it} = \sum imp\_sh_{ij} * Domestic\_KS_{jt}$$

where $imp\_sh_{ij} = M_{ij} / \sum_{i \neq j} M_{ij}$, $\sum imp\_sh_{ij} = 1$ and Mij is country i's imports of goods and services from country j. Bilateral imports data are from the OECD Trade Database. The average bilateral import share for each country is used. In the above formula, imp_sh_{ij} is substituted by the knowledge flow coefficient KF_{ij} as estimated by Verdolini and Galeotti (2011) in case of green energy technology. We add a lag to foreign knowledge stock to take into account barriers that may slow-down the flow of knowledge.

Finally, we control for the level of domestic competition regulations. In fact, Schumpeterian theories describe a non-linear relationship between competition and innovation. More in detail, market regulation can influence the rate of entry and exit processes of firms, i.e. the so-called process of creative destruction - which is found to be a key driver of country's innovation and growth (Bartelsman et al. 2008; OECD, 2009; Bravo-Biosca et al. 2012). To this end, we include in our analysis the indicator of regulation in energy (ETCR) developed by the OECD. This indicator ranges from 0 (most liberalised) to 6 (least liberalised) and it builds on seven sub-indicators: electricity, telecoms, gas, post, rail, air passenger transport, and road freight (Nicoletti and Scarpetta, 2005). Given our focus on the electricity generation sector, we include in the analysis only the component regarding the first sector. Finally, we include GDP as additional control and we also allow for unobservable factors by introducing country fixed effect (η_i), a full set of time dummies (TD_t) and an error term (ε_{it}) assumed to be uncorrelated with the right hand side variables.

2.3.2. The Econometric specifications

Our dataset is a strongly balanced panel covering 17 countries[4] for a time period of over 32 years (1980 to 2012). Importantly, the first ten years of observations (1980-1989) are used to compute the pre-sample mean necessary to leverage the estimator proposed by Blundell, Griffith and Van Reenen (described in the next paragraphs[5]) and therefore not used for the econometric regression. Given that the EPS data start in 1990, the years before this date are a natural cut-off to compute the pre-sample mean

Generally speaking, patent data are fitted through models such as the Poisson or Negative Binomial distribution. However, three characteristics of our data suggest particular caution in choosing the most appropriate estimator. First of all, the dependent variables – green energy, other green technologies and grey patents by inventor's country of residence – show a high standard deviation that is almost double their mean[6] (Table 1). This high dispersion of observed data is likely to affect the estimation results. In fact, the Poisson's distribution builds on the assumption of a mean equal to λ and a variance equal to λ as well. If not, the key hypothesis of equi-dispersion underlying the Poisson regression is likely to be violated. Under this circumstance, the estimates would be still unbiased but inefficient and therefore produce inconsistent standard errors. A second concern is due to the dynamic specification of our model. In fact, among our regressors we have the knowledge stock that is not contemporaneously correlated with our dependent variable, given the forward lag, but it is still dependent on previous

[4]The following countries are part of our sample: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom and United States.
[5] Please note that Table 1 reports the descriptive statistics only for the years included in the econometric regression (1990 – 2012).
[6] Within green energy patents , 7% of observations are zero while there are no zero observations within the other green technologies group.

realization of the patents flows. More in detail, this might be an issue for the traditional fixed effect approach, which relying on the work of Hausman, Hall and Griliches (HHG), requires strict exogeneity, i.e. the shock $\varepsilon_{c,it}$ must be uncorrelated with x_{it} in all periods (not only contemporaneously), i.e. E{ $\varepsilon_{c,it}$ | x_{it} } = 0 for all t. When using explanatory variables that depend on past realizations of the dependent variable, as in our case the knowledge stocks, this assumption is likely to be violated.

For these reasons, the data are fitted through numerous models in order to test the robustness of the results. First, we leverage a traditional Poisson panel model. As noted by Wooldridge (2002), while the leading application of Poisson's distribution is on count data, the fixed effects Poisson estimator can also be applied to non-negative continuous variable. This application is common in the trade literature (Silva and Tenreyro, 2006) but is not limited to this field (for example Ang et al. 2017). However, given the possible violation of the equi-dispersion assumption and the dynamic specification of our model, we replicate our estimation using two additional models

More precisely, we leverage the negative binomial pre-sample mean (PSM) estimator proposed by Blundell, Griffith and Van Reenen (1999) that is robust to over-dispersion and to the relaxation of the strict exogeneity assumption. The PSM relies on introducing a control function term for the fixed effects, which is identified by the logarithm of the average realizations of the dependent variable in a pre-sample period. The theoretical results on the properties of the estimator build on an assumption that the number of pre-sample periods approaches infinity but Blundell et al. (2002) demonstrate that the pre-sample mean estimators perform reasonably well even when the number of time periods is relatively small. Importantly, the "traditional" negative binomial estimator is more limitedly applied to non-negative continuous variables than Poisson. For this reason, we test for the robustness of these results leveraging the approach of Tavassoli and Carbonara (2014). The authors - who analyse fractional patent data - apply the negative binomial model on the original data and, then, on their rounded values. The authors underline how "the result of binomial regressions before and after rounding is quite similar". Also in our case, the estimations obtained with the rounded and fractional values are remarkably similar (the results on the rounded data are reported in the appendix A as a robustness test).

As a third robustness test, we repeat the estimations using the two-step negative binomial QMLE (NB- QMLE) estimator that has been proposed to study continuous non-negative variables by Head et al. (2009) and that has been applied in several studies (e.g. Briant et al, 2014. Castellani et al., 2013). Also in this case, we control for the fixed effects using the pre-sample mean. It should be noted, however, as underlined by Bosquet and Boulhol (2010), that the two step NGQML may be inappropriate when the choice of unit of the dependent variable is arbitrary (e.g. meters versus kilometres or billions versus millions). In case of patent data, this issue is likely to be less relevant since patent data are not usually expressed in different unit of measures than the single digit, also because yearly granted patents in several countries do not go above 1,500 units per year (with notable exceptions as, for instance, the USA where the annual average is

150,000 units per year).

The results (reported in tables 2-10) are consistent among these three methodologies in relation to green energy patents. More precisely, increasingly stringent market-based regulation (lagged) is significantly and positively correlated with innovation in green energy generation technologies across all four models. The second main results of our paper, namely the negative impact of increasingly stringent regulation on other technological areas, are statistically significant only when the negative binomial models are considered.

Table 1: Descriptive Statistics

2.4. Main results

2.4.1. The weak version of the Porter's Hypothesis: does increasing environmental policy stringency lead to more green innovation?

Our first concern regards the impact of increasing environmental policy stringency on the technology that is meant to promote (in our case, green energy generation). As such, the following tables show the impact that overall, market-based and not-market-based environmental policy stringency has on green energy innovation (Tables 2, 3 and 4). In these tables, as in all the following ones, we start our analysis at current time (t=0) and different lag and forward structures are tested until the first insignificant coefficient is found. This is due, as discussed, to the competing assumptions that regulations are known in advance and that market-based instruments should provide higher dynamic incentives chiefly after their introduction. For each time structure, we control for the fixed effects a là Haussman, Hall and Griliches in the Poisson model (columns titled as "HGG") while the pre-sample mean estimator is leveraged when the negative binomials distribution is assumed (columns titled as "BVGR" and "NBGML"). All estimates include year dummies and GDP.

As reported in tables 2.A, 2.C (forward structure) and 2.B, 2.D (lag structure), increasing *overall policy stringency (eps)* seems to have a positive impact on green energy innovation when a forward structure is considered. More in detail, both the BVGR - Columns (3) and (4) in table 2.A - and the NBGML - table 2.C – estimators suggest that firms take their investment decisions in green innovation based on the expectations about the level of overall environmental policy stringency over a time horizon of around two years, which appears to be reasonable. Interestingly, the two-step negative binomial estimator seems to suggest the presence also of a lagged impact for the EPS variable (table 2.D).

Tables 3.A-3.D report the results of increasingly stringent market-based environmental regulation (eps_market) on green energy innovation. As discussed, market-based instruments are usually favoured given their higher likelihood to provide incentives to innovate. More in detail, their higher dynamic performance is grounded on the reasoning that firms will keep innovating in order to minimize the payments (either in forms of taxes or permits) due to the cost of their environmental externalities. The positive and statistically significant coefficient associated to the lagged eps_market variables across all models provide a remarkably robust evidence of this dynamic (lagged) effect.

Finally, tables 4.A – 4.D provide the estimation results when non-market-based regulation is considered. Confirming the hypothesis on their lower dynamic efficiency, the coefficients associated to non-market regulation (eps_nonmarket) are positive on green energy innovation but always insignificant. Overall, the estimations of Tables 3.A - 3.D and 4.A - 4.D seem mostly to confirm the higher dynamic properties of market-based regulation.

The variables capturing the domestic knowledge stocks (in logs) take signs weakly consistent with the path dependency hypothesis in innovation. In fact, previous domestic experience with green energy technologies is a significant good predictor of innovation in the same technological area. However, the evidence for the "negative" side of path dependency is somewhat weak. In fact, the coefficients associated to domestic cumulated knowledge stocks in grey technologies are not statistically significant in most of the models. Surprisingly, the cumulated domestic knowledge stock in other green technologies appears to have a negative, albeit again insignificant across all models, impact on domestic green energy innovation. Once we turn to the foreign knowledge stocks (named "FKS_*"), we find two main results. First of all, larger cumulated foreign expertise with "other green technologies" seems to be associated with a decrease in domestic green energy innovation. This negative effect, which seems to be operating both on a domestic and foreign level, might suggest that countries tend to specialise in certain segments within the spectrum of environmental technologies and/or that green energy and other green technologies compete for similar resources. Secondly, the coefficients associated to the stock of foreign grey knowledge - albeit not always significant – are positive except for a few cases when they are insignificant. This positive feedback between foreign grey knowledge and domestic green energy innovation underlines the importance of having access to the numerous general purpose technologies included in the foreign grey knowledge stock for domestic green energy innovation.

Table 2. Green Energy Innovation: Overall environmental policy stringency

Table 3. Green Energy Innovation: Market-based policy stringency

Table 4. Green Energy Innovation: Non-market-based policy stringency

Finally, it is interesting to notice the stability of the significantly negative sign of the ETCR Index on renewable energy patenting. This seems to suggest that the lack of competition within the electricity sector leads firms (incumbents) to focus on traditional fossil fuel technologies instead of pursuing more disruptive green technologies[7].

[7] The coefficient of GDP is positive and significant but not in all models. This might suggest that larger economies tend to have a more suitable environmental for green innovation. Alternatively, it might be linked to the environmental Kuznet curves

2.4.2. Direction of technological change: Does increasingly stringent environmental regulation crowd out other types of innovation?

Our second research question concerns the direction of technological change or, otherwise said, the possibility that promoting innovation along a given technological trajectory might crowd innovation out of other technological areas. To this end, the impact of increasingly stringent policy on "grey" and on "other green" technologies is estimated in the tables from 5.A to 10.D.

Tables 5.A-D and 7.A-D provide some evidence that increasingly stringent environmental policy decreases innovative efforts in "grey" technological areas. In fact, one of our estimator (BVGR) suggests a negative impact of the variable of overall policy stringency (EPS in tables 5.A and 5.B) and of the forward structure of non-market based regulation (table 7.A). However, our most robust result concerns the negative effect of the lagged non-market-based regulation. In fact, both binomial models (BVGR and NBGML) estimate a statistically significant negative impact of increasingly stringent non-market-based regulations on grey innovation when a lagged structure is considered (Tables 7.B and 7.D). This robust negative effect can be explained assuming that non-market based regulation, like performance standards or "bans", may erase off the board specific (polluting) technological trajectories that are included in the grey group.

Unfortunately, our pre-sample mean is not significant when the two-step negative binomial model is applied to other green technologies (Tables 8.C-D, 9.C-D and 10.C-D). Therefore, we cannot be sure we are controlling for the fixed effects and, as such, we avoid any interpretation based on this estimator (NBGML). At the same time, the coefficients associated to the policy variables are never significant when the Poisson's distribution is considered (Tables 8.A-B, 9.A-B and 10.A-B). Given that only the BVGR estimator provides some evidence of the effect of environmental policy stringency on this technological area, we only briefly comment these results. More precisely, the tables 8.A-B, 9.A-B and 10.A-B suggest that increasingly stringent regulation for the energy sector may decrease innovation not only for polluting technologies but also in other environmental technologies. The time structure of this impact depends on the type of regulation considered. In fact, companies seem to change their innovation focus before the entry into of force market-based regulations (Table 9.A) and, for non-market-based regulation, on the year of their introduction (Table 10.A). This negative effect may be due to firms that are operating in the field of environmental technologies and that may decide to shift the focus of their R&D towards areas where the regulation is becoming more stringent in order to profit from increasing market opportunities. However, as discussed, the evidence is rather weak since these results hinge only on one model.

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hypothesis since an increase in GDP seems to stimulate demand for green innovation.

Table 5. Grey Innovation: Overall environmental policy stringency

Table 6. Grey Innovation: Market-based policy stringency

Table 7. Grey Innovation: Non-market-based policy stringency

In relation to the path dependency hypothesis, the results presented earlier are confirmed. In fact, the likelihood of successful innovation in a given technological area increases in the relative domestic cumulated knowledge as shown by the positive and significant coefficient of the domestic grey knowledge stock on grey innovation (tables 5, 6 and 7) and of the domestic other green knowledge stock on other green innovation (table 8, 9 and 10). Regarding foreign knowledge stocks, the coefficients associated to grey knowledge are statistically significant and positive when both grey (Table 5, 6 and 7) and other green patents (Tables 8, 9 and 10) are considered, thus strengthening the previous consideration on the importance of having access to foreign general purpose technologies for domestic – whether environmental or not - innovation. Finally, larger foreign knowledge stocks in the field of other green technologies seem to hinder not only grey but – interestingly - also innovation the same technological area. As such, we cannot conclude that this is an example of negative path dependency (i.e. past success history in a given technological area hampering innovation in other scientific fields).

Finally, it is interesting to notice the stability of the significantly negative sign of the ETCR Index on the grey patents. This suggests that not only innovation in green electricity generation but also in polluting technologies is hindered by high barriers to entry. Instead, given that the ETCR index focuses on competition in the electricity sector, its lack of significance for the other green technologies is expected

Table 8. Other green innovation: Overall environmental policy stringency

Table 9. Other green Innovation: Market-based policy stringency

Table 10. Other green Innovation: Non-market-based policy stringency

2.5. Conclusions

This paper focuses on two main hypotheses. First of all, we investigate whether market-based regulation stimulates higher rates of green innovation than non-market-based regulations. Secondly, we check whether this potential increase in the technologies that environmental policies aim to promote is associated to a decrease in innovation in other technological areas.

The empirical results, whose robustness is tested through several models, provide evidence of the higher dynamic incentives of market-based regulations. In fact, across all the models considered, increasingly stringent market-based regulation is associated to higher rate of green innovation while we find no evidence of a similar effect for non-market policies. Furthermore, the estimations underline the importance of appropriately considering the timing of the evaluation. In fact, the hypothesis on higher dynamic performance of market-based instruments is grounded on the assumption that firms will keep innovating in order to minimize the payments (either in forms of taxes or permits) due to the internalised cost of their environmental externalities. Otherwise said, this means that we expect the lagged structure of market-based instruments to be chiefly positive. Indeed, our estimations provide strong evidence of this lagged positive impact.

The evidence on the "*crowding-out*" effect of environmental policy is rather mixed. We test for the presence of this potential *crowding-out effect* in two technological areas, namely *grey* innovation - defined as a mixed group including all "non-environmental technologies" - and *other green technologies* - defined as those environmental technologies that are not explicitly targeted by the policies captured by our proxy of environmental policy stringency. We find a strong evidence of a negative impact of non-market-based instruments on *grey* innovation and we suggest that this decrease is due to the polluting technologies included in this group. Instead, only a weak evidence of a similar negative effect on "other green" technologies is found. This decrease may suggest that companies that are already operating in the field of environmental technologies may redirect their innovation efforts towards areas where the regulation is becoming more stringent in order to profit from increasing market opportunities. However, we highlight once more how this evidence is rather weak since these results hinge only on one model.

These results provide important insights for policy makers and suggest some possible venues for further research. First of all, policy makers interested in stimulating green innovation should rely mainly on market-based instruments. However, it is important to underline how non-market based regulations should not be disregarded since, if well designed, they may provide incentive to innovate as well (e.g. the Japanese top-runner standard). Finally, the "ability" of environmental regulation of discouraging competing innovation needs further studies. This is specially true since, as discussed, the innovations required to comply with certain regulation are not necessarily developed within the regulated sector. From this standpoint, this reallocation of resources might be working also in scientific fields that societies do wish to encourage (e.g. health, education or other environmental technologies as investigated in this paper). In this regard, additional research on the substitutability between different technologies is deemed as necessary

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Tables

TABLE 1 – Descriptive statistics

VARIABLES	N	mean	sd	min	max
Environmental policy stringency (EPS)	386	1.55	0.9	0.3	4.20
Market-based env. policy stringency (eps_market)	391	0.92	0.8	0.0	3.67
Non-market-based env. policy stringency (eps_nonmarket)	386	2.17	1.3	0.5	5.31
Green energy patents (pat_greenenergy)	391	88	162.2	0.0	1103.7
Patents in other green tech. (pat_othergreentech.)	391	304.9	523.6	2.0	3311.7
Patents in "grey"tech. (pat_grey)	391	2980.4	4399.3	45.2	18154.9
Knowledge stock in green energy tech. (KS_greenenergy)	391	571.9	1037.2	0.0	6287.1
Knowledge stock in other green tech. (KS_othergreen)	391	2466.3	3951.7	20.0	21024.6
Knowledge stock in grey tech. (KS_grey)	391	19584.31	28327.1	326.1	103318.5
Foreign Knowl. stock in green energy tech. (FKS_greenenergy)	391	1230.2	726.2	286.7	3451.1
Foreign Knowl. stock in other green tech. (FKS_othergreen)	391	3255.2	1240.9	1328.5	8264.4
Foreign Knowl. stock in grey tech (FKS_grey)	391	25058.4	9913.5	13720.2	67279.67
Gross Domestic product (gdp)	391	1,832,384	2,942,613	125,071	15,600,000
Regulation of the electricity sector (etcr)	371	3.36	1.6	0.87	6

Table 2.A – Forward structure

VARIABLES	(1) HGG - GREEN	(2) BGVR - GREEN	(3) HGG - GREEN	(4) BGVR - GREEN	(5) HGG - GREEN	(6) BGVR - GREEN	(7) HGG - GREEN	(8) BGVR - GREEN	(9)	(10)
eps	0.0912	0.0361								
	(0.0645)	(0.0347)								
F.eps			0.0811	0.0644**						
			(0.0583)	(0.0327)						
F2.eps					0.0786	0.0734**				
					(0.0639)	(0.0343)				
F3.eps							0.0106	0.0155		
							(0.0545)	(0.0374)		
KS_greenenergy	0.883***	0.742***	0.893***	0.738***	0.866***	0.701***	0.889***	0.656***		
	(0.147)	(0.0792)	(0.127)	(0.0772)	(0.151)	(0.0788)	(0.163)	(0.0886)		
KS_othergreen	-0.566	-0.167	-0.563	-0.166	-0.541	-0.205	-0.567	-0.232		
	(0.491)	(0.147)	(0.475)	(0.144)	(0.477)	(0.148)	(0.502)	(0.164)		
KS_grey	-0.480	-0.270	-0.467	-0.242	-0.534	-0.300*	-0.658	-0.368**		
	(0.456)	(0.167)	(0.476)	(0.164)	(0.518)	(0.169)	(0.530)	(0.184)		
L1.FKS_greenenergy	6.045***	0.0261	5.263***	-0.0140	3.326	-0.0776	4.650*	0.0153		
	(1.697)	(0.173)	(1.774)	(0.166)	(2.292)	(0.171)	(2.619)	(0.188)		
L1.FKS_othergreen	-0.392	-1.052***	-0.675	-1.125***	-1.213	-1.348***	-0.905	-1.297***		
	(1.312)	(0.406)	(1.379)	(0.398)	(1.516)	(0.416)	(1.511)	(0.437)		
L1.FKS_grey	-0.312	0.511	0.0966	0.593	1.246	0.837**	0.617	0.765*		
	(1.625)	(0.398)	(1.687)	(0.390)	(2.085)	(0.415)	(2.325)	(0.438)		
PSMpatge		0.343***		0.329***		0.423***		0.498***		
		(0.0950)		(0.0907)		(0.110)		(0.128)		
etcr	-0.0898**	-0.0356	-0.0901**	-0.0360	-0.0973**	-0.0474*	-0.107***	-0.0550**		
	(0.0395)	(0.0257)	(0.0389)	(0.0254)	(0.0382)	(0.0252)	(0.0401)	(0.0262)		
lgdp	-1.203	0.223***	-1.124	0.218***	-0.821	0.265***	-0.555	0.310***		
	(0.874)	(0.0683)	(0.839)	(0.0665)	(0.795)	(0.0685)	(0.692)	(0.0740)		
Constant		0.522		0.433		0.333		0.211		
		(1.753)		(1.696)		(1.797)		(1.970)		
Observations	337	337	338	338	323	323	307	307		
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES		

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2.B – Lagged structure

VARIABLES	(1) HGG - GREEN	(2) BGVR - GREEN	(3) HGG - GREEN	(4) BGVR - GREEN	(5)	(6)	(7)	(8)	(9)	(10)
eps	0.0912	0.0361								
	(0.0645)	(0.0347)								
L.eps			0.112	0.0370						
			(0.0710)	(0.0362)						
KS_greenenergy	0.883***	0.742***	1.016***	0.766***						
	(0.147)	(0.0792)	(0.0793)	(0.0777)						
KS_othergreen	-0.566	-0.167	-0.426	-0.142						
	(0.491)	(0.147)	(0.389)	(0.143)						
KS_grey	-0.480	-0.270	-0.322	-0.263						
	(0.456)	(0.167)	(0.462)	(0.162)						
L1.FKS_greenenergy	6.045***	0.0261	7.703***	0.0376						
	(1.697)	(0.173)	(1.723)	(0.166)						
L1.FKS_othergreen	-0.392	-1.052***	0.205	-1.026**						
	(1.312)	(0.406)	(1.106)	(0.400)						
L1.FKS_grey	-0.312	0.511	-0.560	0.486						
	(1.625)	(0.398)	(1.376)	(0.389)						
PSMpatge		0.343***		0.299***						
		(0.0950)		(0.0861)						
etcr	-0.0898**	-0.0356	-0.0774**	-0.0306						
	(0.0395)	(0.0257)	(0.0361)	(0.0252)						
lgdp	-1.203	0.223***	-1.014	0.216***						
	(0.874)	(0.0683)	(0.740)	(0.0660)						
Constant		0.522		0.479						
		(1.753)		(1.690)						
Observations	337	337	334	334						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.C – Forward structure

VARIABLES	(1) NBGML - GREEN	(2) NBGML - GREEN	(3) NBGML - GREEN	(4) NBGML - GREEN	(5) NBGML - GREEN
eps	0.128***				
	(0.0416)				
F.eps		0.126***			
		(0.0407)			
F2.eps			0.119***		
			(0.0411)		
F3.eps				0.0905*	
				(0.0465)	
F4.eps					0.0707
					(0.0514)
KS_greenenergy	0.664***	0.681***	0.643***	0.560***	0.476***
	(0.148)	(0.135)	(0.131)	(0.159)	(0.180)
KS_othergreen	-0.127	-0.102	-0.0587	-0.0640	-0.0125
	(0.106)	(0.104)	(0.102)	(0.112)	(0.115)
KS_grey	-0.187	-0.204	-0.246**	-0.222*	-0.218
	(0.127)	(0.125)	(0.122)	(0.130)	(0.134)
L1.FKS_greenenergy	-0.117*	-0.119*	-0.0984	-0.0952	-0.0939
	(0.0693)	(0.0694)	(0.0694)	(0.0768)	(0.0847)
L1.FKS_othergreen	-1.282***	-1.193***	-1.229***	-1.501***	-1.661***
	(0.449)	(0.409)	(0.388)	(0.443)	(0.485)
L1.FKS_grey	0.829**	0.723*	0.721**	1.022**	1.254***
	(0.411)	(0.372)	(0.350)	(0.409)	(0.454)
etcr	-0.0197	-0.0149	-0.0136	-0.0224	-0.0268
	(0.0188)	(0.0177)	(0.0174)	(0.0190)	(0.0209)
lgdp	0.293***	0.287***	0.308***	0.320***	0.328***
	(0.0722)	(0.0673)	(0.0642)	(0.0689)	(0.0707)
PSMpatge	0.276***	0.260***	0.266***	0.299***	0.310**
	(0.106)	(0.0969)	(0.0943)	(0.112)	(0.126)
Constant	-0.359	-0.00472	0.111	-0.659	-1.732
	(1.104)	(1.072)	(1.051)	(1.148)	(1.203)
Observations	337	338	323	307	291
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.D – Lagged structure

VARIABLES	(1) NBGML - GREEN	(2) NBGML - GREEN	(3) NBGML - GREEN	(4) NBGML - GREEN	(5) NBGML - GREEN
eps	0.128***				
	(0.0416)				
L.eps		0.125***			
		(0.0403)			
L2.eps			0.100**		
			(0.0413)		
L3.eps				0.118***	
				(0.0407)	
L4.eps					0.122***
					(0.0427)
KS_greenenergy	0.664***	0.791***	0.802***	0.840***	1.031***
	(0.148)	(0.0728)	(0.0763)	(0.0770)	(0.0685)
KS_othergreen	-0.127	-0.119	-0.0834	-0.102	-0.106
	(0.106)	(0.106)	(0.108)	(0.113)	(0.118)
KS_grey	-0.187	-0.159	-0.217*	-0.215*	-0.0795
	(0.127)	(0.119)	(0.122)	(0.126)	(0.130)
L1.FKS_greenenergy	-0.117*	-0.110	-0.104	-0.101	-0.0751
	(0.0693)	(0.0680)	(0.0674)	(0.0701)	(0.0750)
L1.FKS_othergreen	-1.282***	-0.931***	-0.734***	-0.622**	-0.192
	(0.449)	(0.273)	(0.266)	(0.267)	(0.267)
L1.FKS_grey	0.829**	0.504*	0.310	0.236	-0.158
	(0.411)	(0.263)	(0.258)	(0.259)	(0.260)
etcr	-0.0197	-0.0102	-0.0147	-0.0213	-0.0167
	(0.0188)	(0.0173)	(0.0174)	(0.0181)	(0.0191)
lgdp	0.293***	0.235***	0.239***	0.241***	0.143***
	(0.0722)	(0.0457)	(0.0471)	(0.0488)	(0.0431)
PSMpatge	0.276***	0.194***	0.205***	0.197***	
	(0.106)	(0.0615)	(0.0633)	(0.0650)	
Constant	-0.359	0.208	0.554	0.399	0.681
	(1.104)	(1.029)	(1.019)	(1.000)	(1.059)
Observations	337	334	318	302	286
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.A – Forward structure

VARIABLES	(1) HGG - GREEN	(2) BGVR - GREEN	(3) HGG - GREEN	(4) BGVR - GREEN	(5)	(6)	(7)	(8)	(9)	(10)
eps_market	0.0288	0.0379								
	(0.0361)	(0.0303)								
F.eps_market			0.0275	0.0459						
			(0.0336)	(0.0285)						
KS_greenenergy	0.870***	0.673***	0.869***	0.677***						
	(0.152)	(0.0787)	(0.151)	(0.0786)						
KS_othergreen	-0.555	-0.165	-0.552	-0.163						
	(0.496)	(0.146)	(0.500)	(0.144)						
KS_grey	-0.491	-0.267	-0.483	-0.254						
	(0.513)	(0.166)	(0.522)	(0.164)						
L1.FKS_greenenergy	5.138***	0.0239	5.022**	-0.00192						
	(1.990)	(0.170)	(2.056)	(0.166)						
L1.FKS_othergreen	-0.636	-1.137***	-0.631	-1.124***						
	(1.403)	(0.403)	(1.428)	(0.399)						
L1.FKS_grey	0.153	0.619	0.287	0.628						
	(1.855)	(0.396)	(1.932)	(0.393)						
PSMpatge		0.384***		0.376***						
		(0.0949)		(0.0937)						
etcr	-0.0911**	-0.0438*	-0.0935**	-0.0452*						
	(0.0379)	(0.0256)	(0.0397)	(0.0255)						
lgdp	-0.900	0.232***	-0.890	0.225***						
	(0.798)	(0.0698)	(0.788)	(0.0689)						
Constant		0.244		0.201						
		(1.751)		(1.719)						
Observations	339	339	339	339						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.B – Lagged structure

VARIABLES	(1) HGG - GREEN	(2) BGVR - GREEN	(3) HGG - GREEN	(4) BGVR - GREEN	(5) HGG - GREEN	(6) BGVR - GREEN	(7) HGG - GREEN	(8) BGVR - GREEN	(9) HGG - GREEN	(10) BGVR - GREEN
eps_market	0.0288	0.0379								
	(0.0361)	(0.0303)								
L.eps_market			0.0951**	0.0874***						
			(0.0459)	(0.0314)						
L2.eps_market					0.0972*	0.0982***				
					(0.0546)	(0.0331)				
L3.eps_market							0.111**	0.0857**		
							(0.0528)	(0.0345)		
L4.eps_market									0.0980*	0.0621*
									(0.0549)	(0.0365)
KS_greenenergy	0.870***	0.673***	0.842***	0.672***	0.861***	0.714***	0.903***	0.757***	1.099***	0.811***
	(0.152)	(0.0787)	(0.156)	(0.0761)	(0.136)	(0.0769)	(0.169)	(0.0804)	(0.112)	(0.0823)
KS_othergreen	-0.555	-0.165	-0.598	-0.135	-0.561	-0.123	-0.611	-0.156	-0.494	-0.205
	(0.496)	(0.146)	(0.462)	(0.139)	(0.474)	(0.140)	(0.510)	(0.144)	(0.413)	(0.147)
KS_grey	-0.491	-0.267	-0.343	-0.238	-0.450	-0.251	-0.543	-0.228	-0.398	-0.167
	(0.513)	(0.166)	(0.451)	(0.155)	(0.472)	(0.155)	(0.492)	(0.158)	(0.494)	(0.163)
L1.FKS_greenenergy	5.138***	0.0239	5.281***	-0.0100	6.198***	-0.0170	7.067***	-0.00827	8.697***	0.00662
	(1.990)	(0.170)	(1.832)	(0.147)	(1.666)	(0.135)	(1.628)	(0.133)	(1.443)	(0.138)
L1.FKS_othergreen	-0.636	-1.137***	-0.618	-1.174***	-0.563	-1.104***	-0.256	-0.926**	0.290	-0.814**
	(1.403)	(0.403)	(1.388)	(0.375)	(1.357)	(0.371)	(1.378)	(0.375)	(1.126)	(0.387)
L1.FKS_grey	0.153	0.619	0.329	0.666*	0.376	0.583*	-0.0651	0.416	-0.857	0.309
	(1.855)	(0.396)	(1.744)	(0.364)	(1.667)	(0.353)	(1.801)	(0.354)	(1.513)	(0.366)
PSMpatge		0.384***		0.348***		0.318***		0.299***		0.263***
		(0.0949)		(0.0843)		(0.0783)		(0.0779)		(0.0763)
etcr	-0.0911**	-0.0438*	-0.0803**	-0.0355	-0.0839***	-0.0296	-0.0908***	-0.0361	-0.0828**	-0.0413
	(0.0379)	(0.0256)	(0.0325)	(0.0249)	(0.0316)	(0.0248)	(0.0332)	(0.0257)	(0.0327)	(0.0266)
lgdp	-0.900	0.232***	-1.158	0.215***	-1.189	0.211***	-1.469	0.202***	-1.096	0.182***
	(0.798)	(0.0698)	(0.780)	(0.0631)	(0.828)	(0.0606)	(0.906)	(0.0607)	(0.763)	(0.0620)
Constant		0.244		0.183		0.469		0.538		0.827
		(1.751)		(1.557)		(1.452)		(1.437)		(1.495)
Observations	339	339	339	339	323	323	307	307	291	291
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.C – Forward structure

VARIABLES	(1) NBGML - GREEN	(2) NBGML - GREEN	(3) NBGML - GREEN	(4) NBGML - GREEN	(5) NBGML - GREEN
eps_market	0.137***				
	(0.0330)				
F.eps_market		0.122***			
		(0.0309)			
F2.eps_market			0.0996***		
			(0.0334)		
F3.eps_market				0.0753**	
				(0.0369)	
F4.eps_market					0.0582
					(0.0418)
KS_greenenergy	0.647***	0.676***	0.639***	0.576***	0.489***
	(0.154)	(0.140)	(0.150)	(0.166)	(0.185)
KS_othergreen	-0.135	-0.0965	-0.0744	-0.0630	-0.00840
	(0.106)	(0.103)	(0.104)	(0.111)	(0.114)
KS_grey	-0.149	-0.187	-0.215*	-0.216*	-0.218
	(0.130)	(0.127)	(0.124)	(0.130)	(0.134)
L1.FKS_greenenergy	-0.0964	-0.0970	-0.0783	-0.0758	-0.0799
	(0.0685)	(0.0669)	(0.0687)	(0.0744)	(0.0810)
L1.FKS_othergreen	-1.417***	-1.274***	-1.341***	-1.507***	-1.661***
	(0.447)	(0.403)	(0.419)	(0.439)	(0.469)
L1.FKS_grey	0.992**	0.816**	0.855**	1.024***	1.247***
	(0.402)	(0.356)	(0.369)	(0.394)	(0.430)
etcr	-0.0346*	-0.0282	-0.0272	-0.0291	-0.0317
	(0.0191)	(0.0177)	(0.0184)	(0.0187)	(0.0198)
lgdp	0.218***	0.222***	0.251***	0.274***	0.293***
	(0.0786)	(0.0739)	(0.0754)	(0.0792)	(0.0844)
PSMpatge	0.288***	0.264***	0.273***	0.294**	0.307**
	(0.108)	(0.0998)	(0.105)	(0.115)	(0.127)
Constant	-0.0845	0.442	0.329	-0.178	-1.299
	(1.006)	(0.961)	(0.974)	(1.090)	(1.184)
Observations	339	339	323	307	291
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.D – Lagged structure

VARIABLES	(1) NBGML - GREEN	(2) NBGML - GREEN	(3) NBGML - GREEN	(4) NBGML - GREEN	(5) NBGML - GREEN
eps_market	0.137***				
	(0.0330)				
L.eps_market		0.141***			
		(0.0302)			
L2.eps_market			0.121***		
			(0.0320)		
L3.eps_market				0.147***	
				(0.0320)	
L4.eps_market					0.141***
					(0.0315)
KS_greenenergy	0.647***	0.648***	0.673***	0.698***	1.035***
	(0.154)	(0.148)	(0.137)	(0.161)	(0.0711)
KS_othergreen	-0.135	-0.137	-0.0598	-0.117	-0.123
	(0.106)	(0.103)	(0.105)	(0.106)	(0.113)
KS_grey	-0.149	-0.160	-0.279**	-0.247*	-0.0572
	(0.130)	(0.129)	(0.131)	(0.132)	(0.126)
L1.FKS_greenenergy	-0.0964	-0.0774	-0.0472	-0.0504	-0.0310
	(0.0685)	(0.0668)	(0.0667)	(0.0675)	(0.0732)
L1.FKS_othergreen	-1.417***	-1.400***	-1.221***	-1.164**	-0.343
	(0.447)	(0.435)	(0.406)	(0.475)	(0.263)
L1.FKS_grey	0.992**	0.962**	0.718**	0.715*	-0.0138
	(0.402)	(0.394)	(0.361)	(0.426)	(0.255)
etcr	-0.0346*	-0.0329*	-0.0277	-0.0399**	-0.0283
	(0.0191)	(0.0189)	(0.0187)	(0.0194)	(0.0192)
lgdp	0.218***	0.220***	0.248***	0.241***	0.0796*
	(0.0786)	(0.0748)	(0.0700)	(0.0775)	(0.0418)
PSMpatge	0.288***	0.295***	0.291***	0.302***	
	(0.108)	(0.105)	(0.0956)	(0.108)	
Constant	-0.0845	0.0212	0.812	0.617	1.190
	(1.006)	(1.017)	(1.011)	(1.000)	(0.998)
Observations	339	339	323	307	291
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4.A – Forward structure

VARIABLES	(1) HGG - GREEN	(2) BGVR - GREEN	(3) HGG - GREEN	(4) BGVR - GREEN	(5)	(6)	(7)	(8)	(9)	(10)
eps_nonmarket	0.0686	0.00750								
	(0.0513)	(0.0236)								
F.eps_nonmarket			0.0516	0.0253						
			(0.0362)	(0.0207)						
KS_greenenergy	0.902***	0.746***	0.914***	0.736***						
	(0.133)	(0.0808)	(0.111)	(0.0789)						
KS_othergreen	-0.549	-0.187	-0.556	-0.188						
	(0.497)	(0.149)	(0.478)	(0.148)						
KS_grey	-0.596	-0.296*	-0.585	-0.285*						
	(0.465)	(0.170)	(0.467)	(0.169)						
L1.FKS_greenenergy	6.528***	0.0575	5.550***	0.0400						
	(1.978)	(0.182)	(1.716)	(0.180)						
L1.FKS_othergreen	-0.348	-1.062**	-0.769	-1.145***						
	(1.358)	(0.421)	(1.394)	(0.421)						
L1.FKS_grey	-0.718	0.505	-0.323	0.574						
	(1.799)	(0.415)	(1.602)	(0.413)						
PSMpatge		0.372***		0.367***						
		(0.0961)		(0.0936)						
etcr	-0.0921**	-0.0376	-0.0880**	-0.0374						
	(0.0407)	(0.0258)	(0.0384)	(0.0256)						
lgdp	-1.116	0.231***	-1.004	0.237***						
	(0.817)	(0.0715)	(0.778)	(0.0703)						
Constant		0.626		0.589						
		(1.851)		(1.840)						
Observations	337	337	338	338						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4.B – Lagged structure

VARIABLES	(1) HGG - GREEN	(2) BGVR - GREEN	(3) HGG - GREEN	(4) BGVR - GREEN	(5)	(6)	(7)	(8)	(9)	(10)
eps_nonmarket	0.0686	0.00750								
	(0.0513)	(0.0236)								
L.eps_nonmarket			0.0386	-0.0212						
			(0.0428)	(0.0253)						
KS_greenenergy	0.902***	0.746***	1.041***	0.790***						
	(0.133)	(0.0808)	(0.0855)	(0.0803)						
KS_othergreen	-0.549	-0.187	-0.393	-0.181						
	(0.497)	(0.149)	(0.424)	(0.147)						
KS_grey	-0.596	-0.296*	-0.452	-0.304*						
	(0.465)	(0.170)	(0.493)	(0.167)						
L1.FKS_greenenergy	6.528***	0.0575	7.316***	0.0795						
	(1.978)	(0.182)	(2.000)	(0.181)						
L1.FKS_othergreen	-0.348	-1.062**	0.0495	-1.029**						
	(1.358)	(0.421)	(1.163)	(0.425)						
L1.FKS_grey	-0.718	0.505	-0.499	0.485						
	(1.799)	(0.415)	(1.437)	(0.419)						
PSMpatge		0.372***		0.345***						
		(0.0961)		(0.0923)						
etcr	-0.0921**	-0.0376	-0.0835**	-0.0340						
	(0.0407)	(0.0258)	(0.0378)	(0.0252)						
lgdp	-1.116	0.231***	-0.703	0.211***						
	(0.817)	(0.0715)	(0.712)	(0.0708)						
Constant		0.626		0.728						
		(1.851)		(1.850)						
Observations	337	337	334	334						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 4.C – Forward structure

VARIABLES	(1) NBGML - GREEN	(2) NBGML - GREEN
eps_nonmarket	0.0317	
	(0.0296)	
F.eps_nonmarket		0.0348
		(0.0284)
KS_greenenergy	0.670***	0.674***
	(0.144)	(0.138)
KS_othergreen	-0.0752	-0.0700
	(0.107)	(0.106)
KS_grey	-0.262**	-0.265**
	(0.127)	(0.126)
L1.FKS_greenenergy	-0.0747	-0.0747
	(0.0721)	(0.0716)
L1.FKS_othergreen	-1.153***	-1.133***
	(0.439)	(0.425)
L1.FKS_grey	0.614	0.589
	(0.402)	(0.387)
etcr	-0.00686	-0.00513
	(0.0184)	(0.0180)
lgdp	0.298***	0.298***
	(0.0751)	(0.0731)
PSMpatge	0.278***	0.274***
	(0.101)	(0.0979)
Constant	0.638	0.687
	(1.128)	(1.115)
Observations	337	338
Fixed Effects - Time Dummies	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4.D – Lagged structure

VARIABLES	(1) NBGML - GREEN	(2) NBGML - GREEN
eps_nonmarket	0.0317	
	(0.0296)	
L.eps_nonmarket		0.0312
		(0.0298)
KS_greenenergy	0.670***	0.796***
	(0.144)	(0.0765)
KS_othergreen	-0.0752	-0.0808
	(0.107)	(0.109)
KS_grey	-0.262**	-0.213*
	(0.127)	(0.120)
L1.FKS_greenenergy	-0.0747	-0.0834
	(0.0721)	(0.0705)
L1.FKS_othergreen	-1.153***	-0.820***
	(0.439)	(0.284)
L1.FKS_grey	0.614	0.330
	(0.402)	(0.268)
etcr	-0.00686	-0.000666
	(0.0184)	(0.0171)
lgdp	0.298***	0.239***
	(0.0751)	(0.0516)
PSMpatge	0.278***	0.196***
	(0.101)	(0.0630)
Constant	0.638	0.983
	(1.128)	(1.036)
Observations	337	334
Fixed Effects - Time Dummies	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5.A – Forward structure

VARIABLES	(1) HGG - GREY	(2) BGVR - GREY	(3) HGG - GREY	(4) BGVR - GREY	(5) HGG - GREY	(6) BGVR - GREY	(7) HGG - GREY	(8) BGVR - GREY	(9) HGG - GREY	(10) BGVR - GREY
Eps	0.0514	-0.0488***								
	(0.0421)	(0.0163)								
F.eps			0.0662*	-0.0285*						
			(0.0345)	(0.0156)						
F2.eps					0.0421	-0.0251*				
					(0.0269)	(0.0139)				
F3.eps							0.0202	-0.0305**		
							(0.0230)	(0.0134)		
F4.eps									0.00806	-0.0312**
									(0.0195)	(0.0130)
KS_greenenergy	-0.0304	-0.0254	-0.0111	-0.0254	0.0722*	0.00436	0.0886**	0.0156	0.104**	0.0370
	(0.0997)	(0.0369)	(0.0775)	(0.0367)	(0.0425)	(0.0298)	(0.0430)	(0.0308)	(0.0432)	(0.0325)
KS_othergreen	-0.240	-0.0627	-0.237	-0.109	-0.300	-0.0665	-0.314	-0.0854	-0.342	-0.132*
	(0.264)	(0.0783)	(0.232)	(0.0764)	(0.244)	(0.0707)	(0.255)	(0.0721)	(0.257)	(0.0742)
KS_grey	0.862***	0.757***	0.902***	0.831***	0.835***	0.802***	0.797***	0.760***	0.763***	0.726***
	(0.198)	(0.109)	(0.187)	(0.106)	(0.171)	(0.0979)	(0.182)	(0.0970)	(0.192)	(0.0952)
L1.FKS_greenenergy	3.727***	0.345	3.624***	0.307	2.508***	-0.249	2.010***	-0.666**	1.694**	-0.841**
	(0.949)	(0.345)	(0.764)	(0.356)	(0.513)	(0.331)	(0.605)	(0.336)	(0.687)	(0.333)
L1.FKS_othergreen	-0.463	-0.826**	-0.506	-0.854**	-1.082*	-1.474***	-1.349**	-1.702***	-1.568**	-1.864***
	(0.700)	(0.346)	(0.652)	(0.357)	(0.629)	(0.297)	(0.649)	(0.284)	(0.664)	(0.280)
L1.FKS_grey	-0.459	1.295***	-0.275	1.495***	0.651	1.922***	1.136	2.294***	1.391*	2.496***
	(0.730)	(0.458)	(0.678)	(0.472)	(0.595)	(0.397)	(0.731)	(0.385)	(0.728)	(0.370)
PSMpatgrey		0.635***		0.627***		0.786***		0.886***		0.946***
		(0.0798)		(0.0814)		(0.0803)		(0.0827)		(0.0840)
etcr	-0.00351	-0.0218*	-0.00279	-0.0225*	-0.00643	-0.0122	-0.0158	-0.0167*	-0.0205	-0.0183*
	(0.0152)	(0.0115)	(0.0146)	(0.0116)	(0.0143)	(0.0104)	(0.0154)	(0.0101)	(0.0158)	(0.00986)
lgdp	-2.267***	-1.278***	-2.297***	-1.335***	-1.948***	-1.185***	-1.772***	-1.066***	-1.636***	-0.968***
	(0.474)	(0.130)	(0.409)	(0.130)	(0.362)	(0.120)	(0.343)	(0.114)	(0.346)	(0.114)
Constant		1.912		0.931		1.864		0.845		0.0614
		(3.358)		(3.454)		(3.161)		(2.976)		(2.808)
Observations	337	337	338	338	323	323	307	307	291	291
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5.B – Lagged structure

VARIABLES	(1) HGG - GREY	(2) BGVR - GREY	(3) HGG - GREY	(4) BGVR - GREY	(5) HGG - GREY	(6) BGVR - GREY	(7) HGG - GREY	(8) BGVR - GREY	(9) HGG - GREY	(10) BGVR - GREY
eps	0.0514	-0.0488***								
	(0.0421)	(0.0163)								
L.eps			0.0111	-0.0726***						
			(0.0391)	(0.0179)						
L2.eps					0.000534	-0.0625***				
					(0.0340)	(0.0201)				
L3.eps							-0.00558	-0.0382*		
							(0.0264)	(0.0196)		
L4.eps									0.00843	-0.0200
									(0.0243)	(0.0197)
KS_greenenergy	-0.0304	-0.0254	0.0442	-0.00770	0.0675	0.0178	0.0919	0.0573	0.108**	0.0728*
	(0.0997)	(0.0369)	(0.0633)	(0.0374)	(0.0576)	(0.0393)	(0.0598)	(0.0400)	(0.0549)	(0.0422)
KS_othergreen	-0.240	-0.0627	-0.161	0.00635	-0.0911	-0.0106	-0.0672	-0.123	-0.0285	-0.169*
	(0.264)	(0.0783)	(0.261)	(0.0819)	(0.249)	(0.0908)	(0.241)	(0.0888)	(0.217)	(0.0874)
KS_grey	0.862***	0.757***	0.876***	0.697***	0.853***	0.724***	0.788***	0.753***	0.832***	0.870***
	(0.198)	(0.109)	(0.203)	(0.112)	(0.211)	(0.122)	(0.204)	(0.121)	(0.213)	(0.127)
L1.FKS_greenenergy	3.727***	0.345	3.840***	0.341	4.107***	0.419	4.328***	0.579	4.616***	0.646
	(0.949)	(0.345)	(0.916)	(0.335)	(0.844)	(0.351)	(0.871)	(0.376)	(0.898)	(0.396)
L1.FKS_othergreen	-0.463	-0.826**	-0.392	-0.849**	-0.188	-0.805**	-0.0669	-0.753*	0.176	-0.690*
	(0.700)	(0.346)	(0.646)	(0.337)	(0.629)	(0.355)	(0.613)	(0.388)	(0.570)	(0.416)
L1.FKS_grey	-0.459	1.295***	-0.372	1.174***	-0.451	1.222***	-0.658	1.137**	-0.867	1.114**
	(0.730)	(0.458)	(0.651)	(0.436)	(0.636)	(0.458)	(0.699)	(0.502)	(0.722)	(0.538)
PSMpatgrey		0.635***		0.605***		0.574***		0.559***		0.490***
		(0.0798)		(0.0808)		(0.0856)		(0.0912)		(0.0976)
etcr	-0.00351	-0.0218*	0.00141	-0.0194*	0.00228	-0.0187	0.00252	-0.0242**	0.00843	-0.0243**
	(0.0152)	(0.0115)	(0.0135)	(0.0115)	(0.0134)	(0.0118)	(0.0139)	(0.0119)	(0.0127)	(0.0124)
lgdp	-2.267***	-1.278***	-1.996***	-1.183***	-1.980***	-1.236***	-2.039***	-1.355***	-2.030***	-1.405***
	(0.474)	(0.130)	(0.447)	(0.133)	(0.407)	(0.138)	(0.377)	(0.135)	(0.352)	(0.146)
Constant		1.912		2.273		1.725		3.217		3.060
		(3.358)		(3.237)		(3.372)		(3.594)		(3.835)
Observations	337	337	334	334	318	318	302	302	286	286
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5.C – Forward structure

VARIABLES	(1) NBGML - GREY	(2) NBGML - GREY
eps	-0.00968	
	(0.0192)	
F.eps		-0.00249
		(0.0216)
KS_greenenergy	-0.0965	-0.0914
	(0.0934)	(0.0863)
KS_othergreen	-0.0520	-0.0556
	(0.0675)	(0.0681)
KS_grey	0.960***	0.966***
	(0.0788)	(0.0789)
L1.FKS_greenenergy	-0.0851	-0.0884
	(0.0550)	(0.0547)
L1.FKS_othergreen	-1.058***	-1.046***
	(0.348)	(0.317)
L1.FKS_grey	1.107***	1.097***
	(0.349)	(0.316)
etcr	-0.0333**	-0.0332**
	(0.0151)	(0.0142)
lgdp	0.00973	0.00962
	(0.0257)	(0.0247)
PSMpatgrey	0.102*	0.0974*
	(0.0603)	(0.0585)
Constant	-3.158***	-3.160***
	(0.887)	(0.791)
Observations	337	338
Fixed Effects - Time Dummies	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5.D – Lagged structure

VARIABLES	(1) NBGML - GREY	(2) NBGML - GREY
eps	-0.00968	
	(0.0192)	
L.eps		-0.0174
		(0.0220)
KS_greenenergy	-0.0965	0.0181
	(0.0934)	(0.0230)
KS_othergreen	-0.0520	-0.113**
	(0.0675)	(0.0459)
KS_grey	0.960***	1.015***
	(0.0788)	(0.0618)
L1.FKS_greenenergy	-0.0851	-0.130***
	(0.0550)	(0.0380)
L1.FKS_othergreen	-1.058***	-0.657***
	(0.348)	(0.129)
L1.FKS_grey	1.107***	0.706***
	(0.349)	(0.130)
etcr	-0.0333**	-0.0207**
	(0.0151)	(0.00946)
lgdp	0.00973	-0.0171
	(0.0257)	(0.0159)
PSMpatgrey	0.102*	0.0628
	(0.0603)	(0.0500)
Constant	-3.158***	-2.091***
	(0.887)	(0.399)
Observations	337	334
Fixed Effects - Time Dummies	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6.A – Forward structure

VARIABLES	(1) HGG - GREY	(2) BGVR - GREY	(3) HGG - GREY	(4) BGVR - GREY	(5)	(6)	(7)	(8)	(9)	(10)
eps_market	0.0163	-0.0130								
	(0.0218)	(0.0161)								
F.eps_market			0.0341	-0.00233						
			(0.0215)	(0.0154)						
KS_greenenergy	0.0425	0.00326	0.0369	0.000132						
	(0.0458)	(0.0288)	(0.0474)	(0.0286)						
KS_othergreen	-0.213	-0.145*	-0.226	-0.156**						
	(0.255)	(0.0753)	(0.252)	(0.0739)						
KS_grey	0.829***	0.858***	0.882***	0.890***						
	(0.192)	(0.111)	(0.193)	(0.109)						
L1.FKS_greenenergy	3.660***	0.295	3.563***	0.266						
	(0.733)	(0.347)	(0.685)	(0.353)						
L1.FKS_othergreen	-0.506	-0.938***	-0.490	-0.939***						
	(0.714)	(0.357)	(0.702)	(0.360)						
L1.FKS_grey	-0.408	1.653***	-0.182	1.729***						
	(0.712)	(0.448)	(0.702)	(0.452)						
PSMpatgrey		0.612***		0.614***						
		(0.0805)		(0.0811)						
etcr	0.000695	-0.0208*	-0.00117	-0.0208*						
	(0.0144)	(0.0116)	(0.0153)	(0.0116)						
lgdp	-2.066***	-1.331***	-2.149***	-1.362***						
	(0.375)	(0.135)	(0.380)	(0.133)						
Constant		0.0314		-0.294						
		(3.490)		(3.479)						
Observations	339	339	339	339						
Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6.B – Lagged structure

VARIABLES	(1) HGG - GREY	(2) BGVR - GREY	(3) HGG - GREY	(4) BGVR - GREY	(5) HGG - GREY	(6) BGVR - GREY	(7)	(8)	(9)	(10)
eps_market	0.0163	-0.0130								
	(0.0218)	(0.0161)								
L.eps_market			0.0160	-0.0301*						
			(0.0270)	(0.0165)						
L2.eps_market					0.0148	-0.0185				
					(0.0246)	(0.0173)				
KS_greenenergy	0.0425	0.00326	0.0430	0.00914	0.00416	0.00434				
	(0.0458)	(0.0288)	(0.0461)	(0.0290)	(0.0734)	(0.0387)				
KS_othergreen	-0.213	-0.145*	-0.214	-0.132*	-0.178	-0.159**				
	(0.255)	(0.0753)	(0.256)	(0.0752)	(0.244)	(0.0767)				
KS_grey	0.829***	0.858***	0.826***	0.814***	0.771***	0.851***				
	(0.192)	(0.111)	(0.197)	(0.110)	(0.208)	(0.112)				
L1.FKS_greenenergy	3.660***	0.295	3.702***	0.337	3.863***	0.313				
	(0.733)	(0.347)	(0.761)	(0.341)	(0.943)	(0.364)				
L1.FKS_othergreen	-0.506	-0.938***	-0.508	-0.920***	-0.407	-0.961***				
	(0.714)	(0.357)	(0.718)	(0.353)	(0.716)	(0.369)				
L1.FKS_grey	-0.408	1.653***	-0.426	1.531***	-0.396	1.698***				
	(0.712)	(0.448)	(0.709)	(0.445)	(0.768)	(0.462)				
PSMpatgrey		0.612***		0.613***		0.631***				
		(0.0805)		(0.0799)		(0.0843)				
etcr	0.000695	-0.0208*	0.00181	-0.0225*	-0.00236	-0.0240**				
	(0.0144)	(0.0116)	(0.0138)	(0.0116)	(0.0125)	(0.0118)				
lgdp	-2.066***	-1.331***	-2.058***	-1.305***	-2.142***	-1.385***				
	(0.375)	(0.135)	(0.379)	(0.132)	(0.387)	(0.135)				
Constant		0.0314		0.712		0.499				
		(3.490)		(3.489)		(3.525)				
Observations	339	339	339	339	323	323				
Time Dummies	YES	YES	YES	YES	YES	YES				

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6.C – Forward structure

VARIABLES	(1) NBGML - GREY	(2) NBGML - GREY
eps_market	0.0147	
	(0.0189)	
F.eps_market		0.0172
		(0.0198)
KS_greenenergy	-0.0184	-0.0182
	(0.0381)	(0.0382)
KS_othergreen	-0.116**	-0.118**
	(0.0484)	(0.0484)
KS_grey	0.980***	0.983***
	(0.0836)	(0.0858)
L1.FKS_greenenergy	-0.111**	-0.113**
	(0.0462)	(0.0475)
L1.FKS_othergreen	-0.961***	-0.968***
	(0.245)	(0.242)
L1.FKS_grey	1.004***	1.013***
	(0.230)	(0.227)
etcr	-0.0295***	-0.0300***
	(0.0111)	(0.0108)
lgdp	0.00627	0.00474
	(0.0329)	(0.0349)
PSMpatgrey	0.0861	0.0858
	(0.0553)	(0.0554)
Constant	-2.754***	-2.770***
	(0.520)	(0.506)
Observations	339	339
Fixed Effects - Time Dummies	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6.D – Lagged structure

VARIABLES	(1) NBGML - GREY	(2) NBGML - GREY
eps_market	0.0147	
	(0.0189)	
L.eps_market		0.0116
		(0.0198)
KS_greenenergy	-0.0184	-0.0185
	(0.0381)	(0.0382)
KS_othergreen	-0.116**	-0.114**
	(0.0484)	(0.0484)
KS_grey	0.980***	0.977***
	(0.0836)	(0.0834)
L1.FKS_greenenergy	-0.111**	-0.109**
	(0.0462)	(0.0459)
L1.FKS_othergreen	-0.961***	-0.953***
	(0.245)	(0.246)
L1.FKS_grey	1.004***	0.994***
	(0.230)	(0.232)
etcr	-0.0295***	-0.0290***
	(0.0111)	(0.0112)
lgdp	0.00627	0.00785
	(0.0329)	(0.0327)
PSMpatgrey	0.0861	0.0867
	(0.0553)	(0.0554)
Constant	-2.754***	-2.737***
	(0.520)	(0.523)
Observations	339	339
Fixed Effects - Time Dummies	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7.A – Forward structure

VARIABLES	(1) HGG - GREY	(2) BGVR - GREY	(3) HGG - GREY	(4) BGVR - GREY	(5) HGG - GREY	(6) BGVR - GREY	(7) HGG - GREY	(8) BGVR - GREY	(9)	(10)
eps_nonmarket	0.0329	-0.0321***								
	(0.0274)	(0.00988)								
F.eps_nonmarket			0.0326	-0.0216**						
			(0.0204)	(0.00966)						
F2.eps_nonmarket					0.0252	-0.0155*				
					(0.0163)	(0.00879)				
F3.eps_nonmarket							0.0157	-0.0129		
							(0.0152)	(0.00868)		
KS_greenenergy	-0.0161	-0.0351	0.00630	-0.0306	0.0786*	0.00142	0.0910**	0.0141		
	(0.0945)	(0.0370)	(0.0726)	(0.0367)	(0.0433)	(0.0299)	(0.0435)	(0.0311)		
KS_othergreen	-0.222	-0.0615	-0.210	-0.1000	-0.286	-0.0714	-0.308	-0.0998		
	(0.260)	(0.0762)	(0.232)	(0.0753)	(0.237)	(0.0695)	(0.247)	(0.0708)		
KS_grey	0.794***	0.810***	0.805***	0.858***	0.776***	0.837***	0.772***	0.802***		
	(0.188)	(0.100)	(0.179)	(0.0992)	(0.166)	(0.0930)	(0.175)	(0.0940)		
L1.FKS_greenenergy	3.879***	0.302	3.753***	0.296	2.595***	-0.294	2.013***	-0.743**		
	(0.977)	(0.349)	(0.774)	(0.355)	(0.505)	(0.330)	(0.586)	(0.339)		
L1.FKS_othergreen	-0.447	-0.797**	-0.527	-0.840**	-1.138*	-1.484***	-1.395**	-1.732***		
	(0.702)	(0.348)	(0.674)	(0.355)	(0.656)	(0.297)	(0.675)	(0.287)		
L1.FKS_grey	-0.666	1.369***	-0.586	1.498***	0.442	2.008***	1.091	2.472***		
	(0.781)	(0.448)	(0.660)	(0.458)	(0.527)	(0.381)	(0.674)	(0.373)		
PSMpatgrey		0.640***		0.628***		0.796***		0.904***		
		(0.0799)		(0.0809)		(0.0803)		(0.0833)		
etcr	-0.00406	-0.0215*	-0.00116	-0.0226**	-0.00475	-0.0129	-0.0145	-0.0181*		
	(0.0153)	(0.0115)	(0.0142)	(0.0115)	(0.0144)	(0.0104)	(0.0151)	(0.0102)		
lgdp	-2.174***	-1.336***	-2.135***	-1.367***	-1.853***	-1.231***	-1.727***	-1.127***		
	(0.407)	(0.123)	(0.355)	(0.125)	(0.319)	(0.116)	(0.308)	(0.111)		
Constant		1.595		1.033		1.696		0.263		
		(3.283)		(3.382)		(3.127)		(2.972)		
Observations	337	337	338	338	323	323	307	307		
Fixed effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES		

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7.B – Lagged structure

VARIABLES	(1) HGG - GREY	(2) BGVR - GREY	(3) HGG - GREY	(4) BGVR - GREY	(5) HGG - GREY	(6) BGVR - GREY	(7) HGG - GREY	(8) BGVR - GREY	(9) HGG - GREY	(10) BGVR - GREY
eps_nonmarket	0.0329	-0.0321***								
	(0.0274)	(0.00988)								
L.eps_nonmarket			-0.00332	-0.0425***						
			(0.0219)	(0.0113)						
L2.eps_nonmarket					-0.0102	-0.0351***				
					(0.0204)	(0.0119)				
L3.eps_nonmarket							-0.0215	-0.0215*		
							(0.0153)	(0.0115)		
L4.eps_nonmarket									-0.0241	-0.00667
									(0.0191)	(0.0119)
KS_greenenergy	-0.0161	-0.0351	0.0469	-0.0250	0.0674	0.00407	0.0908	0.0499	0.112**	0.0698*
	(0.0945)	(0.0370)	(0.0646)	(0.0381)	(0.0602)	(0.0401)	(0.0631)	(0.0406)	(0.0573)	(0.0424)
KS_othergreen	-0.222	-0.0615	-0.150	-0.00134	-0.0809	-0.0258	-0.0553	-0.129	0.000395	-0.185**
	(0.260)	(0.0762)	(0.255)	(0.0815)	(0.238)	(0.0881)	(0.231)	(0.0872)	(0.211)	(0.0877)
KS_grey	0.794***	0.810***	0.857***	0.781***	0.842***	0.791***	0.771***	0.779***	0.776***	0.899***
	(0.188)	(0.100)	(0.184)	(0.102)	(0.186)	(0.110)	(0.192)	(0.115)	(0.216)	(0.125)
L1.FKS_greenenergy	3.879***	0.302	3.674***	0.202	3.979***	0.354	4.204***	0.564	4.516***	0.635
	(0.977)	(0.349)	(0.848)	(0.344)	(0.765)	(0.361)	(0.796)	(0.386)	(0.811)	(0.403)
L1.FKS_othergreen	-0.447	-0.797**	-0.435	-0.865**	-0.209	-0.791**	-0.0978	-0.722*	0.174	-0.702
	(0.702)	(0.348)	(0.631)	(0.341)	(0.620)	(0.363)	(0.613)	(0.396)	(0.554)	(0.427)
L1.FKS_grey	-0.666	1.369***	-0.299	1.390***	-0.390	1.353***	-0.699	1.167**	-1.099	1.161**
	(0.781)	(0.448)	(0.585)	(0.426)	(0.574)	(0.451)	(0.662)	(0.504)	(0.721)	(0.551)
PSMpatgrey		0.640***		0.613***		0.573***		0.554***		0.485***
		(0.0799)		(0.0816)		(0.0864)		(0.0915)		(0.0979)
etcr	-0.00406	-0.0215*	0.00102	-0.0165	0.00259	-0.0174	0.00417	-0.0235*	0.0116	-0.0243*
	(0.0153)	(0.0115)	(0.0147)	(0.0118)	(0.0147)	(0.0121)	(0.0150)	(0.0120)	(0.0145)	(0.0125)
lgdp	-2.174***	-1.336***	-1.928***	-1.248***	-1.938***	-1.288***	-2.003***	-1.364***	-1.958***	-1.419***
	(0.407)	(0.123)	(0.389)	(0.125)	(0.354)	(0.129)	(0.340)	(0.132)	(0.321)	(0.149)
Constant		1.595		1.397		1.084		2.797		2.880
		(3.283)		(3.213)		(3.357)		(3.579)		(3.846)
Observations	337	337	334	334	318	318	302	302	286	286
Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7.C – Forward structure

VARIABLES	(1) NBGML - GREY	(2) NBGML - GREY
eps_nonmarket	-0.0175	
	(0.0118)	
F.eps_nonmarket		-0.0114
		(0.0127)
KS_greenenergy	-0.0952	-0.0903
	(0.0934)	(0.0861)
KS_othergreen	-0.0496	-0.0527
	(0.0652)	(0.0647)
KS_grey	0.957***	0.961***
	(0.0755)	(0.0744)
L1.FKS_greenenergy	-0.0817	-0.0850
	(0.0545)	(0.0527)
L1.FKS_othergreen	-1.057***	-1.041***
	(0.355)	(0.325)
L1.FKS_grey	1.105***	1.090***
	(0.357)	(0.327)
etcr	-0.0335**	-0.0332**
	(0.0152)	(0.0144)
lgdp	-0.000849	0.00228
	(0.0270)	(0.0267)
	(0.0552)	(0.0559)
PSMpatgrey	0.105*	0.100*
	(0.0593)	(0.0572)
Constant	-3.033***	-3.046***
	(0.923)	(0.843)
Observations	337	338
Fixed Effects - Time Dummies	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7.D – Lagged structure

VARIABLES	(1) NBGML - GREY	(2) NBGML - GREY	(3) NBGML - GREY	(4) NBGML - GREY	(5) NBGML - GREY
eps_nonmarket	-0.0175				
	(0.0118)				
L.eps_nonmarket		-0.0296**			
		(0.0140)			
L2.eps_nonmarket			-0.0280**		
			(0.0138)		
L3.eps_nonmarket				-0.0254**	
				(0.0129)	
L4.eps_nonmarket					-0.0267**
					(0.0127)
KS_greenenergy	-0.0952	0.0198	0.0296	0.0382	0.0487*
	(0.0934)	(0.0228)	(0.0239)	(0.0264)	(0.0272)
KS_othergreen	-0.0496	-0.111**	-0.123***	-0.152***	-0.161***
	(0.0652)	(0.0442)	(0.0435)	(0.0437)	(0.0437)
KS_grey	0.957***	1.011***	1.026***	1.045***	1.031***
	(0.0755)	(0.0595)	(0.0615)	(0.0643)	(0.0649)
L1.FKS_greenenergy	-0.0817	-0.124***	-0.143***	-0.164***	-0.180***
	(0.0545)	(0.0370)	(0.0372)	(0.0385)	(0.0385)
L1.FKS_othergreen	-1.057***	-0.646***	-0.549***	-0.530***	-0.483***
	(0.355)	(0.129)	(0.111)	(0.114)	(0.115)
L1.FKS_grey	1.105***	0.697***	0.625***	0.628***	0.580***
	(0.357)	(0.129)	(0.113)	(0.115)	(0.115)
etcr	-0.0335**	-0.0212**	-0.0212**	-0.0241**	-0.0215**
	(0.0152)	(0.00898)	(0.00928)	(0.00968)	(0.00905)
lgdp	-0.000849	-0.0343*	-0.0401**	-0.0416**	-0.0430**
	(0.0270)	(0.0188)	(0.0180)	(0.0186)	(0.0190)
PSMpatgrey	0.105*	0.0693	0.0786	0.0919*	0.114**
	(0.0593)	(0.0502)	(0.0506)	(0.0521)	(0.0517)
Constant	-3.033***	-1.912***	-1.901***	-2.025***	-1.803***
	(0.923)	(0.397)	(0.394)	(0.414)	(0.403)
Observations	337	334	318	302	286
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 8.A – Forward structure

VARIABLES	(1) HGG - GO	(2) BGVR - GO	(3) HGG - GO	(4) BGVR - GO	(5)	(6)	(7)	(8)	(9)	(10)
eps	0.0521	-0.0942***								
	(0.0661)	(0.0281)								
F.eps			0.0694	-0.0398						
			(0.0576)	(0.0284)						
KS_greenenergy	0.101	0.0622	0.116	0.0508						
	(0.117)	(0.0682)	(0.0916)	(0.0693)						
KS_othergreen	0.312	0.628***	0.314	0.607***						
	(0.459)	(0.135)	(0.420)	(0.140)						
KS_grey	-0.243	-0.455***	-0.203	-0.390**						
	(0.426)	(0.165)	(0.423)	(0.171)						
L1.FKS_greenenergy	4.788***	-0.0766	4.475***	0.0287						
	(1.141)	(0.300)	(1.071)	(0.335)						
L1.FKS_othergreen	0.00962	-1.033**	-0.119	-0.972**						
	(1.111)	(0.436)	(1.142)	(0.460)						
L1.FKS_grey	-0.466	1.102**	-0.175	1.103**						
	(1.240)	(0.508)	(1.297)	(0.558)						
PSMpatgo		0.583***		0.553***						
		(0.0819)		(0.0801)						
etcr	-0.0134	0.00591	-0.0132	0.00677						
	(0.0291)	(0.0196)	(0.0293)	(0.0201)						
lgdp	-1.881**	-0.0985	-1.912***	-0.184						
	(0.772)	(0.142)	(0.677)	(0.157)						
Constant		-1.688		-1.942						
		(3.095)		(3.397)						
Observations	337	337	338	338						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 8.B – Lagged structure

VARIABLES	(1) HGG - GO	(2) BGVR - GO	(3) HGG - GO	(4) BGVR - GO	(5) HGG - GO	(6) BGVR - GO	(7) HGG - GO	(8) BGVR - GO	(9) HGG - GO	(10) BGVR - GO
eps	0.0521	-0.0942***								
	(0.0661)	(0.0281)								
L.eps			0.0807	-0.0933***						
			(0.0653)	(0.0293)						
L2.eps					0.0554	-0.0971***				
					(0.0604)	(0.0307)				
L3.eps							-0.00443	-0.127***		
							(0.0527)	(0.0340)		
L4.eps									0.00900	-0.101***
									(0.0502)	(0.0346)
KS_greenenergy	0.101	0.0622	0.200**	0.0792	0.216**	0.0715	0.279**	0.0882	0.294**	0.00129
	(0.117)	(0.0682)	(0.0932)	(0.0686)	(0.0962)	(0.0715)	(0.126)	(0.0761)	(0.128)	(0.0657)
KS_othergreen	0.312	0.628***	0.384	0.645***	0.486	0.646***	0.556	0.692***	0.568	0.705***
	(0.459)	(0.135)	(0.429)	(0.134)	(0.400)	(0.142)	(0.414)	(0.146)	(0.396)	(0.114)
KS_grey	-0.243	-0.455***	-0.138	-0.430***	-0.124	-0.414**	-0.265	-0.487**	-0.190	-0.00352
	(0.426)	(0.165)	(0.395)	(0.164)	(0.459)	(0.180)	(0.508)	(0.190)	(0.542)	(0.161)
L1.FKS_greenenergy	4.788***	-0.0766	5.906***	-0.136	6.048***	-0.0796	6.642***	-0.0323	7.187***	-0.238**
	(1.141)	(0.300)	(1.393)	(0.300)	(1.272)	(0.331)	(1.301)	(0.337)	(1.272)	(0.110)
L1.FKS_othergreen	0.00962	-1.033**	0.417	-1.122**	0.557	-1.138**	0.583	-1.172**	0.740	-0.921***
	(1.111)	(0.436)	(1.043)	(0.440)	(0.963)	(0.468)	(0.958)	(0.469)	(0.934)	(0.308)
L1.FKS_grey	-0.466	1.102**	-0.664	1.303**	-0.339	1.426**	-0.0272	1.371**	0.0221	0.800***
	(1.240)	(0.508)	(1.154)	(0.525)	(1.089)	(0.577)	(1.148)	(0.582)	(1.213)	(0.305)
PSMpatgo		0.583***		0.562***		0.569***		0.581***		0.236***
		(0.0819)		(0.0875)		(0.0932)		(0.0998)		(0.0804)
etcr	-0.0134	0.00591	-0.00374	0.00751	-0.00679	0.00533	-0.0153	0.000726	-0.0105	0.0196
	(0.0291)	(0.0196)	(0.0272)	(0.0196)	(0.0273)	(0.0199)	(0.0304)	(0.0199)	(0.0309)	(0.0191)
lgdp	-1.881**	-0.0985	-1.867***	-0.117	-1.624**	-0.216	-1.457**	-0.205	-1.367***	0.0139
	(0.772)	(0.142)	(0.724)	(0.145)	(0.632)	(0.162)	(0.565)	(0.168)	(0.493)	(0.0518)
Constant		-1.688		-2.569		-2.639		-2.074		-2.454*
		(3.095)		(3.023)		(3.333)		(3.353)		(1.382)
Observations	337	337	334	334	318	318	302	302	286	286
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8.C – Forward structure

VARIABLES	(1) NBGML - GO	(2) NBGML - GO
Eps	-0.000944	
	(0.0360)	
F.eps		-0.00405
		(0.0374)
KS_greenenergy	-0.0652	-0.0790
	(0.117)	(0.111)
KS_othergreen	0.635***	0.636***
	(0.0930)	(0.0934)
KS_grey	0.382***	0.381***
	(0.0958)	(0.0971)
L1.FKS_greenenergy	-0.200***	-0.196***
	(0.0612)	(0.0623)
L1.FKS_othergreen	-1.384***	-1.437***
	(0.416)	(0.394)
L1.FKS_grey	1.320***	1.371***
	(0.407)	(0.384)
etcr	-0.00268	-0.00373
	(0.0195)	(0.0190)
Lgdp	-0.0236	-0.0195
	(0.0432)	(0.0420)
PSMpatgo	0.0152	0.0198
	(0.0668)	(0.0669)
Constant	-3.180***	-3.284***
	(1.182)	(1.123)
Observations	337	338
Fixed Effects - Time Dummies	YES	YES

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8.D – Lagged structure

VARIABLES	(1) NBGML - GO	(2) NBGML - GO
Eps	-0.000944	
	(0.0360)	
L.eps		0.00290
		(0.0330)
KS_greenenergy	-0.0652	0.0421
	(0.117)	(0.0443)
KS_othergreen	0.635***	0.605***
	(0.0930)	(0.0803)
KS_grey	0.382***	0.395***
	(0.0958)	(0.0885)
L1.FKS_greenenergy	-0.200***	-0.234***
	(0.0612)	(0.0469)
L1.FKS_othergreen	-1.384***	-0.978***
	(0.416)	(0.192)
L1.FKS_grey	1.320***	0.919***
	(0.407)	(0.189)
etcr	-0.00268	0.0129
	(0.0195)	(0.0147)
Lgdp	-0.0236	-0.0580*
	(0.0432)	(0.0298)
PSMpatgo	0.0152	-0.00260
	(0.0668)	(0.0648)
Constant	-3.180***	-2.174***
	(1.182)	(0.742)
Observations	337	334
Fixed Effects - Time Dummies	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 9.A – Forward structure

VARIABLES	(1) HGG - GO	(2) BGVR - GO	(3) HGG - GO	(4) BGVR - GO	(5) HGG - GO	(6) BGVR - GO	(7) HGG - GO	(8) BGVR - GO	(9) HGG - GO	(10) BGVR - GO
eps_market	0.0327	-0.0444*								
	(0.0511)	(0.0251)								
F.eps_market			0.0141	-0.0420*						
			(0.0499)	(0.0240)						
F2.eps_market					0.00301	-0.0478**				
					(0.0404)	(0.0236)				
F3.eps_market							-0.0152	-0.0695***		
							(0.0484)	(0.0235)		
F4.eps_market									-0.0191	-0.0731***
									(0.0431)	(0.0243)
KS_greenenergy	0.135**	0.0526	0.143**	0.0492	0.136**	0.0448	0.169***	0.0628	0.196***	0.110*
	(0.0610)	(0.0565)	(0.0629)	(0.0563)	(0.0592)	(0.0530)	(0.0592)	(0.0545)	(0.0538)	(0.0622)
KS_othergreen	0.322	0.605***	0.336	0.608***	0.402	0.657***	0.374	0.641***	0.388	0.588***
	(0.439)	(0.140)	(0.448)	(0.141)	(0.471)	(0.140)	(0.472)	(0.144)	(0.486)	(0.155)
KS_grey	-0.220	-0.410**	-0.267	-0.415**	-0.348	-0.546***	-0.420	-0.602***	-0.485	-0.610***
	(0.397)	(0.172)	(0.419)	(0.173)	(0.449)	(0.178)	(0.451)	(0.177)	(0.458)	(0.178)
L1.FKS_greenenergy	4.517***	-0.0423	4.523***	0.0117	4.824***	0.243	4.486**	-0.158	3.904*	-0.330
	(1.034)	(0.325)	(1.134)	(0.329)	(1.271)	(0.362)	(1.766)	(0.334)	(2.351)	(0.317)
L1.FKS_othergreen	-0.0400	-1.079**	-0.0460	-1.041**	0.0176	-0.945**	-0.353	-1.343***	-0.687	-1.605***
	(1.133)	(0.454)	(1.144)	(0.453)	(1.163)	(0.464)	(1.237)	(0.470)	(1.368)	(0.491)
L1.FKS_grey	-0.216	1.209**	-0.261	1.114**	-0.488	0.863	-0.000142	1.311**	0.522	1.644***
	(1.309)	(0.544)	(1.499)	(0.548)	(1.645)	(0.574)	(1.908)	(0.549)	(2.127)	(0.548)
PSMpatgo		0.560***		0.552***		0.578***		0.622***		0.619***
		(0.0809)		(0.0801)		(0.0792)		(0.0827)		(0.0835)
etcr	-0.0110	0.00525	-0.0131	0.00753	-0.0198	0.000513	-0.0330	-0.00748	-0.0421	-0.0108
	(0.0275)	(0.0199)	(0.0309)	(0.0198)	(0.0314)	(0.0195)	(0.0307)	(0.0192)	(0.0314)	(0.0191)
lgdp	-1.762***	-0.162	-1.672***	-0.156	-1.590***	-0.185	-1.376***	-0.0177	-1.167**	0.105
	(0.623)	(0.156)	(0.616)	(0.156)	(0.603)	(0.152)	(0.529)	(0.136)	(0.566)	(0.120)
Constant		-1.853		-1.596		-0.231		-0.786		-2.258
		(3.385)		(3.405)		(3.700)		(3.286)		(3.002)
Observations	339	339	339	339	323	323	307	307	291	291
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1.

TABLE 9.B – Lagged structure

VARIABLES	(1) HGG - GO	(2) BGVR - GO	(3) HGG - GO	(4) BGVR - GO	(5)	(6)	(7)	(8)	(9)	(10)
eps_market	0.0327	-0.0444*								
	(0.0511)	(0.0251)								
L.eps_market			0.0673	-0.0361						
			(0.0442)	(0.0265)						
KS_greenenergy	0.135**	0.0526	0.123**	0.0551						
	(0.0610)	(0.0565)	(0.0580)	(0.0569)						
KS_othergreen	0.322	0.605***	0.290	0.589***						
	(0.439)	(0.140)	(0.425)	(0.141)						
KS_grey	-0.220	-0.410**	-0.138	-0.378**						
	(0.397)	(0.172)	(0.359)	(0.171)						
L1.FKS_greenenergy	4.517***	-0.0423	4.668***	-0.0792						
	(1.034)	(0.325)	(1.031)	(0.337)						
L1.FKS_othergreen	-0.0400	-1.079**	-0.0145	-1.075**						
	(1.133)	(0.454)	(1.117)	(0.460)						
L1.FKS_grey	-0.216	1.209**	-0.135	1.289**						
	(1.309)	(0.544)	(1.172)	(0.558)						
PSMpatgo		0.560***		0.562***						
		(0.0809)		(0.0819)						
etcr	-0.0110	0.00525	-0.00389	0.00326						
	(0.0275)	(0.0199)	(0.0231)	(0.0203)						
lgdp	-1.762***	-0.162	-1.907***	-0.206						
	(0.623)	(0.156)	(0.597)	(0.154)						
Constant		-1.853		-2.021						
		(3.385)		(3.476)						
Observations	339	339	339	339						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9.C – Forward structure

VARIABLES	(1) NBGML - GO	(2) NBGML - GO
eps_market	0.0713**	
	(0.0341)	
F.eps_market		0.0542
		(0.0339)
KS_greenenergy	-0.0413	-0.0404
	(0.0625)	(0.0627)
KS_othergreen	0.586***	0.592***
	(0.0816)	(0.0820)
KS_grey	0.440***	0.427***
	(0.101)	(0.102)
L1.FKS_greenenergy	-0.215***	-0.217***
	(0.0569)	(0.0566)
L1.FKS_othergreen	-1.509***	-1.469***
	(0.335)	(0.325)
L1.FKS_grey	1.479***	1.430***
	(0.309)	(0.298)
etcr	-0.0129	-0.0102
	(0.0160)	(0.0159)
lgdp	-0.0542	-0.0471
	(0.0514)	(0.0518)
PSMpatgo	-0.000514	0.00420
	(0.0649)	(0.0652)
Constant	-3.408***	-3.297***
	(0.827)	(0.814)
Observations	339	339
Fixed Effects - Time Dummies	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9.D – Lagged structure

VARIABLES	(1) NBGML - GO	(2) NBGML - GO	(3) NBGML - GO	(4) NBGML - GO	(5) NBGML - GO
eps_market	0.0713**				
	(0.0341)				
L.eps_market		0.0652*			
		(0.0340)			
L2.eps_market			0.0603*		
			(0.0351)		
L3.eps_market				0.0620**	
				(0.0294)	
L4.eps_market					0.0693**
					(0.0283)
KS_greenenergy	-0.0413	-0.0416	-0.0963	-0.0841	0.0465
	(0.0625)	(0.0620)	(0.122)	(0.143)	(0.0558)
KS_othergreen	0.586***	0.588***	0.649***	0.659***	0.619***
	(0.0816)	(0.0823)	(0.0974)	(0.104)	(0.0854)
KS_grey	0.440***	0.433***	0.396***	0.375***	0.412***
	(0.101)	(0.0998)	(0.0979)	(0.105)	(0.0976)
L1.FKS_greenenergy	-0.215***	-0.209***	-0.193***	-0.195***	-0.238***
	(0.0569)	(0.0565)	(0.0626)	(0.0639)	(0.0489)
L1.FKS_othergreen	-1.509***	-1.487***	-1.576***	-1.509***	-0.946***
	(0.335)	(0.333)	(0.432)	(0.502)	(0.227)
L1.FKS_grey	1.479***	1.453***	1.518***	1.454***	0.926***
	(0.309)	(0.307)	(0.417)	(0.484)	(0.222)
etcr	-0.0129	-0.0110	-0.0171	-0.0200	-0.00767
	(0.0160)	(0.0162)	(0.0186)	(0.0190)	(0.0153)
lgdp	-0.0542	-0.0503	-0.0291	-0.0166	-0.0569*
	(0.0514)	(0.0498)	(0.0497)	(0.0527)	(0.0328)
PSMpatgo	-0.000514	0.00153	0.00594	0.00340	-0.0278
	(0.0649)	(0.0652)	(0.0665)	(0.0681)	(0.0634)
Constant	-3.408***	-3.373***	-3.344***	-3.143***	-2.277***
	(0.827)	(0.825)	(1.170)	(1.194)	(0.786)
Observations	339	339	323	307	291
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 10.A – Forward structure.

VARIABLES	(1) HGG - GO	(2) BGVR - GO	(3) HGG - GO	(4) BGVR - GO	(5)	(6)	(7)	(8)	(9)	(10)
eps_nonmarket	0.0232	-0.0590***								
	(0.0329)	(0.0191)								
F.eps_nonmarket			0.0474	-0.00875						
			(0.0289)	(0.0183)						
KS_greenenergy	0.117	0.0575	0.140*	0.0539						
	(0.105)	(0.0685)	(0.0832)	(0.0692)						
KS_othergreen	0.329	0.625***	0.330	0.592***						
	(0.464)	(0.134)	(0.420)	(0.141)						
KS_grey	-0.313	-0.375**	-0.307	-0.334**						
	(0.425)	(0.161)	(0.412)	(0.167)						
L1.FKS_greenenergy	4.839***	-0.105	4.790***	-0.0333						
	(1.122)	(0.309)	(1.018)	(0.347)						
L1.FKS_othergreen	-0.00956	-1.014**	-0.155	-1.037**						
	(1.115)	(0.442)	(1.155)	(0.469)						
L1.FKS_grey	-0.598	1.176**	-0.617	1.264**						
	(1.207)	(0.518)	(1.157)	(0.567)						
PSMpatgo		0.566***		0.547***						
		(0.0818)		(0.0810)						
etcr	-0.0143	0.00902	-0.0106	0.00771						
	(0.0298)	(0.0196)	(0.0280)	(0.0203)						
lgdp	-1.744**	-0.163	-1.805***	-0.245						
	(0.688)	(0.144)	(0.595)	(0.154)						
Constant		-2.064		-2.159						
		(3.129)		(3.504)						
Observations	337	337	338	338						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 10.B – Lagged structure

VARIABLES	(1) HGG - GO	(2) BGVR - GO	(3) HGG - GO	(4) BGVR - GO	(5) HGG - GO	(6) BGVR - GO	(7) HGG - GO	(8) BGVR - GO	(9) HGG - GO	(10) BGVR - GO
eps_nonmarket	0.0232	-0.0590***								
	(0.0329)	(0.0191)								
L.eps_nonmarket			0.0278	-0.0665***						
			(0.0310)	(0.0203)						
L2.eps_nonmarket					-0.0176	-0.0855***				
					(0.0284)	(0.0215)				
L3.eps_nonmarket							-0.0495*	-0.101***		
							(0.0297)	(0.0249)		
L4.eps_nonmarket									-0.0293	-0.0843***
									(0.0306)	(0.0239)
KS_greenenergy	0.117	0.0575	0.224**	0.0716	0.239**	0.0513	0.284**	0.0421	0.305**	-0.0134
	(0.105)	(0.0685)	(0.0910)	(0.0684)	(0.103)	(0.0710)	(0.129)	(0.0770)	(0.129)	(0.0564)
KS_othergreen	0.329	0.625***	0.420	0.659***	0.542	0.684***	0.574	0.710***	0.591	0.711***
	(0.464)	(0.134)	(0.442)	(0.131)	(0.412)	(0.136)	(0.408)	(0.140)	(0.397)	(0.0975)
KS_grey	-0.313	-0.375**	-0.242	-0.373**	-0.218	-0.373**	-0.305	-0.381**	-0.251	0.116
	(0.425)	(0.161)	(0.416)	(0.159)	(0.464)	(0.169)	(0.499)	(0.190)	(0.553)	(0.122)
L1.FKS_greenenergy	4.839***	-0.105	5.714***	-0.160	5.544***	-0.143	6.290***	-0.0990	7.059***	-0.227***
	(1.122)	(0.309)	(1.287)	(0.289)	(1.147)	(0.300)	(1.240)	(0.303)	(1.242)	(0.0787)
L1.FKS_othergreen	-0.00956	-1.014**	0.328	-1.100**	0.429	-1.080**	0.456	-1.079**	0.716	-0.835***
	(1.115)	(0.442)	(1.029)	(0.434)	(0.966)	(0.449)	(0.984)	(0.453)	(0.968)	(0.251)
L1.FKS_grey	-0.598	1.176**	-0.656	1.286**	-0.0937	1.321**	-0.109	1.207**	-0.271	0.719***
	(1.207)	(0.518)	(1.091)	(0.510)	(0.975)	(0.543)	(1.126)	(0.557)	(1.362)	(0.243)
PSMpatgo		0.566***		0.538***		0.549***		0.537***		0.177***
		(0.0818)		(0.0882)		(0.0973)		(0.123)		(0.0542)
etcr	-0.0143	0.00902	-0.00838	0.0148	-0.00875	0.0152	-0.0111	0.0133	-0.00557	0.0330*
	(0.0298)	(0.0196)	(0.0300)	(0.0195)	(0.0292)	(0.0196)	(0.0310)	(0.0201)	(0.0308)	(0.0186)
lgdp	-1.744**	-0.163	-1.620**	-0.127	-1.321**	-0.174	-1.350***	-0.169	-1.284***	-0.0339
	(0.688)	(0.144)	(0.652)	(0.139)	(0.565)	(0.157)	(0.504)	(0.183)	(0.457)	(0.0442)
Constant		-2.064		-2.723		-2.635		-1.887		-2.494**
		(3.129)		(2.896)		(3.025)		(3.004)		(1.121)
Observations	337	337	334	334	318	318	302	302	286	286
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10.C – Forward structure

VARIABLES	(1) NBGML - GO	(2) NBGML - GO
eps_nonmarket	-0.0461**	
	(0.0209)	
F.eps_nonmarket		-0.0355
		(0.0219)
KS_greenenergy	-0.0548	-0.0718
	(0.111)	(0.110)
KS_othergreen	0.643***	0.639***
	(0.0900)	(0.0911)
KS_grey	0.360***	0.367***
	(0.0914)	(0.0926)
L1.FKS_greenenergy	-0.189***	-0.188***
	(0.0571)	(0.0596)
L1.FKS_othergreen	-1.318***	-1.407***
	(0.400)	(0.395)
L1.FKS_grey	1.238***	1.331***
	(0.394)	(0.389)
Etcr	0.000671	-0.00255
	(0.0188)	(0.0189)
Lgdp	-0.0531	-0.0418
	(0.0443)	(0.0444)
PSMpatgo	0.0301	0.0305
	(0.0652)	(0.0649)
Constant	-2.520**	-2.833**
	(1.167)	(1.162)
Observations	337	338
Fixed Effects - Time Dummies	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10.D – Lagged structure

VARIABLES	(1) NBGML - GO	(2) NBGML - GO	(3) NBGML - GO	(4) NBGML - GO	(5) NBGML - GO
eps_nonmarket	-0.0461**				
	(0.0209)				
L.eps_nonmarket		-0.0407*			
		(0.0214)			
L2.eps_nonmarket			-0.0671***		
			(0.0195)		
L3.eps_nonmarket				-0.0726***	
				(0.0218)	
L4.eps_nonmarket					-0.0834***
					(0.0228)
KS_greenenergy	-0.0548	0.0443	0.0415	0.0497	0.0568
	(0.111)	(0.0436)	(0.0438)	(0.0462)	(0.0497)
KS_othergreen	0.643***	0.620***	0.668***	0.668***	0.660***
	(0.0900)	(0.0800)	(0.0787)	(0.0811)	(0.0808)
KS_grey	0.360***	0.367***	0.312***	0.302***	0.295***
	(0.0914)	(0.0860)	(0.0873)	(0.0921)	(0.0955)
L1.FKS_greenenergy	-0.189***	-0.218***	-0.208***	-0.210***	-0.234***
	(0.0571)	(0.0466)	(0.0447)	(0.0448)	(0.0442)
L1.FKS_othergreen	-1.318***	-0.926***	-0.781***	-0.732***	-0.697***
	(0.400)	(0.189)	(0.161)	(0.167)	(0.178)
L1.FKS_grey	1.238***	0.850***	0.687***	0.647***	0.608***
	(0.394)	(0.186)	(0.163)	(0.169)	(0.178)
etcr	0.000671	0.0155	0.0166	0.0136	0.0168
	(0.0188)	(0.0141)	(0.0136)	(0.0136)	(0.0136)
lgdp	-0.0531	-0.0811**	-0.0906***	-0.0877***	-0.0879***
	(0.0443)	(0.0315)	(0.0300)	(0.0303)	(0.0317)
PSMpatgo	0.0301	0.0132	0.0338	0.0403	0.0585
	(0.0652)	(0.0642)	(0.0669)	(0.0691)	(0.0720)
Constant	-2.520**	-1.626**	-0.965	-0.925	-0.709
	(1.167)	(0.730)	(0.713)	(0.733)	(0.751)
Observations	337	334	318	302	286
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix A – BVGR – Rounded values

Table 11.A – Forward structure

VARIABLES	(1) HGG - GREEN	(2) BGVR - GREEN	(3) HGG - GREEN	(4) BGVR - GREEN	(5) HGG - GREEN	(6) BGVR - GREEN	(7) HGG - GREEN	(8) BGVR - GREEN	(9)	(10)
eps	0.0381	0.0352								
	(0.0362)	(0.0347)								
F.eps			0.0586	0.0623*						
			(0.0363)	(0.0327)						
F2.eps					0.0575	0.0712**				
					(0.0385)	(0.0343)				
F3.eps							0.0180	0.0124		
							(0.0415)	(0.0372)		
KS_greenenergy	0.885***	0.744***	0.872***	0.736***	0.817***	0.698***	0.773***	0.652***		
	(0.0899)	(0.0789)	(0.0888)	(0.0772)	(0.0915)	(0.0788)	(0.102)	(0.0887)		
KS_othergreen	-0.254	-0.164	-0.271	-0.165	-0.260	-0.207	-0.233	-0.236		
	(0.185)	(0.147)	(0.184)	(0.144)	(0.188)	(0.148)	(0.204)	(0.164)		
KS_grey	-0.184	-0.275*	-0.145	-0.249	-0.117	-0.310*	-0.219	-0.382**		
	(0.226)	(0.167)	(0.229)	(0.164)	(0.227)	(0.170)	(0.237)	(0.187)		
L1. FKS_greenenergy	1.588***	0.0178	1.482***	-0.0200	1.142**	-0.0841	1.548***	0.00917		
	(0.472)	(0.172)	(0.482)	(0.166)	(0.506)	(0.172)	(0.506)	(0.191)		
L1.FKS_othergreen	-1.083*	-1.043**	-1.206*	-1.125***	-1.419**	-1.357***	-1.118*	-1.311***		
	(0.614)	(0.405)	(0.616)	(0.399)	(0.633)	(0.418)	(0.679)	(0.441)		
L1.FKS_grey	-0.290	0.505	-0.177	0.594	0.228	0.848**	-0.275	0.782*		
	(0.766)	(0.397)	(0.767)	(0.391)	(0.792)	(0.419)	(0.844)	(0.444)		
PSMpatge		0.344***		0.334***		0.433***		0.513***		
		(0.0951)		(0.0916)		(0.113)		(0.131)		
etcr2_ele	-0.0456*	-0.0353	-0.0463*	-0.0362	-0.0535*	-0.0480*	-0.0602**	-0.0561**		
	(0.0275)	(0.0256)	(0.0276)	(0.0254)	(0.0277)	(0.0252)	(0.0283)	(0.0262)		
lgdp	0.00352	0.222***	-0.0159	0.220***	0.0712	0.268***	0.148	0.313***		
	(0.161)	(0.0682)	(0.163)	(0.0667)	(0.164)	(0.0691)	(0.172)	(0.0749)		
Constant	2.122	0.600	2.759	0.504	1.535	0.393	1.378	0.279		
	(5.160)	(1.750)	(5.100)	(1.701)	(5.132)	(1.814)	(5.248)	(2.002)		
Observations	337	337	338	338	323	323	307	307		
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES		

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 11.B – Lagged structure

VARIABLES	(1) HGG - GREEN	(2) BGVR - GREEN	(3) HGG - GREEN	(4) BGVR - GREEN	(5)	(6)	(7)	(8)	(9)	(10)
eps	0.0381	0.0352								
	(0.0362)	(0.0347)								
L.eps			0.0311	0.0364						
			(0.0372)	(0.0361)						
KS_greenenergy	0.885***	0.744***	0.906***	0.767***						
	(0.0899)	(0.0789)	(0.0881)	(0.0774)						
KS_othergreen	-0.254	-0.164	-0.253	-0.137						
	(0.185)	(0.147)	(0.180)	(0.143)						
KS_grey	-0.184	-0.275*	-0.216	-0.269*						
	(0.226)	(0.167)	(0.217)	(0.162)						
L1. FKS_greenenergy	1.588***	0.0178	1.532***	0.0303						
	(0.472)	(0.172)	(0.475)	(0.165)						
L1.FKS_othergreen	-1.083*	-1.043**	-1.279**	-1.017**						
	(0.614)	(0.405)	(0.619)	(0.398)						
L1.FKS_grey	-0.290	0.505	0.273	0.480						
	(0.766)	(0.397)	(0.835)	(0.388)						
PSMpatge		0.344***		0.298***						
		(0.0951)		(0.0859)						
etcr2_ele	-0.0456*	-0.0353	-0.0471*	-0.0303						
	(0.0275)	(0.0256)	(0.0273)	(0.0251)						
lgdp	0.00352	0.222***	0.0305	0.215***						
	(0.161)	(0.0682)	(0.158)	(0.0658)						
Constant	2.122	0.600	-1.453	0.549						
	(5.160)	(1.750)	(5.883)	(1.686)						
Observations	337	337	334	334						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 12.A – Forward structure

VARIABLES	(1) HGG - GREEN	(2) BGVR - GREEN	(3) HGG - GREEN	(4) BGVR - GREEN	(5)	(6)	(7)	(8)	(9)	(10)
eps_market	0.0368	0.0370								
	(0.0302)	(0.0303)								
F.eps_market			0.0282	0.0443						
			(0.0293)	(0.0285)						
KS_greenenergy	0.796***	0.670***	0.794***	0.674***						
	(0.0910)	(0.0786)	(0.0916)	(0.0786)						
KS_othergreen	-0.280	-0.165	-0.275	-0.162						
	(0.184)	(0.146)	(0.185)	(0.144)						
KS_grey	-0.107	-0.274*	-0.0991	-0.261						
	(0.226)	(0.166)	(0.229)	(0.165)						
L1. FKS_greenenergy	1.520***	0.0165	1.467***	-0.00790						
	(0.468)	(0.170)	(0.475)	(0.167)						
L1.FKS_othergreen	-1.198*	-1.141***	-1.211*	-1.128***						
	(0.627)	(0.403)	(0.629)	(0.400)						
L1.FKS_grey	-0.0877	0.624	-0.0299	0.632						
	(0.780)	(0.397)	(0.783)	(0.394)						
PSMpatge		0.389***		0.382***						
		(0.0958)		(0.0947)						
etcr2_ele	-0.0532*	-0.0439*	-0.0549**	-0.0454*						
	(0.0277)	(0.0255)	(0.0278)	(0.0254)						
lgdp	0.00518	0.234***	0.0144	0.228***						
	(0.165)	(0.0700)	(0.165)	(0.0692)						
Constant	1.481	0.309	1.161	0.268						
	(5.157)	(1.753)	(5.143)	(1.725)						
Observations	339	339	339	339						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 12.B – Lagged structure

VARIABLES	(1) HGG - GREEN	(2) BGVR - GREEN	(3) HGG - GREEN	(4) BGVR - GREEN	(5) HGG - GREEN	(6) BGVR - GREEN	(7) HGG - GREEN	(8) BGVR - GREEN	(9) HGG - GREEN	(10) BGVR - GREEN
eps_market	0.0368	0.0370								
	(0.0302)	(0.0303)								
L.eps_market			0.0707**	0.0869***						
			(0.0317)	(0.0313)						
L2.eps_market					0.0645*	0.0968***				
					(0.0352)	(0.0331)				
L3.eps_market							0.0588*	0.0850**		
							(0.0356)	(0.0344)		
L4.eps_market									0.0351	0.0624*
									(0.0382)	(0.0363)
KS_greenenergy	0.796***	0.670***	0.788***	0.670***	0.833***	0.709***	0.885***	0.756***	0.931***	0.809***
	(0.0910)	(0.0786)	(0.0909)	(0.0760)	(0.0940)	(0.0769)	(0.0990)	(0.0803)	(0.103)	(0.0820)
KS_othergreen	-0.280	-0.165	-0.261	-0.134	-0.272	-0.121	-0.289	-0.153	-0.331	-0.203
	(0.184)	(0.146)	(0.183)	(0.138)	(0.189)	(0.140)	(0.198)	(0.144)	(0.201)	(0.147)
KS_grey	-0.107	-0.274*	-0.0878	-0.243	-0.111	-0.256*	-0.137	-0.231	-0.118	-0.166
	(0.226)	(0.166)	(0.224)	(0.154)	(0.239)	(0.155)	(0.252)	(0.158)	(0.259)	(0.163)
L1.FKS_greenenergy	1.520***	0.0165	1.525***	-0.0171	1.570***	-0.0225	1.684***	-0.0134	1.466***	0.000105
	(0.468)	(0.170)	(0.468)	(0.147)	(0.487)	(0.135)	(0.505)	(0.133)	(0.523)	(0.138)
L1.FKS_othergreen	-1.198*	-1.141***	-1.210**	-1.176***	-1.285**	-1.108***	-0.945	-0.919**	-0.971	-0.809**
	(0.627)	(0.403)	(0.617)	(0.375)	(0.633)	(0.372)	(0.658)	(0.375)	(0.682)	(0.386)
L1.FKS_grey	-0.0877	0.624	-0.0916	0.669*	-0.0639	0.587*	-0.568	0.411	-0.189	0.308
	(0.780)	(0.397)	(0.772)	(0.364)	(0.786)	(0.355)	(0.811)	(0.354)	(0.907)	(0.365)
PSMpatge		0.389***		0.352***		0.322***		0.300***		0.262***
		(0.0958)		(0.0849)		(0.0791)		(0.0780)		(0.0760)
etcr2_ele	-0.0532*	-0.0439*	-0.0470*	-0.0356	-0.0448	-0.0300	-0.0530*	-0.0365	-0.0610**	-0.0417
	(0.0277)	(0.0255)	(0.0276)	(0.0249)	(0.0280)	(0.0248)	(0.0284)	(0.0257)	(0.0291)	(0.0265)
lgdp	0.00518	0.234***	0.00640	0.216***	-0.0173	0.213***	-0.0152	0.202***	0.0299	0.181***
	(0.165)	(0.0700)	(0.159)	(0.0632)	(0.164)	(0.0609)	(0.168)	(0.0607)	(0.168)	(0.0619)
Constant	1.481	0.309	1.314	0.245	1.733	0.535	3.179	0.587	0.622	0.856
	(5.157)	(1.753)	(5.119)	(1.556)	(5.212)	(1.458)	(5.239)	(1.441)	(5.753)	(1.494)
Observations	339	339	339	339	323	323	307	307	291	291
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 13.A – Forward structure

VARIABLES	(1) HGG - GREEN	(2) BGVR - GREEN	(3) HGG - GREEN	(4) BGVR - GREEN	(5)	(6)	(7)	(8)	(9)	(10)
eps_nonmarket	0.0104	0.00686								
	(0.0259)	(0.0235)								
F.eps_nonmarket			0.0334	0.0244						
			(0.0245)	(0.0207)						
KS_greenenergy	0.893***	0.748***	0.879***	0.734***						
	(0.0904)	(0.0805)	(0.0885)	(0.0788)						
KS_othergreen	-0.260	-0.184	-0.282	-0.187						
	(0.185)	(0.149)	(0.184)	(0.148)						
KS_grey	-0.209	-0.302*	-0.192	-0.292*						
	(0.223)	(0.169)	(0.225)	(0.169)						
L1. FKS_greenenergy	1.623***	0.0486	1.558***	0.0319						
	(0.472)	(0.181)	(0.475)	(0.180)						
L1.FKS_othergreen	-1.112*	-1.052**	-1.274**	-1.146***						
	(0.614)	(0.420)	(0.617)	(0.421)						
L1.FKS_grey	-0.268	0.500	-0.248	0.577						
	(0.766)	(0.414)	(0.762)	(0.414)						
PSMpatge		0.373***		0.372***						
		(0.0962)		(0.0943)						
etcr2_ele	-0.0465*	-0.0373	-0.0445	-0.0375						
	(0.0275)	(0.0257)	(0.0275)	(0.0256)						
lgdp	0.0340	0.229***	0.0274	0.238***						
	(0.158)	(0.0713)	(0.159)	(0.0705)						
Constant	1.739	0.708	3.347	0.659						
	(5.238)	(1.847)	(5.214)	(1.841)						
Observations	337	337	338	338						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 13.B – Lagged structure

VARIABLES	(1) HGG - GREEN	(2) BGVR - GREEN	(3) HGG - GREEN	(4) BGVR - GREEN	(5)	(6)	(7)	(8)	(9)	(10)
eps_nonmarket	0.0104	0.00686								
	(0.0259)	(0.0235)								
L.eps_nonmarket			-0.0124	-0.0216						
			(0.0266)	(0.0252)						
KS_greenenergy	0.893***	0.748***	0.927***	0.792***						
	(0.0904)	(0.0805)	(0.0881)	(0.0800)						
KS_othergreen	-0.260	-0.184	-0.260	-0.177						
	(0.185)	(0.149)	(0.178)	(0.146)						
KS_grey	-0.209	-0.302*	-0.235	-0.310*						
	(0.223)	(0.169)	(0.213)	(0.167)						
L1. FKS_greenenergy	1.623***	0.0486	1.540***	0.0715						
	(0.472)	(0.181)	(0.476)	(0.180)						
L1.FKS_othergreen	-1.112*	-1.052**	-1.307**	-1.021**						
	(0.614)	(0.420)	(0.619)	(0.424)						
L1.FKS_grey	-0.268	0.500	0.441	0.481						
	(0.766)	(0.414)	(0.841)	(0.418)						
PSMpatge		0.373***		0.345***						
		(0.0962)		(0.0923)						
etcr2_ele	-0.0465*	-0.0373	-0.0493*	-0.0337						
	(0.0275)	(0.0257)	(0.0270)	(0.0251)						
lgdp	0.0340	0.229***	0.0600	0.210***						
	(0.158)	(0.0713)	(0.155)	(0.0706)						
Constant	1.739	0.708	-3.132	0.807						
	(5.238)	(1.847)	(6.009)	(1.847)						
Observations	337	337	334	334						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 14.A – Forward structure

VARIABLES	(1) HGG - GREY	(2) BGVR - GREY	(3) HGG - GREY	(4) BGVR - GREY	(5) HGG - GREY	(6) BGVR - GREY	(7) HGG - GREY	(8) BGVR - GREY	(9) HGG - GREY	(10) BGVR - GREY
Eps	-0.0410**	-0.0489***								
	(0.0181)	(0.0163)								
F.eps			-0.0273	-0.0286*						
			(0.0178)	(0.0156)						
F2.eps					-0.0360**	-0.0251*				
					(0.0176)	(0.0139)				
F3.eps							-0.0392**	-0.0305**		
							(0.0183)	(0.0134)		
F4.eps									-0.0353*	-0.0313**
									(0.0185)	(0.0130)
KS_greenenergy	0.0754**	-0.0255	0.0742**	-0.0255	0.0864***	0.00421	0.0915***	0.0155	0.0901***	0.0369
	(0.0350)	(0.0369)	(0.0343)	(0.0367)	(0.0315)	(0.0298)	(0.0335)	(0.0308)	(0.0332)	(0.0325)
KS_othergreen	-0.140	-0.0624	-0.168**	-0.109	-0.156*	-0.0663	-0.149	-0.0853	-0.181*	-0.132*
	(0.0866)	(0.0783)	(0.0848)	(0.0764)	(0.0848)	(0.0707)	(0.0928)	(0.0721)	(0.0982)	(0.0742)
KS_grey	0.825***	0.757***	0.863***	0.831***	0.856***	0.801***	0.827***	0.761***	0.806***	0.726***
	(0.113)	(0.109)	(0.112)	(0.106)	(0.111)	(0.0978)	(0.119)	(0.0970)	(0.125)	(0.0952)
L1. FKS_greenenergy	1.762***	0.346	1.733***	0.308	1.535***	-0.248	1.595***	-0.666**	1.710***	-0.840**
	(0.370)	(0.345)	(0.371)	(0.356)	(0.383)	(0.331)	(0.408)	(0.336)	(0.423)	(0.333)
L1.FKS_othergreen	-0.978**	-0.826**	-0.988**	-0.854**	-1.484***	-1.474***	-1.644***	-1.702***	-1.828***	-1.864***
	(0.428)	(0.346)	(0.433)	(0.357)	(0.427)	(0.297)	(0.451)	(0.284)	(0.482)	(0.280)
L1.FKS_grey	-0.293	1.294***	-0.176	1.494***	0.0295	1.921***	0.204	2.294***	0.315	2.495***
	(0.509)	(0.458)	(0.517)	(0.472)	(0.495)	(0.397)	(0.516)	(0.385)	(0.536)	(0.370)
PSMpatgrey		0.635***		0.627***		0.786***		0.886***		0.946***
		(0.0798)		(0.0814)		(0.0802)		(0.0827)		(0.0840)
etcr2_ele	-0.0289**	-0.0219*	-0.0291**	-0.0226*	-0.0283**	-0.0122	-0.0327***	-0.0168*	-0.0364***	-0.0183*
	(0.0120)	(0.0115)	(0.0120)	(0.0116)	(0.0117)	(0.0104)	(0.0120)	(0.0101)	(0.0119)	(0.00986)
Lgdp	-1.083***	-1.279***	-1.102***	-1.335***	-1.059***	-1.185***	-0.985***	-1.066***	-0.942***	-0.968***
	(0.117)	(0.130)	(0.118)	(0.130)	(0.120)	(0.120)	(0.126)	(0.114)	(0.131)	(0.114)
Constant	11.33***	1.923	10.58***	0.943	13.13***	1.875	11.53***	0.851	11.01**	0.0713
	(3.988)	(3.359)	(4.038)	(3.455)	(4.059)	(3.162)	(4.218)	(2.976)	(4.314)	(2.809)
Observations	337	337	338	338	323	323	307	307	291	291
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 14.B – Lagged structure

VARIABLES	(1) HGG - GREY	(2) BGVR - GREY	(3) HGG - GREY	(4) BGVR - GREY	(5) HGG - GREY	(6) BGVR-GREY	(7) HGG - GREY	(8) BGVR - GREY	(9) HGG - GREY	(10) BGVR - GREY
eps	-0.0410**	-0.0489***								
	(0.0181)	(0.0163)								
L.eps			-0.0512***	-0.0727***						
			(0.0186)	(0.0179)						
L2.eps					-0.0345*	-0.0625***				
					(0.0199)	(0.0201)				
L3.eps							-0.0121	-0.0383*		
							(0.0197)	(0.0196)		
L4.eps									-0.000980	-0.0200
									(0.0199)	(0.0197)
KS_greenenergy	0.0754**	-0.0255	0.0917***	-0.00781	0.117***	0.0177	0.154***	0.0570	0.155***	0.0724*
	(0.0350)	(0.0369)	(0.0344)	(0.0374)	(0.0359)	(0.0393)	(0.0362)	(0.0400)	(0.0386)	(0.0422)
KS_othergreen	-0.140	-0.0624	-0.111	0.00662	-0.144	-0.0104	-0.221**	-0.123	-0.216**	-0.168*
	(0.0866)	(0.0783)	(0.0871)	(0.0819)	(0.0918)	(0.0907)	(0.0897)	(0.0888)	(0.0888)	(0.0874)
KS_grey	0.825***	0.757***	0.835***	0.697***	0.892***	0.724***	0.859***	0.753***	0.967***	0.870***
	(0.113)	(0.109)	(0.114)	(0.112)	(0.121)	(0.122)	(0.124)	(0.121)	(0.132)	(0.127)
L1.FKS_greenenergy	1.762***	0.346	1.548***	0.342	1.531***	0.419	1.731***	0.579	1.581***	0.646
	(0.370)	(0.345)	(0.373)	(0.335)	(0.393)	(0.351)	(0.407)	(0.376)	(0.424)	(0.396)
L1.FKS_othergreen	-0.978**	-0.826**	-1.076**	-0.849**	-1.010**	-0.805**	-0.806*	-0.754*	-0.745	-0.691*
	(0.428)	(0.346)	(0.429)	(0.337)	(0.447)	(0.355)	(0.468)	(0.388)	(0.475)	(0.416)
L1.FKS_grey	-0.293	1.294***	-0.000371	1.174***	0.161	1.222***	-0.178	1.137**	-0.0700	1.115**
	(0.509)	(0.458)	(0.514)	(0.436)	(0.539)	(0.458)	(0.579)	(0.502)	(0.595)	(0.538)
PSMpatgrey		0.635***		0.605***		0.574***		0.558***		0.490***
		(0.0798)		(0.0808)		(0.0856)		(0.0912)		(0.0976)
etcr2_ele	-0.0289**	-0.0219*	-0.0288**	-0.0195*	-0.0281**	-0.0187	-0.0316***	-0.0242**	-0.0300**	-0.0244**
	(0.0120)	(0.0115)	(0.0119)	(0.0115)	(0.0120)	(0.0118)	(0.0119)	(0.0119)	(0.0124)	(0.0124)
lgdp	-1.083***	-1.279***	-1.088***	-1.184***	-1.146***	-1.236***	-1.183***	-1.355***	-1.258***	-1.405***
	(0.117)	(0.130)	(0.115)	(0.133)	(0.118)	(0.138)	(0.118)	(0.135)	(0.126)	(0.146)
Constant	11.33***	1.923	10.40***	2.281	8.884**	1.731	10.40**	3.227	10.01**	3.069
	(3.988)	(3.359)	(3.893)	(3.238)	(4.023)	(3.373)	(4.249)	(3.595)	(4.527)	(3.837)
Observations	337	337	334	334	318	318	302	302	286	286
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 15.A – Forward structure

VARIABLES	(1) HGG - GREY	(2) BGVR - GREY	(3) HGG - GREY	(4) BGVR - GREY	(5)	(6)	(7)	(8)	(9)	(10)
eps_market	-0.00688	-0.0130								
	(0.0180)	(0.0161)								
F.eps_market			-0.000597	-0.00231						
			(0.0175)	(0.0154)						
KS_greenenergy	0.0698**	0.00300	0.0684**	-0.000125						
	(0.0295)	(0.0288)	(0.0294)	(0.0286)						
KS_othergreen	-0.201**	-0.145*	-0.206**	-0.156**						
	(0.0834)	(0.0753)	(0.0830)	(0.0739)						
KS_grey	0.891***	0.858***	0.904***	0.890***						
	(0.116)	(0.111)	(0.116)	(0.109)						
L1. FKS_greenenergy	1.626***	0.296	1.625***	0.267						
	(0.368)	(0.347)	(0.369)	(0.353)						
L1.FKS_othergreen	-1.073**	-0.939***	-1.057**	-0.940***						
	(0.443)	(0.357)	(0.443)	(0.360)						
L1.FKS_grey	0.0381	1.653***	0.0580	1.729***						
	(0.517)	(0.448)	(0.519)	(0.452)						
PSMpatgrey		0.612***		0.614***						
		(0.0805)		(0.0811)						
etcr2_ele	-0.0303**	-0.0209*	-0.0304**	-0.0208*						
	(0.0120)	(0.0116)	(0.0120)	(0.0116)						
lgdp	-1.106***	-1.332***	-1.114***	-1.363***						
	(0.120)	(0.135)	(0.120)	(0.133)						
Constant	9.878**	0.0396	9.602**	-0.285						
	(4.101)	(3.491)	(4.087)	(3.480)						
Observations	339	339	339	339						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 15.B – Lagged structure

VARIABLES	(1) HGG - GREY	(2) BGVR - GREY	(3) HGG - GREY	(4) BGVR - GREY	(5) HGG - GREY	(6) BGVR - GREY	(7)	(8)	(9)	(10)
eps_market	-0.00688	-0.0130								
	(0.0180)	(0.0161)								
L.eps_market			-0.0255	-0.0301*						
			(0.0187)	(0.0165)						
L2.eps_market					-0.00746	-0.0184				
					(0.0194)	(0.0173)				
KS_greenenergy	0.0698**	0.00300	0.0748**	0.00887	0.101***	0.00413				
	(0.0295)	(0.0288)	(0.0297)	(0.0290)	(0.0363)	(0.0387)				
KS_othergreen	-0.201**	-0.145*	-0.187**	-0.131*	-0.226***	-0.159**				
	(0.0834)	(0.0753)	(0.0835)	(0.0752)	(0.0859)	(0.0767)				
KS_grey	0.891***	0.858***	0.855***	0.815***	0.890***	0.851***				
	(0.116)	(0.111)	(0.116)	(0.110)	(0.120)	(0.112)				
L1. FKS_greenenergy	1.626***	0.296	1.635***	0.338	1.779***	0.313				
	(0.368)	(0.347)	(0.365)	(0.341)	(0.387)	(0.364)				
L1.FKS_othergreen	-1.073**	-0.939***	-1.097**	-0.921***	-0.993**	-0.962***				
	(0.443)	(0.357)	(0.437)	(0.353)	(0.459)	(0.369)				
L1.FKS_grey	0.0381	1.653***	-0.0471	1.531***	-0.0583	1.698***				
	(0.517)	(0.448)	(0.515)	(0.445)	(0.533)	(0.462)				
PSMpatgrey		0.612***		0.613***		0.631***				
		(0.0805)		(0.0799)		(0.0843)				
etcr2_ele	-0.0303**	-0.0209*	-0.0313***	-0.0226*	-0.0313***	-0.0241**				
	(0.0120)	(0.0116)	(0.0119)	(0.0116)	(0.0121)	(0.0118)				
lgdp	-1.106***	-1.332***	-1.094***	-1.306***	-1.132***	-1.386***				
	(0.120)	(0.135)	(0.119)	(0.132)	(0.120)	(0.135)				
Constant	9.878**	0.0396	10.87***	0.718	9.634**	0.509				
	(4.101)	(3.491)	(4.105)	(3.490)	(4.216)	(3.527)				
Observations	339	339	339	339	323	323				
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES				

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 16.A – Forward structure

VARIABLES	(1) HGG - GREY	(2) BGVR - GREY	(3) HGG - GREY	(4) BGVR - GREY	(5) HGG - GREY	(6) BGVR - GREY	(7) HGG - GREY	(8) BGVR - GREY	(9) HGG - GREY	(10) BGVR - GREY
eps_nonmarket	-0.0275**	-0.0321***								
	(0.0109)	(0.00987)								
F.eps_nonmarket			-0.0204*	-0.0216**						
			(0.0109)	(0.00966)						
F2.eps_nonmarket					-0.0225**	-0.0155*				
					(0.0110)	(0.00879)				
F3.eps_nonmarket							-0.0200*	-0.0129		
							(0.0116)	(0.00868)		
F4.eps_nonmarket									-0.00494	-0.00859
									(0.0118)	(0.00835)
KS_greenenergy	0.0708**	-0.0352	0.0714**	-0.0307	0.0838***	0.00128	0.0899***	0.0139	0.0895***	0.0353
	(0.0352)	(0.0370)	(0.0345)	(0.0367)	(0.0317)	(0.0299)	(0.0336)	(0.0310)	(0.0328)	(0.0327)
KS_othergreen	-0.136	-0.0611	-0.162*	-0.0997	-0.160*	-0.0712	-0.161*	-0.0997	-0.187*	-0.146**
	(0.0854)	(0.0762)	(0.0839)	(0.0753)	(0.0839)	(0.0694)	(0.0918)	(0.0708)	(0.0980)	(0.0733)
KS_grey	0.853***	0.810***	0.883***	0.858***	0.890***	0.836***	0.860***	0.802***	0.807***	0.760***
	(0.109)	(0.100)	(0.109)	(0.0992)	(0.109)	(0.0929)	(0.119)	(0.0940)	(0.126)	(0.0937)
L1. FKS_greenenergy	1.794***	0.303	1.759***	0.298	1.555***	-0.292	1.620***	-0.742**	1.698***	-0.918***
	(0.373)	(0.349)	(0.373)	(0.355)	(0.387)	(0.330)	(0.413)	(0.339)	(0.428)	(0.337)
L1.FKS_othergreen	-0.875**	-0.797**	-0.917**	-0.840**	-1.397***	-1.484***	-1.547***	-1.733***	-1.744***	-1.892***
	(0.433)	(0.348)	(0.436)	(0.355)	(0.433)	(0.297)	(0.459)	(0.287)	(0.494)	(0.285)
L1.FKS_grey	-0.318	1.368***	-0.206	1.497***	0.0395	2.006***	0.229	2.471***	0.349	2.692***
	(0.507)	(0.448)	(0.512)	(0.458)	(0.498)	(0.381)	(0.526)	(0.373)	(0.556)	(0.363)
PSMpatgrey		0.640***		0.628***		0.796***		0.904***		0.971***
		(0.0798)		(0.0809)		(0.0802)		(0.0833)		(0.0848)
etcr2_ele	-0.0287**	-0.0215*	-0.0293**	-0.0227**	-0.0292**	-0.0129	-0.0346***	-0.0181*	-0.0374***	-0.0196*
	(0.0120)	(0.0115)	(0.0119)	(0.0115)	(0.0116)	(0.0104)	(0.0119)	(0.0102)	(0.0120)	(0.0101)
lgdp	-1.105***	-1.337***	-1.121***	-1.368***	-1.092***	-1.231***	-1.024***	-1.127***	-0.964***	-1.037***
	(0.114)	(0.123)	(0.116)	(0.125)	(0.118)	(0.116)	(0.124)	(0.111)	(0.128)	(0.109)
Constant	10.63***	1.608	10.21***	1.046	12.43***	1.707	10.69**	0.270	10.39**	-0.606
	(3.916)	(3.284)	(3.956)	(3.382)	(3.985)	(3.128)	(4.169)	(2.973)	(4.372)	(2.846)
Observations	337	337	338	338	323	323	307	307	291	291
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 16.B – Lagged structure

VARIABLES	(1) HGG - GREY	(2) BGVR - GREY	(3) HGG - GREY	(4) BGVR - GREY	(5) HGG - GREY	(6) BGVR - GREY	(7) HGG - GREY	(8) BGVR - GREY	(9) HGG - GREY	(10) BGVR - GREY
eps_nonmarket	-0.0275**	-0.0321***								
	(0.0109)	(0.00987)								
L.eps_nonmarket			-0.0268**	-0.0425***						
			(0.0110)	(0.0113)						
L2.eps_nonmarket					-0.0202*	-0.0351***				
					(0.0113)	(0.0119)				
L3.eps_nonmarket							-0.00868	-0.0216*		
							(0.0113)	(0.0115)		
L4.eps_nonmarket									0.00233	-0.00670
									(0.0117)	(0.0119)
KS_greenenergy	0.0708**	-0.0352	0.0840**	-0.0252	0.111***	0.00390	0.153***	0.0496	0.155***	0.0694
	(0.0352)	(0.0370)	(0.0348)	(0.0381)	(0.0360)	(0.0400)	(0.0363)	(0.0406)	(0.0385)	(0.0423)
KS_othergreen	-0.136	-0.0611	-0.127	-0.000996	-0.149*	-0.0256	-0.217**	-0.129	-0.225**	-0.185**
	(0.0854)	(0.0762)	(0.0863)	(0.0814)	(0.0896)	(0.0881)	(0.0887)	(0.0872)	(0.0893)	(0.0877)
KS_grey	0.853***	0.810***	0.884***	0.781***	0.914***	0.791***	0.858***	0.779***	0.979***	0.899***
	(0.109)	(0.100)	(0.109)	(0.102)	(0.115)	(0.110)	(0.122)	(0.115)	(0.132)	(0.125)
L1. FKS_greenenergy	1.794***	0.303	1.529***	0.203	1.544***	0.354	1.748***	0.564	1.568***	0.635
	(0.373)	(0.349)	(0.378)	(0.344)	(0.396)	(0.361)	(0.410)	(0.386)	(0.427)	(0.403)
L1.FKS_othergreen	-0.875**	-0.797**	-1.018**	-0.866**	-0.957**	-0.792**	-0.773	-0.724*	-0.769	-0.704*
	(0.433)	(0.348)	(0.439)	(0.341)	(0.454)	(0.363)	(0.473)	(0.396)	(0.484)	(0.427)
L1.FKS_grey	-0.318	1.368***	0.0827	1.389***	0.172	1.353***	-0.203	1.167**	-0.0318	1.161**
	(0.507)	(0.448)	(0.517)	(0.426)	(0.538)	(0.451)	(0.580)	(0.504)	(0.606)	(0.551)
PSMpatgrey		0.640***		0.613***		0.573***		0.553***		0.484***
		(0.0798)		(0.0816)		(0.0864)		(0.0915)		(0.0979)
etcr2_ele	-0.0287**	-0.0215*	-0.0278**	-0.0166	-0.0275**	-0.0174	-0.0312***	-0.0236**	-0.0303**	-0.0243*
	(0.0120)	(0.0115)	(0.0120)	(0.0118)	(0.0121)	(0.0121)	(0.0119)	(0.0120)	(0.0124)	(0.0125)
lgdp	-1.105***	-1.337***	-1.111***	-1.248***	-1.155***	-1.288***	-1.177***	-1.365***	-1.268***	-1.419***
	(0.114)	(0.123)	(0.113)	(0.125)	(0.115)	(0.129)	(0.118)	(0.132)	(0.129)	(0.149)
Constant	10.63***	1.608	9.288**	1.408	8.272**	1.092	10.19**	2.807	10.00**	2.891
	(3.916)	(3.284)	(3.877)	(3.213)	(3.987)	(3.358)	(4.220)	(3.580)	(4.522)	(3.848)
Observations	337	337	334	334	318	318	302	302	286	286
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 17.A – Forward structure

VARIABLES	(1) HGG - GO	(2) BGVR - GO	(3) HGG - GO	(4) BGVR - GO	(5)	(6)	(7)	(8)	(9)	(10)
eps	-0.0120	-0.0938***								
	(0.0315)	(0.0281)								
F.eps			0.00888	-0.0395						
			(0.0322)	(0.0284)						
KS_greenenergy	0.204***	0.0609	0.190***	0.0496						
	(0.0697)	(0.0680)	(0.0689)	(0.0690)						
KS_othergreen	0.422***	0.626***	0.386**	0.604***						
	(0.159)	(0.135)	(0.159)	(0.140)						
KS_grey	0.0294	-0.456***	0.0603	-0.391**						
	(0.191)	(0.165)	(0.193)	(0.171)						
L1. FKS_greenenergy	1.277***	-0.0819	1.220***	0.0232						
	(0.457)	(0.302)	(0.471)	(0.337)						
L1.FKS_othergreen	-1.436**	-1.042**	-1.492**	-0.983**						
	(0.592)	(0.437)	(0.600)	(0.461)						
L1.FKS_grey	0.187	1.107**	0.277	1.108**						
	(0.709)	(0.510)	(0.735)	(0.560)						
PSMpatgo		0.587***		0.557***						
		(0.0817)		(0.0800)						
etcr2_ele	0.00956	0.00575	0.00857	0.00659						
	(0.0216)	(0.0196)	(0.0218)	(0.0201)						
lgdp	-0.558***	-0.104	-0.567***	-0.190						
	(0.145)	(0.144)	(0.146)	(0.158)						
Constant	7.378	-1.537	7.463	-1.769						
	(5.183)	(3.117)	(5.209)	(3.420)						
Observations	337	337	338	338						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 17.B – Lagged structure

VARIABLES	(1) HGG - GO	(2) BGVR - GO	(3) HGG - GO	(4) BGVR - GO	(5) HGG - GO	(6) BGVR - GO	(7) HGG - GO	(8) BGVR - GO	(9) HGG - GO	(10) BGVR - GO
eps	-0.0120	-0.0938***								
	(0.0315)	(0.0281)								
L.eps			0.000895	-0.0931***						
			(0.0318)	(0.0293)						
L2.eps					-0.0232	-0.0972***				
					(0.0324)	(0.0306)				
L3.eps							-0.0255	-0.126***		
							(0.0354)	(0.0340)		
L4.eps									-0.0237	-0.102***
									(0.0369)	(0.0348)
KS_greenenergy	0.204***	0.0609	0.222***	0.0779	0.212***	0.0709	0.239***	0.0891	0.217***	0.00270
	(0.0697)	(0.0680)	(0.0687)	(0.0684)	(0.0712)	(0.0712)	(0.0759)	(0.0756)	(0.0824)	(0.0661)
KS_othergreen	0.422***	0.626***	0.420***	0.644***	0.421***	0.643***	0.419**	0.689***	0.381**	0.705***
	(0.159)	(0.135)	(0.156)	(0.134)	(0.157)	(0.142)	(0.165)	(0.146)	(0.170)	(0.115)
KS_grey	0.0294	-0.456***	0.0710	-0.433***	0.132	-0.418**	0.111	-0.493***	0.243	-0.0144
	(0.191)	(0.165)	(0.187)	(0.165)	(0.193)	(0.180)	(0.205)	(0.191)	(0.215)	(0.166)
L1.FKS_greenenergy	1.277***	-0.0819	1.131**	-0.139	0.906*	-0.0823	1.108**	-0.0288	0.931*	-0.240**
	(0.457)	(0.302)	(0.460)	(0.303)	(0.473)	(0.334)	(0.497)	(0.340)	(0.521)	(0.112)
L1.FKS_othergreen	-1.436**	-1.042**	-1.546***	-1.130**	-1.731***	-1.149**	-1.724***	-1.183**	-1.703***	-0.926***
	(0.592)	(0.437)	(0.592)	(0.441)	(0.603)	(0.469)	(0.620)	(0.470)	(0.638)	(0.312)
L1.FKS_grey	0.187	1.107**	0.665	1.307**	1.079	1.434**	1.059	1.383**	1.198	0.802***
	(0.709)	(0.510)	(0.724)	(0.526)	(0.744)	(0.578)	(0.761)	(0.583)	(0.781)	(0.310)
PSMpatgo		0.587***		0.567***		0.575***		0.587***		0.242***
		(0.0817)		(0.0872)		(0.0928)		(0.0986)		(0.0845)
etcr2_ele	0.00956	0.00575	0.0100	0.00727	0.00488	0.00501	-0.00329	0.000257	0.00124	0.0192
	(0.0216)	(0.0196)	(0.0216)	(0.0196)	(0.0216)	(0.0199)	(0.0218)	(0.0199)	(0.0225)	(0.0192)
Lgdp	-0.558***	-0.104	-0.589***	-0.122	-0.646***	-0.223	-0.675***	-0.216	-0.698***	0.0150
	(0.145)	(0.144)	(0.144)	(0.146)	(0.144)	(0.162)	(0.149)	(0.167)	(0.150)	(0.0526)
Constant	7.378	-1.537	4.597	-2.435	3.958	-2.481	3.331	-1.924	2.462	-2.375*
	(5.183)	(3.117)	(5.141)	(3.043)	(5.156)	(3.355)	(5.385)	(3.390)	(5.659)	(1.404)
Observations	337	337	334	334	318	318	302	302	286	286
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 18.A – Forward structure

VARIABLES	(1) HGG - GO	(2) BGVR - GO	(3) HGG - GO	(4) BGVR - GO	(5) HGG - GO	(6) BGVR - GO	(7) HGG - GO	(8) BGVR - GO	(9) HGG - GO	(10) BGVR - GO
eps_market	-0.000234	-0.0440*								
	(0.0294)	(0.0251)								
F.eps_market			-0.0123	-0.0416*						
			(0.0287)	(0.0240)						
F2.eps_market					-0.0330	-0.0476**				
					(0.0281)	(0.0236)				
F3.eps_market							-0.0469	-0.0694***		
							(0.0300)	(0.0235)		
F4.eps_market									-0.0153	-0.0735***
									(0.0327)	(0.0242)
KS_greenenergy	0.148**	0.0522	0.151**	0.0489	0.128**	0.0440	0.130**	0.0619	0.146**	0.108*
	(0.0639)	(0.0561)	(0.0636)	(0.0559)	(0.0587)	(0.0525)	(0.0612)	(0.0542)	(0.0662)	(0.0618)
KS_othergreen	0.374**	0.602***	0.375**	0.605***	0.482***	0.656***	0.486***	0.640***	0.493**	0.588***
	(0.159)	(0.140)	(0.160)	(0.141)	(0.162)	(0.140)	(0.180)	(0.145)	(0.200)	(0.155)
KS_grey	0.0822	-0.411**	0.0614	-0.416**	-0.136	-0.549***	-0.184	-0.606***	-0.199	-0.614***
	(0.191)	(0.173)	(0.194)	(0.174)	(0.203)	(0.178)	(0.217)	(0.177)	(0.230)	(0.178)
L1.FKS_greenenergy	1.158**	-0.0483	1.180***	0.00613	1.578***	0.246	1.455***	-0.158	1.585***	-0.332
	(0.454)	(0.328)	(0.454)	(0.331)	(0.476)	(0.364)	(0.499)	(0.336)	(0.520)	(0.319)
L1.FKS_othergreen	-1.565**	-1.090**	-1.594***	-1.052**	-1.389**	-0.945**	-1.673**	-1.344***	-1.546**	-1.605***
	(0.612)	(0.455)	(0.604)	(0.454)	(0.612)	(0.464)	(0.687)	(0.470)	(0.770)	(0.491)
L1.FKS_grey	0.301	1.216**	0.254	1.121**	-0.484	0.854	-0.175	1.305**	-0.148	1.638***
	(0.721)	(0.546)	(0.725)	(0.550)	(0.762)	(0.577)	(0.809)	(0.551)	(0.889)	(0.550)
PSMpatgo		0.564***		0.556***		0.582***		0.626***		0.623***
		(0.0807)		(0.0799)		(0.0791)		(0.0826)		(0.0834)
etcr2_ele	0.00628	0.00516	0.00673	0.00741	0.00296	0.000411	-0.00456	-0.00753	-0.0122	-0.0108
	(0.0218)	(0.0199)	(0.0218)	(0.0198)	(0.0210)	(0.0195)	(0.0216)	(0.0192)	(0.0221)	(0.0190)
lgdp	-0.557***	-0.169	-0.542***	-0.163	-0.534***	-0.191	-0.428***	-0.0223	-0.444**	0.104
	(0.147)	(0.157)	(0.149)	(0.157)	(0.156)	(0.153)	(0.160)	(0.137)	(0.182)	(0.121)
Constant	8.159	-1.685	8.650	-1.426	12.73**	-0.0391	11.70**	-0.630	9.894*	-2.139
	(5.260)	(3.408)	(5.298)	(3.429)	(5.470)	(3.723)	(5.455)	(3.307)	(5.523)	(3.013)
Observations	339	339	339	339	323	323	307	307	291	291
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 18.B – Lagged structure

VARIABLES	(1) HGG - GO	(2) BGVR - GO	(3) HGG - GO	(4) BGVR - GO	(5)	(6)	(7)	(8)	(9)	(10)
eps_market	-0.000234	-0.0440*								
	(0.0294)	(0.0251)								
L.eps_market			0.00869	-0.0359						
			(0.0298)	(0.0265)						
KS_greenenergy	0.148**	0.0522	0.146**	0.0546						
	(0.0639)	(0.0561)	(0.0639)	(0.0565)						
KS_othergreen	0.374**	0.602***	0.374**	0.586***						
	(0.159)	(0.140)	(0.159)	(0.141)						
KS_grey	0.0822	-0.411**	0.0899	-0.379**						
	(0.191)	(0.173)	(0.190)	(0.172)						
L1. FKS_greenenergy	1.158**	-0.0483	1.167**	-0.0849						
	(0.454)	(0.328)	(0.456)	(0.339)						
L1.FKS_othergreen	-1.565**	-1.090**	-1.538**	-1.087**						
	(0.612)	(0.455)	(0.610)	(0.461)						
L1.FKS_grey	0.301	1.216**	0.298	1.296**						
	(0.721)	(0.546)	(0.722)	(0.559)						
PSMpatgo		0.564***		0.566***						
		(0.0807)		(0.0817)						
etcr2_ele	0.00628	0.00516	0.00684	0.00318						
	(0.0218)	(0.0199)	(0.0219)	(0.0203)						
lgdp	-0.557***	-0.169	-0.562***	-0.213						
	(0.147)	(0.157)	(0.145)	(0.155)						
Constant	8.159	-1.685	7.919	-1.849						
	(5.260)	(3.408)	(5.233)	(3.497)						
Observations	339	339	339	339						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 19.A – Forward structure

VARIABLES	(1) HGG - GO	(2) BGVR - GO	(3) HGG - GO	(4) BGVR - GO	(5)	(6)	(7)	(8)	(9)	(10)
eps_nonmarket	-0.0108	-0.0587***								
	(0.0210)	(0.0191)								
F.eps_nonmarket			0.0141	-0.00871						
			(0.0209)	(0.0183)						
KS_greenenergy	0.203***	0.0563	0.191***	0.0526						
	(0.0697)	(0.0683)	(0.0687)	(0.0688)						
KS_othergreen	0.426***	0.623***	0.380**	0.589***						
	(0.159)	(0.134)	(0.160)	(0.141)						
KS_grey	0.0333	-0.377**	0.0595	-0.335**						
	(0.188)	(0.161)	(0.191)	(0.167)						
L1. FKS_greenenergy	1.288***	-0.110	1.186**	-0.0395						
	(0.459)	(0.312)	(0.470)	(0.349)						
L1.FKS_othergreen	-1.405**	-1.023**	-1.541**	-1.048**						
	(0.592)	(0.442)	(0.606)	(0.470)						
L1.FKS_grey	0.176	1.180**	0.316	1.270**						
	(0.709)	(0.520)	(0.729)	(0.569)						
PSMpatgo		0.569***		0.551***						
		(0.0816)		(0.0808)						
etcr2_ele	0.00955	0.00883	0.00934	0.00753						
	(0.0216)	(0.0196)	(0.0219)	(0.0203)						
lgdp	-0.561***	-0.169	-0.564***	-0.252						
	(0.143)	(0.145)	(0.144)	(0.155)						
Constant	7.167	-1.909	7.658	-1.985						
	(5.154)	(3.153)	(5.172)	(3.525)						
Observations	337	337	338	338						
Fixed Effects - Time Dummies	YES	YES	YES	YES						

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 19.B – Lagged structure

VARIABLES	(1) HGG – GO	(2) BGVR - GO	(3) HGG - GO	(4) BGVR - GO	(5) HGG - GO	(6) BGVR - GO	(7) HGG - GO	(8) BGVR - GO	(9) HGG - GO	(10) BGVR - GO
eps_nonmarket	-0.0108	-0.0587***								
	(0.0210)	(0.0191)								
L.eps_nonmarket			-0.00149	-0.0664***						
			(0.0215)	(0.0203)						
L2.eps_nonmarket					-0.0263	-0.0854***				
					(0.0216)	(0.0215)				
L3.eps_nonmarket							-0.0244	-0.109***		
							(0.0236)	(0.0226)		
L4.eps_nonmarket									-0.0273	-0.0841***
									(0.0239)	(0.0239)
KS_greenenergy	0.203***	0.0563	0.223***	0.0703	0.211***	0.0510	0.234***	0.00892	0.212***	-0.0130
	(0.0697)	(0.0683)	(0.0685)	(0.0682)	(0.0713)	(0.0707)	(0.0759)	(0.0615)	(0.0820)	(0.0566)
KS_othergreen	0.426***	0.623***	0.423***	0.658***	0.444***	0.683***	0.435***	0.718***	0.403**	0.712***
	(0.159)	(0.134)	(0.158)	(0.131)	(0.157)	(0.136)	(0.165)	(0.108)	(0.169)	(0.0981)
KS_grey	0.0333	-0.377**	0.0685	-0.377**	0.123	-0.379**	0.106	-0.0305	0.217	0.110
	(0.188)	(0.161)	(0.186)	(0.159)	(0.189)	(0.169)	(0.200)	(0.209)	(0.213)	(0.123)
L1.FKS_greenenergy	1.288***	-0.110	1.133**	-0.162	0.938**	-0.145	1.134**	-0.206*	1.026*	-0.229***
	(0.459)	(0.312)	(0.461)	(0.291)	(0.476)	(0.304)	(0.501)	(0.105)	(0.531)	(0.0798)
L1.FKS_othergreen	-1.405**	-1.023**	-1.543***	-1.107**	-1.662***	-1.090**	-1.651***	-0.992***	-1.567**	-0.839***
	(0.592)	(0.442)	(0.593)	(0.435)	(0.604)	(0.451)	(0.626)	(0.338)	(0.651)	(0.253)
L1.FKS_grey	0.176	1.180**	0.660	1.290**	1.014	1.331**	0.987	0.842**	1.024	0.719***
	(0.709)	(0.520)	(0.725)	(0.512)	(0.740)	(0.545)	(0.763)	(0.342)	(0.800)	(0.245)
PSMpatgo		0.569***		0.543***		0.556***		0.249*		0.179***
		(0.0816)		(0.0877)		(0.0961)		(0.129)		(0.0550)
etcr2_ele	0.00955	0.00883	0.0100	0.0145	0.00641	0.0148	-0.00123	0.0262	0.00430	0.0325*
	(0.0216)	(0.0196)	(0.0215)	(0.0195)	(0.0214)	(0.0195)	(0.0218)	(0.0195)	(0.0226)	(0.0186)
lgdp	-0.561***	-0.169	-0.586***	-0.133	-0.635***	-0.183	-0.662***	-0.0270	-0.683***	-0.0328
	(0.143)	(0.145)	(0.144)	(0.140)	(0.143)	(0.158)	(0.148)	(0.0533)	(0.150)	(0.0445)
Constant	7.167	-1.909	4.573	-2.599	3.640	-2.501	3.076	-1.861	2.381	-2.435**
	(5.154)	(3.153)	(5.146)	(2.918)	(5.104)	(3.057)	(5.345)	(1.314)	(5.619)	(1.128)
Observations	337	337	334	334	318	318	302	302	286	286
Fixed Effects - Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix B. Environmental Patents: Search strategy for each sub - category.

1. ENVIRONMENTAL MANAGEMENT	IPC class
1.1. AIR POLLUTION ABATEMENT	All classes from 1.1.1 to 1.1.3
1.1.1. Emissions Abatement from stationary sources (e.g. SOx, NOx, PM emissions from combustion plants)	
Post--combustion technologies	
Chemical or biological purification of waste gases (e.g. engine exhaust gases, smoke, fumes, flue gases or aerosols;; removing sulfur	B01D53/34--72
Incinerators or other apparatus specially adapted for consuming waste gases or noxious gases	F23g7/06
Arrangements of devices for treating smoke or fumes of purifiers, e.g. for removing noxious material	F23J15
Shaft or like vertical or substantially vertical furnaces;; Arrangements of dust collectors	F27B1/18
Integrated technologies	
Blast furnaces;; Dust arresters	C21B7/22
Manufacture of carbon steel, e.g. plain mild steel, medium carbon steel, or cast--steel;; Removal of waste gases or dust	C21C5/38
Combustion apparatus characterised by means for returning flue gases to the combustion chamber or to the combustion zone	F23B80
Combustion apparatus characterised by arrangements for returning combustion products or flue gases to the combustion chamber	F23C9
Apparatus in which combustion takes place in a fluidised bed of fuel or other particles	F23C10
1.1.2. Emissions Abatement from mobile sources (e.g. NOx, CO, HC, PM emissions from motor vehicles)	
Post--combustion technologies	
Processes, apparatus or devices specially adapted for purification of engine exhaust gases	B01D53/92
	B01D53/94
Regeneration, reactivation or recycling of reactants	B01D53/96
Catalysts comprising metals or metal oxides or hydroxides;; of noble metals;; of the platinum group metals	B01J23/38--46
Crankcase ventilating or breathing	F01M13/02--04
Methods of operating engines involving adding non--fuel substances including exhaust gas to combustion air, fuel, or fuel--air mixtures of	F02B47/08--10
Controlling engines characterised by their being supplied with non--fuel gas added to combustion--air, such as the exhaust gas of engine,	F02D21/06--10
Engine--pertinent apparatus for adding exhaust gases to combustion--air, main fuel, or fuel--air mixture	F02M25/07
Testing of internal--combustion engines by monitoring exhaust gases	g01M15/10
Integrated technologies	
Methods of operating engines involving adding non--fuel substances or anti--knock agents to combustion air, fuel, or fuel--air mixtures of	F02B47/06
Electrical control of supply of combustible mixture or its constituents	F02D41
Conjoint electrical control of two or more functions, *e.g.* ignition, fuel--air mixture, recirculation, supercharging, exhaust--gas treatment	F02D43
Electrical control of combustion engines	F02D45
Idling devices for preventing flow of idling fuel	F02M3/02--055
Apparatus for adding secondary air to fuel--air mixture.	F02M23
Engine--pertinent apparatus for adding non--fuel substances or small quantities of secondary fuel to combustion--air, main fuel, or fuel--air	F02M25
Apparatus for treating combustion--air, fuel, or fuel--air mixture, by catalysts, electric means, magnetism, rays, sonic waves, etc.	F02M27
Apparatus for thermally treating combustion--air, fuel, or fuel--air mixture	F02M31/02--18
Fuel--injection apparatus	F02M39--71
Advancing or retarding ignition;; Control therefore	F02P5

1.1.3. Not eLsewhere cLAssified[24]	
Post--comBustion technoLogies	
Filters or filterinG processes specially modified for separatinG dispersed particles from Gases or vapours	B01D46
SeparatinG dispersed particles from Gases, air or vapours by liquid as separatinG aGent	B01D47
SeparatinG dispersed particles from Gases, air or vapours by other methods	B01D49
Combinations of devices for separatinG particles from Gases or vapours	B01D50
Auxiliary pre--treatment of Gases or vapours to be cleaned from dispersed particles	B01D51
SeparatinG dispersed particles from Gases or vapour, e.G. air, by electrostatic effect	B03C3
Exhaust or silencinG apparatus havinG means for purifyinG or renderinG innocuous	F01N3
Exhaust or silencinG apparatus combined or associated with devices profitinG by exhaust enerGy	F01N5
Exhaust or silencinG apparatus, or parts thereof	F01N7
Exhaust or silencinG apparatus characterised by constructional features	F01N13
Electrical control of exhaust Gas treatinG apparatus	F01N9
MonitorinG or diaGnostic devices for exhaust--Gas treatment apparatus	F01N11
IntegrAted technoLogies	
Use of additives to fuels or fires for particular purposes for reducinG smoke development	C10L10/02
Use of additives to fuels or fires for particular purposes for facilitatinG soot removal	C10L10/06
1.2. WATER POLLUTION ABATEMENT	All classes from 1.2.1 to 1.2.3
1.2.1. Water And wastewater treatment	
ArranGements of installations for treatinG waste--water or sewaGe	B63J4
Treatment of water, waste water, sewaGe or sludGe	C02F
Chemistry;; Materials for treatinG liquid pollutants, e.G. oil, Gasoline, fat	C09K3/32
PlumbinG installations for waste water	E03C1/12
Sewers Cesspools	E03F
1.2.2. Fertilizers from wastewater	
Fertilisers from waste water, sewaGe sludGe, sea slime, ooze or similar masses	C05F7
1.2.3. OiL spiLL cLeAnup	
Devices for cleaninG or keepinG clear the surface of open water from oil or like floatinG materials by separatinG or removinG these	E02B15/04--10
Vessels or like floatinG structures adapted for special purposes -- for collectinG pollution from open water	B63B35/32
Materials for treatinG liquid pollutants, e.G. oil, Gasoline or fat	C09K 3/32
1.3. WASTE MANAGEMENT	All classes from 1.3.1 to 1.3.6
1.3.1. Solid waste collection	
Street cleaninG;; RemovinG undesirable matter, e.G. rubbish, from the land, not otherwise provided for	E01H15
TransportinG;; GatherinG or removal of domestic or like refuse	B65F
1.3.2. Material recovery, recycling and re--use	
Animal feeding--stuffs from distillers' or brewers' waste;; waste products of dairy plant;; meat, fish, or bones;; from kitchen	A23K1/06--10
Footwear made of rubber waste	A43B1/12
Heels or top--pieces made of rubber waste	A43B21/14
Separating solid materials;; General arrangement of separating plant specially adapted for refuse	B03B9/06

[24] Including technologies potentially applicable to both stationary and mobile sources

Manufacture of articles from scrap or waste metal particles	B22F8
Preparing material;; Recycling the material	B29B7/66
Recovery of plastics or other constituents of waste material containing plastics	B29B17
Presses specially adapted for consolidating scrap metal or for compacting used cars	B30B9/32
Systematic disassembly of vehicles for recovery of salvageable components, e.g. for recycling	B62D67
Stripping waste material from cores or formers, e.g. to permit their re--use	B65H73
Applications of disintegrable, dissolvable or edible materials	B65D65/46
Compacting the glass batches, e.g. pelletizing	C03B1/02
Glass batch composition -- containing silicates, e.g. cullet	C03C6/02
Glass batch composition -- containing pellets or agglomerates	C03C6/08
Hydraulic cements from oil shales, residues or waste other than slag	C04B7/24--30
Calcium sulfate cements starting from phosphogypsum or from waste, e.g. purification products of smoke	C04B11/26
Use of agglomerated or waste materials or refuse as fillers for mortars, concrete or artificial stone;; Waste materials or	C04B18/04--10
Clay--wares;; Waste materials or Refuse	C04B33/132
Recovery or working--up of waste materials (plastics)	C08J11
Luminescent, e.g. electroluminescent, chemiluminescent, materials;; Recovery of luminescent materials	C09K11/01
Working--up used lubricants to recover useful products	C10M175
Working--up raw materials other than ores, e.g. scrap, to produce non--ferrous metals or compounds thereof	C22B7
Obtaining zinc or zinc oxide;; From muffle furnace residues;; From metallic residues or scraps	C22B19/28--30
Obtaining tin;; From scrap, especially tin scrap	C22B25/06
Textiles;; Disintegrating fibre--containing articles to obtain fibres for re--use	D01g11
Paper--making;; Fibrous raw materials or their mechanical treatment -- using waste paper	D21B1/08--10
Paper--making;; Fibrous raw materials or their mechanical treatment;; Defibrating by other means -- of waste paper	D21B1/32
Paper--making;; Other processes for obtaining cellulose;; Working--up waste paper	D21C5/02
Paper--making;; Pulping;; Non--fibrous material added to the pulp;; Waste products	D21H17/01
Apparatus or processes for salvaging material from electric cables	H01B 15/00
Recovery of material from discharge tubes or lamps	H01J 9/52
Reclaiming serviceable parts of waste cells or batteries	H01M 6/52
Reclaiming serviceable parts of waste accumulators	H01M 10/54
1.3.3. Fertilizers from waste	
Fertilisers made from animal corpses, or parts thereof	C05F1
Fertilisers from distillery wastes, molasses, vinasses, sugar plant, or similar wastes or residues	C05F5
Fertilisers from waste water, sewage sludge, sea slime, ooze or similar masses	C05F7
Fertilizers from household or town refuse	C05F9
Preparation of fertilizers characterized by the composting step	C05F17
1.3.4. Incineration and energy recoVery	
Solid fuels essentially based on materials of non--mineral origin;; on sewage, house, or town refuse;; on industrial residues or waste	C10L5/46--48
Cremation furnaces;; Incineration of waste;; Incinerator constructions;; Details, accessories or control therefor	F23G5
Cremation furnaces;; Incinerators or other apparatus specially adapted for consuming specific waste or low grade fuels	F23G7
1.3.5. Landfilling	
[Search strategy currently not available] *Note: Landfilling patents are largely covered by IPC class B09B. However, this class also covers many aspects of recycling and inceneration. Therefore B090B is used only to generate aggregate "waste management" counts*	

1.3.6. Waste management Not elsewhere classified	
Disposal of solid waste	B09B
Production of liquid hydrocarbon mixtures from rubber or rubber waste	C10G1/10
Medical or veterinary science;; Disinfection or sterilising methods specially adapted for refuse	A61L11
1.4. SOIL REMEDIATION	
Reclamation of contaminated soil	B09C
1.5. ENVIRONMENTAL MONITORING	
Monitoring or diagnostic devices for exhaust--Gas treatment apparatus	F01N11
Alarms responsive to a single specified undesired or abnormal condition and not otherwise provided for, e.G. pollution alarms;;	G08B21/12--14
Note: This search strategy is under development, the counts generated are most likely incomplete.	

2. WATER--RELATED ADAPTATION TECHNOLOGIES	**IPC or CPC class**
2.1. DEMAND--SIDE TECHNOLOGIES (water conservation)	
2.1.1. Indoor water conservation	
Faucets and showers	
Self--closing valves	
Self--closing valves, i.e. closing automatically after operation, in which the closing movement, either retarded or not, starts immediately	F16K21/06--12
Self--closing valves, i.e. closing automatically after operation, closing after a predetermined quantity of fluid has been delivered	F16K 21/16--20
Aeration of water	
Arrangement or mounting of devices, e.g. valves, for venting or aerating or draining	F16L 55/07
Jet regulators with aerating means	E03C 1/084
Sanitation (dual--flush toilets, dry toilets, closed--circuit toilets)	
Flushing devices discharging variable quantities of water	E03D 3/12
Cisterns discharging variable quantities of water	E03D 1/14
Urinals without flushing	A47K 11/12
Dry closets	A47K 11/02
Waterless or low--flush urinals	E03D13/007
Special constructions of flushing devices with recirculation of bowl--cleaning fluid	E03D5/016
Greywater	
Greywater supply systems	E03B1/041
Home appLiances	
Optimisation of water quantity (for dishwashers)	Y02B 40/46
Optimisation of water quantity (for washing machines)	Y02B 40/56
2.1.2. Irrigation water conservation	
Drip irrigation	
Watering arrangements located above the soil which make use of perforated pipe--lines or pipe--lines with dispensing fittings, e.g. for drip	A01G 25/02
Watering arrangements making use of perforated pipe--lines located in the soil	A01G 25/06

Control of watering	
Control of watering	A01G 25/16
Drought--resistant crops	
Mutation or genetic engineering;; DNA or RNA concerning genetic engineering, vectors, e.g. plasmids, or their isolation, preparation or	C12N15/8273
2.1.3. Water conservation in thermoelectric power production	
Combustion heat from one cycle heating the fluid in another cycle	F01K 23/08--10
Non--positive--displacement machines or engines, e.g. steam turbines / Preventing or minimizing internal leakage of working fluid, e.g.	F01D 11
2.1.4. Water distribution	
Piping reducing leakage and leakage monitoring	
Pipe--line systems / Protection or supervision of installations / Preventing, monitoring, or locating loss	[F17D5/02 and E03]
Devices for covering leaks in pipes or hoses, e.g. hose--menders	[F16L55/16 and E03]
Investigating fluid tightness of structures, by detecting the presence of fluid at the leakage point	[G01M 3/08 or G01M 3/14 or G01M 3/18 or G01M 3/22 or G01M 3/28] and E03
2.2. SUPPLY--SIDE TECHNOLOGIES (water availability)	
2.2.1. Water collection (rain, surface and ground--water)	
Underground water collection	
Use of pumping plants or installations	E03B 5
Methods or installations for obtaining or collecting drinking water or tap water from underground	E03B 3/06--26
Surface water collection	
Methods or installations for drawing--off water	E03B 9
Methods or installations for obtaining or collecting drinking water or tap water from surface water	E03B 3/04;; 28--38
Rainwater water collection	
Methods or installations for obtaining or collecting drinking water or tap water from rainwater	E03B 3/02
Special vessels for collecting or storing rain--water for use in the household, e.g. water--butts	E03B 3/03
Not elsewhere classified	
Methods or installations for obtaining or collecting drinking water or tap water;; rainwater, surface water, or groundwater	E03B 3/00 E03B 3/40
2.2.2. Water storage	
Arrangements or adaptations of tanks for water supply	E03B 11
2.2.3. Desalination of sea water	
[Search strategy under development]	

3. BIODIVERSITY PROTECTION AND ECOSYSTEM HEALTH	**IPC or CPC cLAss**
[Search strategy currently not available]	

4. CLIMATE CHANGE MITIGATION technologies related to energy generation, transmission of distribution	**Y02E**
4.1. RENEWABLE ENERGY GENERATION	**Y02E10**
4.1.1. Wind energy	Y02E10/70
Wind turbines with rotation axis in wind direction: blades or rotors, components or gearbox, control of turbines, generator, nacelles, onshore and offshore towers Wind turbines with rotation axis perpendicular to the wind direction Power conversion electric or electronic aspects;; for grid--connected applications;; concerning power management	Y02E10/70--766
4.1.2. Solar thermal energy	Y02E10/40
Tower concentrators;; Dish collectors;; Fresnel lenses;; Heat exchange systems;; Trough concentrators Conversion of thermal power into mechanical power, e.g. Rankine, Stirling solar thermal engines;; Thermal updraft Mountings or tracking	Y02E10/40--47
4.1.3. Solar photovoltaic (PV) energy	Y02E10/50
PV systems with concentrators Material technologies: CuInSe2 material PV cells;; Dye sensitized solar cells;; Solar cells from group II--VI materials;; Solar cells from group III--V materials;; Microcrystalline silicon PV cells;; Polycrystalline silicon PV cells;; Monocrystalline silicon PV cells;; Amorphous silicon PV cells;; Organic PV cells	Y02E10/50--58
4.1.4. Solar thermal--PV hybrids	Y02E10/60
4.1.5. Geothermal energy	Y02E10/10
Earth coil heat exchangers;; Compact tube assemblies, e.g. Geothermal probes Systems injecting medium directly into Ground, e.g. hot dry rock system, underground water Systems injecting medium into a closed well Systems exchanging heat with fluids in pipes, e.g. fresh water or waste water	Y02E10/10--18
4.1.6. Marine energy	Y02E10/30
Oscillating water column [OWC] Ocean thermal energy conversion [OTEC] Salinity gradient Wave energy or tidal swell, e.g. Pelamis--type	Y02E10/30--38
4.1.7. Hydro energy	Y02E10/20
Conventional, e.g. with dams, turbines and waterwheels Tidal, stream or damless hydropower, e.g. sea flood and ebb, river, stream	Y02E10/20--28
4.2. ENERGY GENERATION FROM FUELS OF NON--FOSSIL ORIGIN	**Y02E50**
4.2.1. Biofuels	Y02E50/10
CHP turbines for biofeed;; gas turbines for biofeed Bio--diesel Bio--pyrolysis;; Torrefaction of biomass Cellulosic bio--ethanol;; grain bio--ethanol;; Bio--alcohols produced by other means than fermentation	Y02E50/10--18
4.2.2. Fuel from waste	Y02E50/30
Synthesis of alcohols or diesel from waste including a pyrolysis and/or gasification step Methane production by fermentation of organic by--products, e.g. sludge;; Methane from landfill gas	Y02E50/30--346
4.3. COMBUSTION TECHNOLOGIES WITH MITIGATION POTENTIAL (e.g. using fossil fuels, BiomAss, wAste, etc.)	**Y02E20**
4.3.1. Technologies for improved output efficiency (Combined heat and power, combined cycles, etc.)	Y02E20/10--185
Heat utilisation in combustion or incineration of waste	Y02E20/12
Combined heat and power generation [CHP]	Y02E20/14
Combined cycle power plant [CCPP], or combined cycle gas turbine [CCGT]	Y02E20/16
Integrated gasification combined cycle [IGCC]	Y02E20/18
combined with carbon capture and storage [CCS]	Y02E20/185

4.3.2. Technologies for improved input efficiency (Efficient combustion or heat usage)	Y02E20/30--366
Direct CO2 mitigation: Use of synair, i.e. a mixture of recycled CO2 and pure O2;; Use of reactants before or during combustion;; Segregation from fumes, including use of reactants downstream from combustion or deep cooling;; Controls of combustion specifically inferring on CO2 emissions Indirect CO2 mitigation, i.e. by acting on non CO2 directly related matters of the process, e.g. more efficient use	
4.4. NUCLEAR ENERGY	**Y02E30**
4.4.1. Nuclear fusion reactors	
Magnetic plasma confinement [MPC]: Tokamaks;; Stellarators;; Other reactors with MPC;; First wall, divertor, blanket Inertial plasma confinement: Injection systems and targets	Y02E 30/10--18
4.4.2. Nuclear fission reactors	
Boiling water reactors;; Pressurized water reactors;; gas cooled reactors;; Fast breeder reactors;; Liquid metal reactors;; Pebble bed reactors;; Accelerator driven reactors Fuel Control of nuclear reactions	Y02E 30/30--40
4.5. TECHNOLOGIES FOR AN EFFICIENT ELECTRICAL POWER GENERATION, TRANSMISSION OR DISTRIBUTION	**Y02E40**
4.5.1. Superconducting electric elements or equipment	Y02E40/60--69
Superconducting generators: Superconducting synchronous generators;; Superconducting homopolar generators Superconducting transmission lines or power lines or cables or installations thereof Superconducting transformers or inductors Superconducting energy storage for power networks, e.g. SME, superconducting magnetic storage Protective or switching arrangements for superconducting elements or equipment Current limitation using superconducting elements, including multifunctional current limiters	
4.5.2. Not elsewhere classified	
Flexible AC transmission systems [FACTS] Static VAR compensators [SVC], static VAR generators [SVG] or static VAR systems [SVS], including thyristor--controlled reactors [TCR], thyristor--switched reactors [TSR] or thyristor--switched capacitors [TSC] Thyristor--controlled series capacitors [TCSC] Static synchronous compensators [STATCOM]	Y02E40/10--18
Active power filtering [APF] Non--specified or voltage--fed active power filters Current--fed active power filters;; using a multilevel or multicell converter	Y02E40/20--26
Reactive power compensation Reactive power compensation;; using synchronous generators;; for voltage regulation	Y02E40/30--34
Arrangements for reducing harmonics	Y02E40/40
Arrangements for eliminating or reducing asymmetry in polyphase networks	Y02E40/50
Smart Grids Systems characterised by the monitoring, control or operation of energy generation units, e.g. distributed generation [DER] or load--side generation;; Systems characterised by the monitoring, control or operation of flexible AC transmission	Y02E40/70
4.6. ENABLING TECHNOLOGIES (TechnoLogies with potentiaL or indirect contriBution to emissions mitigation)	**Y02E60**
4.6.1. Energy storage	**Y02E60/10--17**
4.6.1.1. Batteries	Y02E60/12
Lithium--ion batteries Alkaline secondary batteries, e.g. NiCd or NiMH Lead--acid batteries Hybrid cells	

4.6.1.2. Capacitors	Y02E60/13
Ultracapacitors, supercapacitors, double--layer capacitors	
4.6.1.3. Thermal storage	Y02E60/14
Sensible heat storage, latent heat storage, Cold storage	
4.6.1.4. Pressurised fluid storage	Y02E60/15
4.6.1.5. Mechanical storag	Y02E60/16
Mechanical energy storage, e.g. flywheels	
4.6.1.6. Pumped storage	Y02E60/17
4.6.2. Hydrogen technology	**Y02E60/30--368**
Hydrogen storage: Storage of liquefied, solidified, or compressed hydrogen in containers;; Storage in caverns;; Reversible uptake of hydrogen by an appropriate medium (e.g. carbon, metal, rare earth metal, metal alloy, organic compound) Hydrogen distribution Hydrogen production from non--carbon containing sources: by chemical reaction with metal hydrides, e.g. hydrolysis of metal borohydrides;; by decomposition of inorganic compounds, e.g. splitting of water other than electrolysis, ammonia borane;; by electrolysis of water;; by photo--electrolysis	
4.6.3. Fuel cells	**Y02E60/50--566**
Fuel cells characterised by type or design: Proton Exchange Membrane Fuel Cells [PEMFC], Direct Alcohol Fuel Cells [DAFC], Direct Methanol Fuel Cells [DMFC];; Solid Oxide Fuel Cells [SOFC];; Molten Carbonate Fuel Cells [MCFC];; Bio Fuel Cells;; Regenerative or indirect fuel cells, e.g. redox flow type batteries	
4.6.4. SmArt grids in the energy sector	**Y02E60/70**
Systems integrating technologies related to power network operation and communication or information technologies mediating in the improvement of the carbon footprint of electrical power generation, transmission or distribution, i.e. smart grids as enabling technology in the energy generation sector	Y02E60/70--7892
4.7. OTHER ENERGY CONVERSION OR MANAGEMENT SYSTEMS REDUCING GHG EMISSIONS	**Y02E70**
Hydrogen from electrolysis with energy of non--fossil origin, e.g. PV, wind power, nuclear Systems combining fuel cells with production of fuel of non--fossil origin Systems combining energy storage with energy generation of non--fossil origin Energy efficient batteries, ultracapacitors, supercapacitors or double--layer capacitors charging or discharging systems or methods, e.g. auxiliary power consumption reduction, resonant chargers or discharGers, resistive losses minimisation	

5. CAPTURE, STORAGE, SEQUESTRATION OR DISPOSAL OF GREENHOUSE GASES	**Y02C**
5.1. CO2 CAPTURE OR STORAGE (CCS)	**Y02C10**
Capture by biological separation Capture by chemical separation Capture by absorption Capture by adsorption Capture by membranes or diffusion Capture by rectification and condensation Subterranean or submarine CO2 storage	Y02C10/00--14
5.2. CAPTURE OR DISPOSAL OF GREENHOUSE GASES OTHER THAN CO2	**Y02C20**
of nitrous oxide (N2O) of methane of perfluorocarbons [PFC], hydrofluorocarbons [HFC] or sulfur hexafluoride [SF6]	Y02C20/00--30

6. CLIMATE CHANGE MITIGATION technologies related to TRANSPORTATION	Y02T
6.1. ROAD TRANSPORT	Y02T10
6.1.1. Conventional Vehicles (Based on internal combustion engine)	Y02T10/10--56
Integrated approaches	
Technologies for the improvement of indicated efficiency of a conventional internal combustion engine (ICE) o Adding non fuel substances to fuel, air or fuel/air mixture o Fuel injection o Combustion chambers and charge mixing enhancing inside the combustion chamber o Treating fuel, air or air/fuel mixture o Methods of operating, e.g. homogeneous charge compression ignition [HCCI], premixed charge compression ignition [PCCI] Technologies for the improvement of mechanical efficiency of a conventional ICE o Methods of operating, e.g. Atkinson cycle, Ericsson o Non naturally aspirated engines, e.g. turbocharging, supercharging o Charge mixing enhancing and kinetic or wave energy of charge outside the combustion chamber, i.e. ICE with external or indirect fuel injection o Downsizing or downspeeding Energy recuperation from low temperature heat sources of the ICE to produce additional power o Turbocompound engines o Waste heat recovering cycles or thermoelectric systems Non--reciprocating piston engines, e.g. rotating motors Varying inlet or exhaust valve operating characteristics Engine management systems o controlling air supply;; controlling fuel supply;; controlling ignition o Exhaust feedback o Switching off the internal combustion engine, e.g. stop and go Intelligent control systems e.g. conjoint control o relating to internal combustion engine fuel consumption o relating to internal combustion engine emissions o Optimising drivetrain operating point	Y02T10/12--18 Y02T10/40--48 Y02T10/50--56
Post--combustion approaches	
Exhaust after--treatment o Three way catalyst technology, i.e. oxidation or reduction at stoichiometric equivalence ratio o Selective Catalytic Reactors for reduction in oxygen rich atmosphere o Thermal conditioning of exhaust after--treatment	Y02T10/20--26
Fuel substitution	
Use of alternative fuels o Gaseous fuels o Non--Gaseous fuels o Multiple fuels, e.g. multi fuel engines o Non--fossil fuels	Y02T10/30--38
6.1.2. Hybrid Vehicles	Y02T10/62
using ICE and mechanical energy storage, e.g. flywheel using ICE and fluidic energy storage, e.g. pressure accumulator using ICE and electric energy storage, i.e. battery, capacitor: of the series type or range extenders;; of the parallel type;; of the series--parallel type;; with motor integrated into gearbox;; Driving a plurality of axles;; provided with means for plug--in Combining different types of energy storage: Battery and capacitor;; Battery and mechanical or fluidic energy	Y02T10/62--6295
6.1.3. Electric Vehicles	
Electric machine technologies for applications in electromobility	
Electric machine technologies for applications in electromobility o characterised by aspects of the electric machine o Control strategies of electric machines for automotive applications o Control strategies for ac machines other than vector control o Control strategies for dc machines o Number of electric drive machines: one, two, or more	Y02T10/64--649

Energy storage for electromobility	
Energy storage for electromobility Batteries, e.g. lithium ion battery, lead acid battery Capacitors, supercapacitors or ultracapacitors Mechanical energy storage devices, e.g. flywheels Energy storage management Electromobility--specific charging systems or methods for batteries, ultracapacitors, supercapacitors or double--layer capacitors	Y02T10/70--7094
Electric energy management in electromobility	
Electric energy management in electromobility Electric power conversion within the vehicle Optimisation of vehicle performance ○ automated control ○ Desired performance achievement ○ Optimisation of energy management ○ Route optimisation	Y02T10/72--7291
6.1.4. Fuel efficiency--improVing Vehicle design (common to all road Vehicles)	
Technologies aiming to reduce greenhouse gas (GHG) emissions common to all road transportation technologies Tools or systems for aerodynamic design Data processing systems or methods, management, administration Optimisation of rolling resistance: Tyres, e.g. materials, shape;; Bearings;; Others, e.g. wheel construction Optimized components or subsystems e.g. lighting, actively controlled glasses Energy harvesting concepts as power supply for auxiliaries' energy consumption e.g. photovoltaic sun--roof Energy efficient charging or discharging systems for batteries, ultracapacitors, supercapacitors or double--layer capacitors specially adapted for vehicles Energy--efficient charging or discharging systems for batteries, ultracapacitors, supercapacitors or double--layer	Y02T10/80--86 Y02T10/90--92
6.2. RAIL TRANSPORT	Y02T30
Transportation of goods or passengers via railways Energy recovery technologies concerning the propulsion system in locomotives or motor railcars ○ In electric locomotives or motor railcars with electric accumulators, e.g. involving regenerative braking ○ In locomotives or motor railcars with pneumatic accumulators ○ In locomotives or motor railcars with two or different kinds or types of engine ○ Specific power storing devices Other technological aspects of railway vehicles ○ Reducing air resistance by modifying contour ○ Composite;; Lightweight materials ○ Device for using the energy of the movements of the vehicle ○ Bogie frames comprising parts made from fiber--reinforced matrix material ○ Applications of solar cells or heat pipes, e.g. on ski--lift cabins or carriages for passengers or goods ○ concerning heating, ventilating or air conditioning	Y02T30/00--42
6.3. AIR TRANSPORT	Y02T50
Aeronautics or air transport Drag reduction ○ Overall configuration, shape or profile of fuselage or wings ○ Adaptive structures: Morphing wings or smart wings ○ by influencing airflow: Wing tip vortex reduction;; Winglets ○ by influencing the boundary layer Wing lift efficiency ○ Optimised high lift wing systems ○ Helicopter rotor blades lift efficiency Weight reduction ○ Airframe: Materials (composites, metallic lightweight);; Design measures ○ Interior: Materials;; Design measures On board measures aiming to increase energy efficiency ○ concerning the electrical systems: Energy recovery, conversion or storage;; Electric actuators or motors ○ Thermal management: Reduction of energy losses;; Optimization of hot and cold sources on board an aircraft Efficient propulsion technologies ○ Electrical ○ Hybrid ○ Propellers ○ Relevant aircraft propulsion technologies: Measures to reduce the propulsor weight (e.g. using composites);Improving the rotor blades aerodynamic;; Enabling an increased combustion temperature by cooling;; Controlling the propulsor to control the emissions;; using fuels of non--fossil origin	Y02T50/00--90

○ Solar cells as on board power source Enabling use of sustainable fuels ○ Synthetic fuels ○ Bio fuels Energy efficient operational measures ○ Related to ground operations: aircraft equipment, e.g. wheel embedded;; ground equipment ○ Related to management of trajectory and mission Eco design, i.e. taking into account the full life cycle of the craft including re--use, recyclability and disposal	
6.4. MARITIME OR WATERWAYS TRANSPORT	Y02T 70
Maritime or waterways transport Measures concerning design or construction of watercraft hulls ○ Improving hydrodynamics of hull: reducing surface friction (air lubrication, air cavity systems;; hull coatings, e.g. biomimicry), lower wave resistance (bow shape), improving wake pattern (reducing the interaction between hull and propeller) ○ Construction of hull: materials (e.g. ultra light steels, composites);; energy efficient measures related to fabrication or assembly of hull Measures at the maintenance or repair stage specially aiming at gHg emissions reduction ○ Surface or tank cleaning and treatment operations ○ Improved operation of fossil fuel transfer, e.g. ship--to--ship oil or gas transfer ○ Handling waste Measures to reduce GHG emissions related to the propulsion system ○ Propulsion power plant Relating to type of fuel: Less carbon--intensive fuels (e.g. natural gas, biofuels);; Non--conventional fuels (e.g. nuclear) Renewable or hybrid--electric solutions (e.g. solar, wind) Other measures to increase efficiency of the power plant: Engine monitoring and control;; Waste heat recovery;; Reducing auxiliary power ○ Propeller Improved propeller design Recovery of rotational energy Wake equalizing arrangements ○ Jets ○ Propulsion by direct use of wind: Energy--efficient technologies involving sails;; Kites ○ Other propulsion concepts for reducing GHG emissions, e.g. wave--powered Technologies for a more efficient operation of the waterborne vessel not otherwise provided for ○ Related to heatinG, ventilation, air conditioninG, or refriGeration systems ○ InteGratinG maritime voyaGe control: Speed reduction;; Weather routinG;; Course optimization Measures concerninG recyclinG, retrofittinG or dismantlinG of waterborne vessels Port equipment or systems reducinG GHG emissions	Y02T 70/00--90
6.5. ENABLING TECHNOLOGIES IN TRANSPORT	Y02T90
6.5.1. Electric Vehicle charging	
Electric charging stations ○ by conductive energy transmission;; by inductive energy transmission ○ by exchange of energy storage elements ○ alignment between the vehicle and the charging station ○ Converters or inverters for charging Plug--in electric vehicles Information or communication technologies [ICT] improving the operation of electric vehicles ○ Navigation ○ ICT for charging station selection (suitability, location, availability) ○ Smart grids as interface for battery charging of electric and hybrid vehicles;; Remote or cooperative charging operation;; aspects supporting the interoperability of electric or hybrid vehicles, e.g. recognition, authentication, identification or billing	Y02T 90/10--169
6.5.2. Application of fuel cell and hydrogen technology to transportation	
Application of fuel cell technology to transportation ○ Fuel cells specially adapted to transport applications, e.g. automobile, bus, ship ○ Fuel cell powered electric vehicles [FCEV] ○ Fuel cells as on--board power source in aeronautics ○ Fuel cells as on--board power source in waterborne transportation Application of hydrogen technology to transportation ○ Hydrogen as fuel for road transportation ○ Hydrogen as fuel in aeronautics ○ Hydrogen as fuel in waterborne transportation	Y02T 90/30--38 Y02T 90/40--46

7. CLIMATE CHANGE MITIGATION technologies related to buildings	Y02B
7.1. INTEGRATION OF RENEWABLE ENERGY SOURCES IN BUILDINGS	**Y02B10**
Photovoltaic [PV]: Roof systems for PV cells;; PV hubs Solar thermal: Evacuated solar collectors;; Air conditioning or refrigeration systems Wind power Geothermal heat--pumps Hydropower in dwellings Use of biomass for heating Hybrid systems;; Uninterruptible or back--up power supplies integrating renewable energies	Y02B 10/00--72
7.2. ENERGY EFFICIENCY IN BUILDINGS	
7.2.1. Lighting	Y02B20
Energy--efficient lighting: Energy saving technologies for incandescent lamps, e.g. halogen lamps gas discharge lamps, e.g. fluorescent lamps, high--intensity discharge lamps [HID], or molecular radiators Semiconductor lamps, e.g. solid state lamps [SSL], light emitting diodes [LED], or organic LED [OLED] Control techniques providing energy savings, e.g. timing or schedule, detection of the user, detection of the illumination level Used in particular applications (e.g. in street lighting)	Y02B 20/00--72
7.2.2. Heating, ventilation or air conditioning [HVAC]	Y02B30
Energy--efficient HVAC systems: relating to domestic heating, space heating or domestic hot water heating or supply systems [DHW] o using boilers (condensing boilers;; modular boilers) o Hot water central heating systems using heat pumps o Central heating systems having more than one heat source o Central heating systems using steam or condensate extracted or exhausted from steam engine plants o Domestic hot--water supply systems using recuperated or waste heat o Heat consumers: i.e. devices to provide the end user with heat (e.g. low--temperature radiators with increased heat--exchange surface;; heating arrangements used in combination with water central heating system) Systems profiting of external/internal conditions o Heat recovery pumps, i.e. heat pump based systems or units able to transfer the thermal energy from one area of the premises or part of the facilities to a different one, improving the overall efficiency o Free--cooling systems (e.g. air based, using dew point control, "Canadian well") o Heat recovery units (air to air;; water to water) Other technologies for heating or cooling o Absorption based systems (e.g. integrating CHP generation systems, i.e. trigeneration) o Adsorption based systems o Magnetic cooling Efficient control or regulation technologies o Electric or electronic refrigerant flow control o Technologies based on motor control (e.g. speed regulation of the compressor/pumps/fans;; condensing pressure control) o Centralised control (e.g. of heating or domestic hot water [DHW] systems;; of refrigeration machines, plants or systems, including combined heating and refrigeration systems;; of air distribution systems) o Ventilation adapted to air quality Ultrasonic humidifiers Passive houses;; Double facade technology	Y02B 30/00--94
7.2.3. Home appliances	Y02B40
Technologies aiming at improving the efficiency of home appliances Relating to domestic cooking o Induction cooking in kitchen stoves (e.g. control circuit, coil) o Microwave ovens (e.g. control circuit, magnetron) o Improved cooking stoves (e.g. fuel--efficient biomass cooking stoves, fuel--efficient gas cooking stoves) o Solar cooking stoves or furnaces Relating to refrigerators or freezers (e.g. compressors, fans, thermal insulation) Relating to dish--washers (e.g. pumps, heat recovery of washing water, optimisation of water quantity of hot water) Relating to washing machines (e.g. drum or pumps, heat recovery, optimisation of water quantity, solar heating) Relating to laundry dryers (e.g. drum or fans, solar heating) Related to vacuum cleaners Energy efficient batteries, ultracapacitors, supercapacitors or double--layer capacitors charging or discharging systems or methods specially adapted for portable applications	Y02B 40/00--90

7.2.4. Elevators, escalators and moving walkways	Y02B50
Energy--efficient elevators, escalators and moving walkways: in elevators ○ Energy saving technologies (e.g. by adapted call allocation, by adapting the motion profile) ○ Energy recuperation technologies (e.g. with electrical, mechanical, or pressure storage or by delivering current to the grid) in escalators and moving walkways ○ Energy saving technologies (e.g. by adapting the motion profile) ○ Energy recuperation technologies	Y02B 50/00--24
7.2.5. Information and communication technologies	Y02B60
Information and communication technologies [ICT] technologies aiming at the reduction of own energy use: Energy efficient computing ○ Reducing energy--consumption at the single machine level, e.g. processors, personal computers, peripheral devices, power supply (e.g. low--power processors, performance modes, cooling means, power mgmt) ○ Reducing energy--consumption by means of multiprocessor or multiprocessing based techniques, other than acting upon the power supply (e.g. resource allocation, scheduling, virtualisation, consolidation, load distribution) ○ Reducing energy--consumption in distributed systems (e.g. delegation or migration, resource sharing) ○ Reducing energy consumption at software or application level (e.g. compilation;; installation;; feedback, prediction, usage patterns;; suspending or hibernating, performance or eco--modes;; information retrieval in databases) Techniques for reducing energy--consumption in wire--line communication networks ○ using reduced link rate ○ using subset functionality ○ by operating in low--power or sleep mode High level techniques for reducing energy--consumption in communication networks ○ by proxying ○ by energy--aware routing ○ by signaling and coordination ○ green peer--to--peer Techniques for reducing energy--consumption in wireless communication networks	Y02B 60/00--50
7.2.6. End--user side	Y02B70
Technologies for an efficient end--user side electric power management and consumption: Technologies improving the efficiency by using switched--mode power supplies, i.e. efficient power electronics conversion ○ Power factor correction technologies for power supplies ○ Reduction of losses in power supplies ○ Efficient standby or energy saving modes, e.g. detecting absence of load or auto--off Systems integrating technologies related to power network operation and ICT for improving the carbon footprint, i.e. smart grids supporting the management or operation of end--user stationary applications ○ End--user application control systems (e.g. load shedding, peak shaving, other demand response systems;; domotics or building automation systems) ○ Smart metering supporting the carbon neutral operation of end--user applications in buildings Systems which determine the environmental impact of user behaviour Systems which monitor performance of renewable electricity generating systems, e.G. solar	Y02B 70/00--346
7.3. ARCHITECTURAL OR CONSTRUCTIONAL ELEMENTS IMPROVING THE THERMAL PERFORMANCE OF BUILDINGS	**Y02B80**
Architectural or constructional elements improving the thermal performance of buildings: Insulation (e.g. slab shaped vacuum insulation, aerogel insulation) Windows or doors (e.g. vacuum glazing, aerogel) Roofs (e.g. roof garden systems, roof coverings with high solar reflectance) Floors specially adapted for storing heat or cold Light--dependent control systems for sun shading	Y02B 80/00--50
7.4. ENABLING TECHNOLOGIES IN BUILDINGS	**Y02B90**
Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation: Applications of fuel cells in buildings ○ Cogeneration of electricity with other electric generators ○ Emergency, uninterruptible or back--up power supplies integrating fuel cells ○ Cogeneration or combined heat and power generation, e.g. for domestic hot water ○ Fuel cells specially adapted to portable applications, e.g. mobile phone, laptop Systems integrating technologies related to power network operation and ICT mediating in the improvement of the carbon footprint of the management of residential or tertiary loads, i.e. smart grids as enabling technology in buildings sector (e.g. related to uninterruptible power supply systems, remote reading systems, etc.)	Y02B 90/00--2692

Source: Hascic and Migotto, 2015.

An experimental approach to climate finance: The impact of auction design and policy uncertainty on renewable energy equity costs

Enrico Botta[a]

[a] Corresponding author: Università degli Studi di Milano e di Pavia,
Via Conservatorio, 7 - 20122 Milan – Italy. Tel. +39 02 503 21508.
Mail: Enrico.botta@unimi.it

Abstract

This paper aims at shedding some lights on how policy induced uncertainty affects the risk-return sought by investors in renewable energy generation capacity. To this end, the paper focuses on auction design and the ongoing Brexit negotiations. The first section of the paper reviews the main characteristics of auction frameworks across Europe and their impact on project risk. Then, a stated preference approach is leveraged to investigate how policy design and the uncertainty regarding the future arrangements between the UK and the EU contributes to determine the cost of equity for renewable energy. The results show that improved auction design can help to lower the equity cost between 0.5% and 1.5%, while the evidence on Brexit is rather weak and - if anything - suggests only a higher relevance of these negotiations for English-based investors than for those based in EU27.

3. An experimental approach to climate finance: The impact of auction design and policy uncertainty on renewable energy equity costs

3.1. Introduction: Transition models and new policy challenges after Paris

The 21st Conference of the Parties (COP21) to the United Nations Framework Convention on Climate Change (UNFCCC) reiterated the pressing need to strengthen the global efforts to counteract the threat of climate change. To this end, a major shift in the way energy is produced is necessary in order to meet the ambitious target of limiting the global temperature rise to *well below 2* degrees Celsius. However, the scale of the required transformation is challenging and the IEA/IRENA (2017) calculates that the share of primary energy demand met by fossil fuels would need to halve while low-carbon sources (including renewables but also nuclear and fossil fuel with carbon capture and storage) would need to increase to meet 70% of energy demand by 2050.

Nevertheless, while the challenge is impressive, renewables have shown fast learning curves and, in some case, an exponential growth of deployed capacity. This rapid progress has been so far promoted through revenue-support policies like green certificates (or tradable portfolio standards certificates) and feed-in tariffs (FiT) in both developed and developing countries. However, as the technology matures and the total costs associated with supporting larger installed capacities increase, governments are progressively turning to tenders as the main mechanism to promote renewable energy deployment. This preference is driven by several factors, including: the possibility to more precisely plan both the capacity to be connected to the grid and the budget spending, reduction of d information asymmetry and increased competition among developers. IRENA and CEM (2015) note that at least 60 countries have adopted renewable energy auctions by 2015, up from 6 in 2005. This trend is likely to accelerate during next years due to the newly adopted "*EU guidelines on state aid (2016) to the energy field" that* established that European countries can provide state aid to renewable generators only through competitive bidding by 2017.

Our main working hypothesis is that, given risk-averse investors, the riskier or less well-design policy instruments would (all other things equal) require higher return on the investment. Therefore, given the State-supported nature of renewable energy investments, higher subsidies are required to keep the risk-return profile of investments interesting. Within this framework, this paper focuses on how the policy planner could improve existing auction frameworks in order to expose investors to lower uncertainty and, consequently, decrease the subsidies paid.

The paper is structured as it follows. First, the empirical literature on the link between policy design and investment decisions is reviewed. Then, the paper discusses the key design options of auction frameworks currently implemented by the EU Member States and how these affect project risk. In addition to specific policy design options, this section highlights how the broader policy uncertainty and the fear of sudden policy shock represent a major road-block to private investment. The third section leverages a stated preference approach to shed some lights on the impact of selected features of the policy framework on the cost of equity for renewable energy by surveying around 40 managers of firms that are developers or pure financial investors in these technologies. The results show that auction design features can lead to a moderate improvement in financing costs by lowering the cost of equity between 0.5% and 1.5%. The evidence on Brexit is rather weak and, if anything, suggests the higher relevance of these negotiations for English-based investors rather than for those based in EU27.

Overall, this paper brings three novel contributions to the literature. First of all, it is one of the first studies that tries to quantitatively estimate the impact of auction design on renewable energy cost. Secondly, this analysis focuses on the cost of capital for renewable energy project, an extremely important variable to smooth the low-carbon transition given the capital-intensive nature of these investments but rarely studied. Finally, this paper transfers an experimental approach that has proven successful in several studies to the field of climate finance.

3.2.Literature review

Notwithstanding the hypothesis originally put forward by Porter stated that *"..<u>properly designed</u> environmental regulation can benefit firms* [and lead to better environmental outcomes]" (Porter and van de Linde, 1995), few theoretical contributions examine what exactly a well-designed regulation is. Within these studies, the importance of limited policy uncertainty is often highlighted. For instance, de Serres et al (2010) discuss how the chosen environmental policy instrument should vary according to the nature of the market failures as well as to the institutional capacities of implementing countries. To this end, they use five criteria to evaluate different policy instruments, including: cost-effectiveness, adoption and compliance incentives, uncertainty and stimulus to innovation. Johnstone et al (2010) identify four key features that should characterize environmental policy aiming at promoting innovation and underline once more the importance of limited policy-induced uncertainty. More precisely, they list four main features for environmental regulations, including: Dynamic efficiency, Uncertainty, Flexibility (defined as the extent to which innovators are free to identify the best way to comply with the environmental regulation) and Incidence (Does the policy target the environmental objective as closely as possible?).

The literature has been mainly conceptualized uncertainty in relation to environmental policies in the form of a sudden policy shocks or revenue uncertainty. The first stream of the literature underlines the negative impact brought by sudden changes in regulation on firms' investment and performance. The damaging impact of such changes is well-known and applies also to the field of environmental regulation (Luthi and Wustenhagen, 2012. IRENA, 2018). Instead, a second stream of literature underlines how policy mechanisms differ on the revenue certainty that they offer to investors. For example, a green trading scheme creates a higher level of variance on expected prices compared to fixed feed-in tariff (FiT). In fact, in the latter case, the investors can precisely predict the revenues that their project will generate once in operation given that the price for each kwh of renewable energy produced is fixed. Instead, in the former case, the uncertainty generated by the normal fluctuation of electricity prices adds to the uncertainty linked to the value of the green energy certificates.

In the empirical literature, revenue-uncertainty induced by environmental policy has been mainly studied through three strategies: option valuation, experimental models and excel based simulations. In the realm of option valuation, one of the first contributions is by Lonfreng (2008) who, following the work of Dixit and Pindyck (1994), derives the threshold condition for which a firm facing uncertainty on the price of a polluting production input will decide to invest in a new abatement technology. The link with environmental regulation lies in the presence of a tax on a polluting fuel. However, this tax is not subject to uncertainty. Kim and Lee (2012) set a constrained maximization model and analyze four different FiT structures (Fixed, min price guarantee and two premia linked to electricity price variations). Devine et al (2014) move from the consideration that different FiT designs do not eliminate market price risk but rather transfer this risk to a counterparty. Through a Constant Relative Risk Aversion (CRRA) utility function they specify the policymaker's risk preferences and, using Stackelberg game theory and option pricing, identify the optimal FiT design. The key assumption is that the optimal division of risk between investors and policymakers/consumers is analogous to the division of risk in the design of insurance contracts. Ritzenhofen (2014) uses a real options approach to analyze the timing and the likelihood of RES investments of a single investor under three different scenarios: (1) fixed FiT regime guaranteeing the investor a deterministic and fixed remuneration for every unit of electricity generated, (2) electricity is sold on the spot or futures market, (3) the investment decision is taken under fixed FIT but the regulator is expected to abolish this FiT regime at the certain point in the future. Since his work considers uncertainty as an unknown future policy change, it might also be included in the category of "sudden policy shock".

The second strategy used by scholars is based on the "stated preferences" approach through conjoint analysis. Importantly, this approach allows broadening the scope of analysis above the revenue certainty including other aspects of policy design that may affect investment risk. Luthi and Wustnhagen (2012) are among the first to introduce a conjoint analysis in the field of environmental policy. They leverage a choice experiment (conjoint analysis) to evaluate the trade-off for an investor in solar PV among five policy attributes. The attributes considered are: 'Level of tariff', 'Duration of tariff', 'Existence of a cap' (no cap, 4 years to be reached, 1 year to be reached), 'Duration of the administrative process' and 'Policy instability' (operationalized as the number of significant unexpected policy changes in the last 5 years). Giebel (2011) performs a conjoint analysis among German wind onshore investors. They compute the "willingness-to-pay" (in terms of more/lower full load hours) to have a given policy feature. Then, they build a baseline model and add (or subtract) full load hours to determine how the IRR changes. This is interpreted as the increased return required to accept a *riskier* policy design. The attributes considered are: Type of FiT (Fixed, variable with cap& floor, premium), 'Full load hours', 'shut down compensation' (Yes or no) and 'Quantity balancing' (Yes or no). Chassot et al. (2014) leverages a small sample of VC investors to understand how their investment decision in renewable energy technologies are taken. The attributes considered are: Regulatory risk ("the risk that regulatory agencies will change policy decision defined as low, medium, etc.), Return potential, Technological maturity, Founder experience, Lead investor (names of famous VC), Deal source (Syndicate partner, fair, etc.). Adopting a behavioral approach, they introduce in their analysis three questions to capture "views on the world" retained by the surveyed investors[8]. Then, the authors regrouped respondents as more or less individualistic and observe how the average part-worth utilities per level of regulatory exposure for each sub-group of investors differ. Masini and Menichetti (2012) study how the investors' a-priori beliefs, their preferences over policy instruments and their attitude toward technological risk affect the likelihood of investing in RE projects. The data are analysed by conjoint analysis and multivariate regressions. In this case, the authors consider the following attributes: type of Policy instruments (tax incentives/investment grants, tender schemes, FiT, Greeen TS), level of support, duration (years), duration of administrative procedure (months), social acceptance of the technology in the region. Two questions capture a-priori believes of investors ("*how much do you agree with…*"). An innovative element of this study is that the average attribute utility, as estimated through the conjoint approach, is leveraged in an OLS regression to evaluate the factors that drive investment in renewable energy. Luthi and Prassler (2011) leverage a survey on US and EU developers to perform a conjoint analysis on a mix of regulatory elements that include: 'Total time to obtain all permits (years)', 'Level of corruption', 'Guaranteed grid access (no, yet, priority dispatch)', 'total remuneration from incentives', 'terms of government soft loans (0.5% below market rates, 1% below market rate,..)', '% of investment cash grants (0, 10%, ..)'. Lüdeke-Freund and Moritz Loock (2010) underline how debt ratio can be very high for renewable energy projects (80-90%) and leverage an ACBC conjoint on German bank managers, who are responsible for loan decisions for PV projects, in order to understand how debt capital providers evaluate loan applications. Attributes are: debt service coverage ratio, installed capacity, brand quality (low, high) for modules and inverters, initiator, equity. Policy induced uncertainty is not included in this study.

[8] The degree of confidence in market efficiency was assessed by means of the following two items: How much do you agree (Likert Scale from 1 to 7) with the following statements: (a) Private enterprise is the best way to solve our country's economic problems. (b) If there is no clear need for government, let them stay out of the way. (c) We would never invest in a firm that relies on government subsidies.

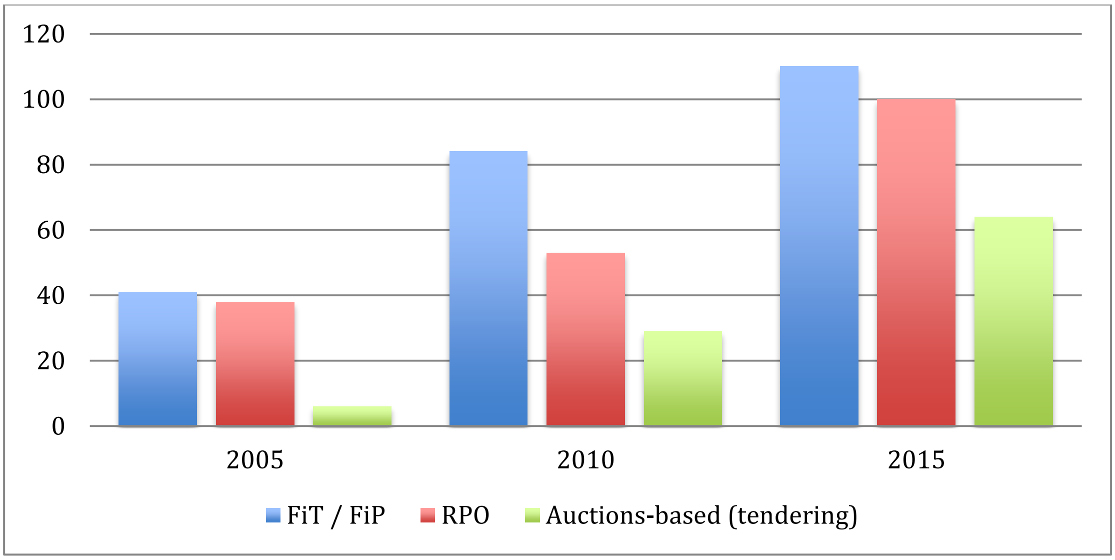
A third group of studies leverages Monte Carlo simulations. Kitzing et all (2014) compute mean and variance of returns to investors under a feed-in Tariff (FiT) and a feed-in premium (FiP) policies, then compute the Sharpe ratio under the two schemes. This way they show that payments have to be higher under the FiP scheme in order to achieve the same Sharpe ratio as under the FiT scheme. The analysis is carried through Monte Carlo simulations in excel. Falconett (2010) assess the effects of governmental grants, FiTs and renewable energy certificates on the distribution of NPV values of small-scale hydroelectric, wind energy and solar PV systems. The uncertain variables are the output of the renewable energy installation (PV and wind) and market prices while the analysis is carried out through Monte Carlo simulation in excel.

Finally, a limited number of studies build on experimental or econometric methods. For instance, Taschini (2014), who conducts an experiment with students, focuses on firms' investment decisions in abatement technologies when an emission-trading scheme is in place and both regulated and not-regulated agents (eco-groups and speculators) operate in the market. The experiment is not meant to focus on uncertainty but the results show that the presence of non-regulated companies increases price but does not affect price variability. Fagiani et Hakvoort (2013) estimate the impact of both the announcement and the actual implementation of the integration of Swedish and Norwegian Green certificate markets on certificate prices through a GARCH model. The results show increased certificate price volatility contributing to exacerbated price risk. Johnstone et al. (2010) show the negative impact of policy uncertainty on environmental innovation. The analysis utilises the WEF questionnaire over 2001-2006 on perceptions of the "stability and clarity" of policy and leverages a negative binomial model. Kalamova et al. (2013) measure uncertainty through a coefficient of variation of government R&D budget.

The above literature review underlines three main gaps. First of all, previous studies focused on FiT since these have been the main mechanism to support the deployment of renewable technologies during past years. However, auctions are emerging as the main incentive to promote investment in renewable energy. The reason behind this shift are numerous, including: more precise planning in relation to both capacity to be connected to the grid and budget spending, reduction of government information asymmetry and increased competition among developers. This process is likely to accelerate during next years due to the newly adopted "*EU guidelines on state aid (2016) to the energy field" that* established that competitive bidding will be main mechanism through which provide state aid for renewable by 2017[9]. Furthermore, while the EU State Aid guidelines contain a "de-minimis" rule stating that plants smaller than 1 MW may be excluded from tenders, some countries (e.g. France) has already conducted tenders for solar roof-top installations above 100 kWp (solar power Europe, 2016).

Figure 4. Number of governments with renewable energy policy, by type

9 Exceptions can be granted if there is (i) a limited number of project available, (ii) competitive bidding would lead to higher support levels and (iii) competitive procedures would results in low projects realization.



Note: Governments include countries/states/provinces. **Source**: REN21 (2016)

Secondly, the literature is largely silent on the impact that the designed policy has on the returns required by the investors. This is a relatively surprising gap since, given the capital-intensive nature of Renewable Energy Technologies (RETs), lowering their financing costs lies at the heart of an efficient low carbon transition.

Thirdly, most of contributions consider policy-induced "riskiness" only as steaming from the implied revenue variance with the exception of the above mentioned conjoint studies. However, as often underlined in the litterature, while the revenue-support mechanism in place is the key driver of the expected revenues, several other elements of environmental (and not) regulations are likely to affect the project risk/return profile through higher or lower business uncertainty or complexity (Ang et al., 2017. OECD, 2015).

3.3.Methods

Our main working hypothesis is that, given risk-averse investors, the riskier or less well-design policy instruments would (all other things equal) require higher return on the investment to compensate for the larger risk. Given the State-supported nature of renewable energy investments, higher subsidies are required to keep the risk-return profile of investments interesting. Within this framework, this paper aims at investigating how existing auction frameworks can be improved in order to expose investors to lower policy uncertainty and, therefore, decrease both the required subsidies and the cost of supporting green technologies to the society[10].

As in previous studies, we assume that each policy framework (in our case auctions) is composed by different attributes, whose levels have an impact on investors' preferences. The impact of these attributes is estimated leveraging an experimental approach, namely conjoint analysis. Briefly summarized, a conjoint analysis consists in showing the respondents several pairs of products (or policy packages) differing for a few attributes (e.g. level of the incentive paid and duration of the administrative process) and asking to select their favorite for each pair. This process is repeated until it is possible to estimate the respondent preference for each attribute. Conjoint analysis is based on the work done in the sixties by the mathematical psychologists and statisticians Luce and Turkey (1964) and it has been introduced into marketing research in the early 1970s (Green and Srinivasan, 1990; Orme, 2007) but it has spread over time to a wide array of research communities such as entrepreneurship (Lohrke et al., 2010), environmental economics (Ahn et al., 2008; Boxall et al., 1996; Casey et al., 2008; Chattopadhyay, 2009; Farber and Griner, 2000; Glenn et al., 2010; Roe et al., 1996), transportation economics (Hensher,1994; Hensher, 2010; Train and Wilson, 2008) and energy efficiency research (Banfi et al., 2008; Moxnes, 2004; Poortinga et al., 2003).

Among different methodologies, the adaptive choice-based conjoint analysis (ACBC) is the most used design in the literature on policy frameworks evaluation. In fact, this has been leveraged by virtually all studies surveyed (Chassot et all, 2014. Gamel et all, 2016, Luthi and Prassler, 2012. Masini et Menichetti, 2012) except for Luthi and Wüstenhagen (2012) where the authors prefer a simple adaptive conjoin analysis (ACA). The ACBC approach builds on two older methods for conjoint analysis: the Choice-Based Conjoint (CBC) and the Adaptive conjoint analysis (ACA). The CBC presents respondents with potential product choices and simply asks them which option they would choose. Instead, the ACA approach is based on the ranking - or rating – of different options by respondents. The CBC design has been among the most preferred by practioners given that it mimics in more detail real world decision-making processes, where respondents evaluate contemporaneously multiple characteristics (attributes) and directly choose the preferred one. However, the

[10] In addition, the stock of capital willing to accept higher risk is limited compared to the stock of capital owned by less risk-prone investors (e.g. VC funds vs. Pension funds). This sets an upper limit to total possible investment, equal to the pool of funds managed by risk-prone investors, if the risk of the investment is too high.

choice tasks are less informative than ranking or rating of concepts given that the tasks reveal only which concept is preferred and nothing about strength of preference or about the relative ordering of the non-preferred concepts. To overcome such limitation, the ACBC methods builds on the work of Huber and Zwerina (1996) who show that choice tasks are more statistically efficient if the alternatives within each task are nearly equal in utility. To this end, the ACBC first includes a task where the respondent is asked to build his own favorite product based on the available attribute and to exclude concepts that she would not even consider investing. Then, the respondent's part-worths are continually re-estimated as the interview progresses, and each next question is chosen, given what is already known about the respondent's values, in order to provide the highest amount of additional information. For this reason, ACBC captures more information at the individual level than traditional, non- adaptive surveys and may be used even with small samples (Shepherd and Zacharakis, 1999; Orme, 2010b). Additionally, the customized approach decreases the time required to complete the survey (Sawtooth Software, 2007).

The ACBC interview is articulated into four steps. First, the respondents are asked to compose their most preferred investment opportunity by choosing their favorite option for each of the attributes included in the conjoint design out of a list of previously defined levels in the "build your own" (or BYO) section (Table 2). Then, during the "screening section" the software generates a series of hypothetical investment opportunities by randomly combining the predefined attribute levels. The different developed product concepts are presented to the respondent in groups of three per screen. Respondents "are not asked to make final choices, but rather just indicate whether they would consider each one a possibility or not a possibility" (Figure 2) (Sawtooth Software, 2007, pag. 5). Finally, all selected investment opportunities enter the third section of the interviewing process (the "choice tournament"). In this last step, the investment options compete against each other in a series of choice tasks until the most preferred alternative is identified. In each choice task, the respondent needs to choose one out of a group of three investment options. Finally, the average part-worth utilities are calculated from the individual part-worth utilities of each respondent, using the hierarchical Bayes (HB) estimation model (Rossi and Allenby, 2003; Orme, 2007a), which has become the standard estimation method for conjoint analysis (Lenk etal.,1996; Rossi and Allenby, 2003; Netzer et al., 2008).

From a theoretical perspective, conjoint analysis is grounded in the theories of discrete choice and random utility. In fact, it is assumed that respondents chose their preferred attribute combination based on maximization of their utility function. At the same time, recognizing the impossibility of completely describing any option's utility, as underlined by the Random Utility Theory (Mansky, 1977), conjoint analysis assumes that the utility function of a person can be broken down into observable (deterministic) and unobservable (stochastic) parts. Following Luthi and Wüstenhagen (2012), the utility of a policy framework can be described as:

$$U = \sum_{i=1}^{n} u_i + e$$

where U is the utility of the chosen auction design, n the number of policy attributes, u_i are the part-worth utilities of the attributes i, and e the unknown characteristic. Part-worth utilities are a measure the impact of the variation to one attribute level to another level on the overall utility.

Figure 5. Screening section

Here are three possible projects. For each one, indicate whether it is **a possibility or not**.

(1 of 5)

Return on equity	8%	6%	6%
Type of auction	Technology specific	Open to all renewable energy technologies	Technology specific
Projects pipeline	An auction is scheduled for next year	An auction is scheduled every year for the next 5 years (one per year)	An auction is scheduled every year for the next 5 years (one per year)
Bid bond* *If the contract is offered and refused, then a bid bond is withheld. The bid bond is equal to:	4% of budgeted costs.	0.4% of budgeted cost (0.2% for coops projects).	4% of budgeted costs.
A final agreement on Brexit is expected to be reached in:	Negotiations have been concluded before the auction	Negotiations have been concluded before the auction	6 months after the auction
	A possibility Won't work for me	A possibility Won't work for me	A possibility Won't work for me

The probability that an investor j will chose the auction design k from choice set C_t is given by the following:

$$Pr_{jk} = \Pr(U_{ik} \geq U_{im})$$

where Pr_{jk} is the probability that an investor chooses the auction framework k and m is the set of all the other alternatives.

Given the part-worth utility estimates, equation 1 can be leveraged in order to compute the average attribute relevance. This "importance score" can be best interpreted as the degree to which a variation from the worst to best level of an attribute influences the overall utility of a concept (see eq 1). More precisely, if a given attribute shows a large discrepancy between the utility provided by its least and most preferred features, then its importance score is higher. Importantly, this is not a measure of absolute importance but relative to the attributes considered in the analysis. In interpreting this score, it is important to underline how the importance score can be driven by the design of the survey since the introduction of extreme levels for one attribute will lead to an higher (or lower) maximum (or minimum utilities) (Wittink et al.,1992; Orme, 2010c). For instance, a range from "no bid bonds" to " bid bonds equal to 50 % of project costs" would result in a higher importance score because such extreme level would elicit strong variation in investors utilities.

$$eq.1 \qquad Rel\_Imp_i = \frac{U_i^{Max} - U_i^{Mim}}{\sum_i^n (U_i^{Max} - U_i^{Mim})}$$

where Rel_Imp_i is relative importance of attribute i, $U_i^{Max}$the maximum utility of attribute i, and $U_i^{Mim}$the minimum utility of attribute *i* and *n* is the total number of considered attributes.

In order to ensure that respondents faced meaningful choices of attribute and levels, the first stage of this research required mapping design options for Renewable Energy Technology (RET) auction framework and identifying the most relevant. To this end, we conducted first an in depth literature review collecting data from academic papers, companies' and association reports, institutional publications and statistics collected by international organisations. This information has been complemented by ten interviews with investors and key European players in renewable energy industry (national associations, public authorities). Furthermore, before launching the survey, a pre-test was conducted in order to further validate the attributes and their relative levels (i.e. their design options) with a limited number of respondents.

Finally, building on the approach of Orme (2010) and Lüthi and Wüstenhagen (2012), the investors' willingness to accept certain policy features in exchange for lower expected returns can be computed as the following:

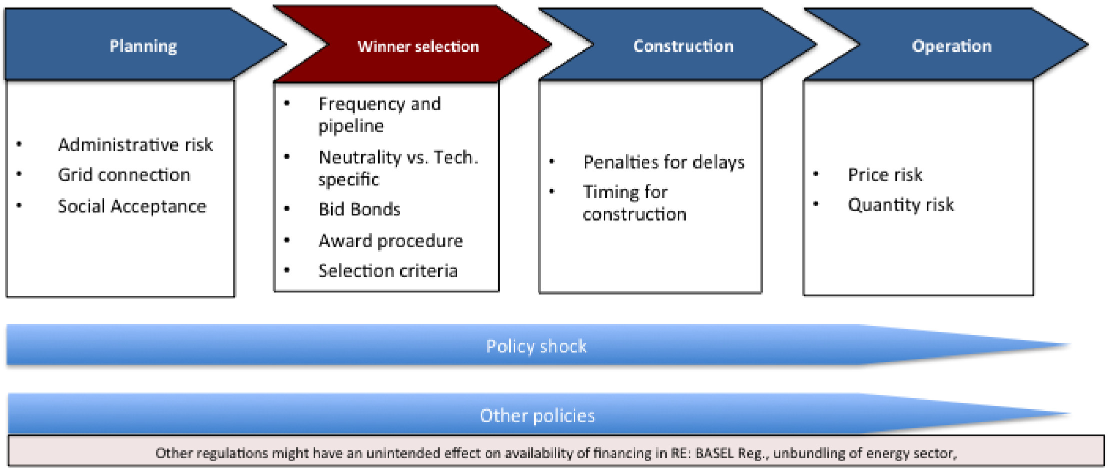
$$eq.2 \qquad WTA_{i,l} = -1(U_l - U_i^{Max}) * \frac{\Delta RoE}{U_{RoE}^{max} - U_{RoE}^{min}}$$

where WTA_l is the implicit WTA of the attribute i and level l; $U_{i,l}$ the partworth utility of the attribute i at level l while U_i^{Max} the maximum partworth utility of the attribute in question; ΔRoE the difference between the maximum and lowest level of the attribute RoE (12% and 6%); and U_{RoE}^{max} is the maximum (minimum) utility of the attribute "Return on equity".

3.4.Design options for renewable energy technology auctions

Overall, project development under a tender can be viewed as a four steps process: planning, winner selection, construction and operation (Figure 2). Within the next paragraph, given the limited space of this paper, only the main policy design options for each stage are reviewed[11]. The policy features connected to the winner selection stage are discussed in more detail since they are the most novel and, to some extent, unique to renewable energy technologies (RET) support through auction.

Figure 6. The four steps of RET development through auction



Source: Author's elaboration

During the planning phase, as in the case of support provided by other policy instruments, developers need to secure numerous permits in order to move projects forward. In the case of auctions, these are often included among the documents that have to be submitted in order to participate in a specific auction round[12]. Multiple policy aspects can complicate the permitting procedures, including: unclear requirements and procedure, extremely strict obligations and/or the need to deal with multiple authorities. The latter case is often cited as one of the main difficulties faced by RET investors (Johnston et al., 2008). To mitigate this issue, some countries have introduced offices – so called "one-stop-shops" (OSSs)[13] - responsible for issuing all the permits required to develop a new plant, thus reducing the uncertainty in dealing with multiple authorities. However, OSSs are not a panacea and their implementation can hide numerous challenges (OECD, 2015). A novel approach - specific to auctions - to the decrease the administrative burden has been introduced in the Dutch systems. Here, the transmission system operator (TSO) is responsible for obtaining all

[11] The interested reader can refer to del Rio et al. (2015) for a more detailed discussion.

[12] Even if these often need to be included in the bid offer, this paper distinguishes them from other "participation requirements" , which discussed below, because of the role of government in issuing these documents

[13] Notably, one-stop-shops are a tool that can be applied to facilitate any permitting procedure and therefore they are not a unique feature of action design.

necessary permits and performs a general EIA for the sites that will be auctioned while the bidders have to submit only a project specific EIA. This design provides a particularly innovative mechanism to mitigate administrative risk by essentially transferring the permitting liability to the TSO who is be better positioned to manage the associated uncertainty and complexity. In fact, private developers face the risk that the costs relative to the administrative and scouting procedures became sunk in case of unsuccessful bids. Instead, from the point of view of the TSO, one project will eventually be built and therefore the sunk investment risk is virtually zero. Furthermore, the TSO should also be better equipped to complete the permitting procedure than a private actor given the likely more complete knowledge of the authorization procedures, thus leading to overall lower transaction costs. However, also this procedure - while very interesting - presents also some drawbacks. First of all, it requires the State to select the sites where projects will be developed, thus limiting the role of the private sector. Secondly, it exhibits an inherent limit to capacity deployments equal to the Government resources dedicated to sites-selection.

During the planning phase, the development of NIMBY syndrome can sensibly decrease the likelihood of a project to be developed. This behavior, generally defined as the recognition of the public value of a project by a person (or by a group) who however opposes to its realization in proximity of their own neighborhood, can be aggravated by poor administrative procedures like the absence of clear mechanism to inform and involve the local communities. In this regard, while most of EU States have requirements in place in order to facilitate the participation of local communities, Denmark distinguished itself for the introduction of an obligation to offer a certain percentage of project shares to local residents. While not exactly a risk mitigation measure, this mechanism results in a larger distribution of the financial gains connected to promotion of renewable and provides also insights onto the large support for renewable energy in Copenhagen (ENS, 2009). During the interviews, developers agreed that offering shares to residents might be an effective tool in reducing the risk of NIMBY but strongly underlined their preference for having the freedom to choose if (and to what extent) sales catered to residents should be designed.

Auctions often introduce criteria to discriminate the technologies allowed to participate in a given auction round. The most commonly considered distinction is between technology neutral and technology specific auctions. In technology neutral auctions, different technologies compete for the deployment of the least-cost option. For instance, Brazil has recently organized open auctions where renewables competed with natural gas. At the opposite side of the spectrum, technology specific auctions (or auctions with predefined bands for each technology) support the development of targeted technologies, as for instance in India. Importantly, the segmentation does not need be only between low- and high carbon technologies and numerous other criteria are possible. For instance, Californian schemes leverage generation profiles to group technologies (base-load electricity, peaking electricity and non-peaking intermittent) (IRENA and CEM, 2015) while renewables are clustered according their level of maturity in the UK. Naturally, the segmentation of technologies reduces competition, thus lowering the cost effectiveness property of this mechanism. While “technological neutrality” favours the “lowest bid” logic, some observers highlight how technology differentiated auctions promote a diversified energy mix that is an important feature of a reliably system (Cretì et al. 2016).

The total capacity auctioned (and frequency of rounds) also can be used to regulate the competitiveness level of the tendering framework. In fact, the larger is the pot offered on auction, the lower is the level of competition (and the business risk) faced by developers. Nevertheless, auction rounds that are too generous can severely undermine the price discovery mechanisms and the overall effectiveness of the auction process (i.e. consider the extreme case where the capacity to auctioned outstrips the capacity to build of developers). However, each round needs to be large enough to not undermine project specific economies of scale that, in turn, varies according to the technology considered (e.g. solar parks versus offshore wind farms). Furthermore, low frequency of rounds is likely to lead to underbidding because losing the auction would result in a long pause in project development with the risk of permits expiration, financial resources unproductively committed, etc.

A long-term schedule is instrumental in improving the effectiveness of the scheme due to both learning effects and avoidance of a “*cliff-edge*”. In fact longer-lived schemes allow investors building familiarity with the tendering process, thus possibly lowering investment risks. In this regard, the German Federal Network Agency (Bundesnetzagetur) pointed out that the rate of bid exclusions is declining as participants are becoming increasingly familiar with the auction scheme. Furthermore, as all start-and-stop policies, the development of a robust supply chain is likely to be impaired by a lack of visibility on future rounds. (Río & Linares, 2014). Finally, short-lived auction schemes (i.e. one-off) create a cliff edge structure where incentives to underbidding increase given the lack of future opportunities to recover initial investments.

Speculative bidding, broadly defined as bids that are priced too low to be economically viable, can severely undermine investment attractiveness. These are often made either with the objective of undermining other players or to lock an incentive at time t while planning to actually develop the project at time t+1 betting on further decrease in the technology costs. However, these behaviors can severely undermine the healthy development of the industry as the market is foreclosed to players truly willing to develop a project at the time of the auction. In addition, this process slows capacity deployment, thus jeopardizing domestic energy security. Furthermore, it can activate a vicious circle where slower deployment results in slower technology learning that, in turns, leads speculators to wait longer to install capacity.

For this reason, bid bonds and pre-qualifications criteria are often introduced. A bid-bond can be defined as a cash deposit subject to forfeiture if the winning contractor fails to build the project in the required time and quality. However, bid bonds have the detrimental effect of increasing the barriers to entry, especially for smaller players. Where these small developers have proven to be large capital contributors (e.g. Germany, where 50% of wind farms are owned by small actors), high financial bid bonds might have severe negative impact on total capital available for project development. In addition, restricting the participation of smaller developers and cooperatives might undermine the mechanisms that decrease the diffusion of NIMBY syndromes. To overcome these challenges, some jurisdictions have introduced lower bonds for developers meeting specific criteria. For instance, in Germany cooperatives benefit from lower bid bonds than regular developers. Also, non-financial penalties are less likely to favour larger developers. For instance, the UK legislators opted for the exclusion of the same site to any subsequent auction round for 13 months as non-delivery incentive. Other qualification requirements introduced in order to avoid speculative bidding include a given track record in terms of project developed or international certification. These, as the financial bib-bonds, are likely to increase the costs of participation because prequalification costs are sunk costs (Moore and Newey 2013). Interestingly, in order to provide investors with an exit option if unforeseeable circumstances take place, the right to transfer the commitment to build in a secondary market may be a valid solution (solar power Europe, 2016).

Once the incentive is awarded to the project, auction scheme may introduce a series of construction milestones with relative penalties in order to ensure the public interest of having the capacity installed in due time. In this regard, it is particularly interesting the UK CfD scheme where a number of milestones have been introduced, possibly to compensate for the lack of financial bid-bonds. Here, the first milestone is set 12 months after the contract award and the penalties for failing to prove of either having spent at least 10 per cent of the estimated total project pre-commissioning costs or providing clear evidence of progress towards timely commissioning can lead to project termination. Another common incentive to meet the project construction schedule is created by establishing that the payments window will start on the expected commissioned date, regardless of project completion [14] (Addleshaw Goddard, 2015). The design risk connected to such milestones lies in the possibility of setting too short or too long deadlines. In the former case, well-reputed developers may decide to not participate in the auctions, thus jeopardizing the overall efficiency of the scheme. At the same time, however, excessively long construction periods increase the risks of excessive remuneration (if the costs of technologies decrease more than expected) or underbidding (del Rio, 2017). Importantly, following the example of the English CfD, winning projects should be given a penalty-free window (i.e. "Target Commissioning Window") during which the bid capacity can be delivered and not a specific date.

Also, auction frameworks introduce some rigidities during the construction phase. In fact, once a project has won the tender, developers cannot freely vary the project size to respond to new opportunities (or challenges) that may arise. To mitigate this issue, some schemes offer the possibility to modify the initial project capacity by a certain percentage[15]. For instance, the project capacity can

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[14] If a project has not been commissioned one year after the end of the commissioning window, then the CfD contract will be terminated (longstop date).

[15] Within the UK CfD, this can be lowered up to 10% from initial bid without incourring into sanctions.

be decreased or increased up to 9% of the original submission in the UK (ECCC; 2016) while Dutch regulations allow only to increase the capacity of the project (interview). Nevertheless, during the interviews emerged that developers regarded these options as a simple "nice to have" and felt overall confident in their ability to deliver the project on time and to correctly size it before the auction. Importantly, low pre-qualification requirements and low penalty levels should not be introduced at the same time, as this might attract speculation and result in poor realisation rates (Wigand et al., 2016).

Once the plant is operative, price and quantity risks are the main uncertainty. The latter can be defined as the uncertainty regarding the possibility of selling all produced electricity while the former refers to the unknowns related to the actual selling price. Both uncertainties have been effectively mitigated in the past through feed-in tariffs (FiT), priority dispatching and the possibility to bank unused amount of generation hours due poor wind or solar conditions to next years. Building on the recognized importance role in FiT in driving investments, most of auctions currently in place offer the winner a fixed price per KWh guaranteed either through a PPA (power purchase agreement) or a traditional FiT. Instead, the legislations that have opted for a top-up on the market price, as for instance the UK or French CfD, have introduced an "off-taker of last resort" in order to ensure that generator will be always able to sell their output. More precisely, these systems require certain entities, identified as the "off-taker of last resorts" (OLR), to make periodic offers to buy the electricity generated under the CfD at a discount to the market reference price set by the law[16] (ECC, 2016). While this mechanism can offer generators some certainty on the presence of customers for generated renewable electricity, its design should ensure that is truly a " last resort" option (generators should always prefer to sell on the market). Interestingly, several developers underlined that the discount needs to set at a reasonable level and argued that currently set levels are too high to offer any attractive fallback options. A similar mechanism is provided in Italy where renewable energy generators can opt for the "ritiro dedicato" instead of a traditional PPA. Through the "ritiro dedicato, the GSE purchase green electricity at prices set through a formula and takes the risk of selling it back to the wholesale market. The recently published proposal for the new clean energy Directive (the so called "winter package"), includes an obligation to remove priority grid dispatch for new renewables and therefore this option not considered here.

IRENA and CEM (2015) underline how the bankability of the off-taker can also be a key driver in determining the attractiveness of the auction framework in several non-OECD countries. While this is not usually questioned in Europe, this has proven an important issue in determining the attractiveness of auctions across the world. Useful mechanisms are the creation of specific funds to ensure the compliance with PPA agreements (e.g. Argentina).

Finally, (a reputation for) an unstable policy framework – for instance because of sudden or, even worse, retroactive changes - is highly deleterious for private

[16] The initial discount is set in the BPPA at £25/MWh adjusted by an inflation factor.

investments. In order to counteract this issue, governments can put in place firm "commitment devices". In this regard, the UK CfD provides two interesting elements to consider. First, the CfD offers a protection to plants operators against changes in the taxation code that would decrease the profitability of the project stating that their fixed price can be increased (or lowered) to compensate for decrease in profitability due to new generation taxes (Addleshow-goddard, 2015). This is important since the CfD operators, contrarily to other power plants, cannot pass increased costs on to the consumers because they are entitled to an overall (maximum) fixed price. Secondly, the CfD auction winners enter a private law contract with a purposively build private company (the Low Carbon Contract Company - LCCC[17]). This enshrines the rights of the auction winners within a private law contractual framework that may result in greater certainty given that future governments could not alter private contracts as easily as public laws.

[17] The LCC manages the Supplier Obligation Levy that funds CFD payments (LCCC website, 2016).

3.5.Attribute selection and survey design

The number of attributes included in the conjoint analysis had to be restricted in order to design a survey that could meet the limited time availability of managers. Three main reasons led to the decision of focusing the experiment on the attributes characterizing the *winner selection stage*. First of all, compared to non-auction frameworks (e.g. FiT or renewable certificate markets), tenders create a cliff edge structure in the investment process. In fact, investors will have to incur in a number of costs (e.g. scouting, planning, engineering planning, permitting, etc.) before having a definitive knowledge about the level of incentive that (if any at all) will be disbursed to the project. Only once the auction is cleared, these unknowns disappear[18]. As such, both the planning stage and the winner selection stage are likely to generate the highest impact on project uncertainty. However, given that permitting - the central issue during the planning stage - has been a central focus of several studies and the uniqueness of the winner selection stage to auctions, the decision to focus on this latter stage was taken. Among the features that characterize this step, three features have been included: the nature of bid bonds, duration of the announced auction schedule and type of auction (Table 2).

In addition, the literature (and also the preliminary interviews) underlines how policy shocks - broadly defined as unexpected changes in existing regulation and/or regulatory uncertainty – remain a clear determinant of the attractiveness of an auction framework. However, policy uncertainty is an extremely difficult variable to articulate in a conjoint study because of a lack of a uniform scale of measurement. To overcome this challenge, previous studies have characterized this feature - obtaining highly significant results - as *number of unexpected policy changes in the past N. years*. To some extent, these studies evaluate how negative governments' reputation weakens the attractiveness of policy framework in place. In fact, these leveraged information on previous (negative) events to evaluate how these "tarnish" government credibility to uphold policies.

Within this study, a novel approach is undertaken exploiting the recent referendum on UK membership to the European Union. In fact, the referendum outcome creates uncertainty on the nature of future arrangements between EU and UK that may affect investments in renewable energy plants through various channels (e.g. disruption of supply chain, turmoil on financial markets, impact on interconnected electricity markets, expected prices of ETS allowances, upholding of English environmental policies emanating from EU regulations and targets, lower electricity demand because of lower GDP growth, etc.). Overall, the uncertainty on Brexit has been often debated in terms of whether the new arrangements will see a "hard" or "soft" Brexit. Nevertheless, the lack of a clear definition of what the two entail and of how they differ makes them not readily operationable for a conjoint study (i.e. respondents would not have a clear and

[18] This not the case for other support scheme that provide the certainty to be entitled to a given revenue support scheme for all projects built within a certain date. In certain cases, a degression scale for the incentive is provided, thus still providing developers with certainty about support level if specific deadlines are missed or certain capacities are reached.

common understanding of their difference). For this reason, this study attempts to capture uncertainty as the relation between the point in time where the investment decision is taken and when the negotiations on "Brexit" are expected to be concluded. Two main possible relations between the timing of negotiations and of the investment decision can be envisaged. One on side, investors may prefer to invest after a Brexit agreement has been reached since this would result in a better visibility on the future "state of world". On the other hand, investors may prefer to invest as early as possible in order to lock-in their investment in current rules. Following this latter interpretation, also winning an auction close to the end of the negotiations may be a less preferred option since project procurement and construction would take place in an uncertain environment.

Finally, the expected return on the equity is a clear driver in driving investment decision and, therefore, it is included as the fifth attribute.

The survey was fielded between February and July 2017. A link to the questionnaire was attached to the mailing list of two national renewable energy associations: the Italian wind energy association (ANEV) and the English Renewable energy association (REA). The latter association agreed to distribute the link to the survey through its mailing list directed only to investors in renewable energy projects. In addition, other 50 targeted invites have been sent to members of selected Linkedin groups and to email addresses identified through web research. Finally, additional responses were collected at three industry fairs that took place between February and June 2017. These were: the E-energy forum in Essen (February 07 – February 09 2017); the Intersolar Conference Fair in Munich (May 31 - June 2, 2017) and the Wind Offshore Fair in London (6-8 June 2017). During these fairs, managers have been approached and asked if they might be interested in participating in the study either during the fair or if they could be reached over the phone at a better timing. In order to improve the accuracy of responses and avoid the risk of "self- assessment", it was guaranteed that the collected information would remain confidential and it was promised to share the final results of the study with respondents (Huber and Power's , 1985).

Overall 56 questionnaires have been collected but 18 questionnaires could not be considered for the analysis because either incomplete or because the respondents indicated their main area of focus as outside the EU28 region. Eight questionnaires were answered directly at one of the above-mentioned fairs[19]. The distribution of the technological areas of expertise of the respondents (table 12) is skewed towards wind (on-shore and off-shore) and solar technologies, which played an important role in the recent expansion of low-carbon generation. Our respondents also reported to be involved in relatively large projects (42% stated the average project size is above 31 MW), thus suggesting that our sample is composed of professionals employed by important players in the market. In terms of countries, the sample is naturally skewed towards the

[19] An additional questionnaire was completed but was excluded from the analysis as a sudden meeting led the respondent to first interrupt answering for a long time and ,then, to rush through the different sections.

States were our distribution channels were stronger, namely Germany (where most of the fairs were held), Italy and UK. In addition, the large majority reported to have been working within this industry longer than 6 years, thus suggesting that we are facing a pool of individuals that have a deep knowledgeable of the sector. The job titles of respondents were not recorded, however, most of questionnaires that were collected during the fairs were answered by “Project Development Managers”.

Table 11. Final sample demographics

Firm Type	Count (N)	Share (%)	**Years of experience**	Count (N)	Share (%)
Project developer	9	23.7%	< 3 years	4	10.5%
IPP	3	7.9%	3 - 5 years	6	15.8%
Utility	9	23.7%	6 - 12 years	20	52.6%
Cooperative	3	7.9%	> 12 years	8	21.1%
Venture Capital, private equity or hybrid	3	7.9%			
Infrastructure fund, Pension fund and Insurance company	7	18.4%			
Bank	1	2.6%			
Private investor	3	7.9%			
Average Project size	Count (N)	Share (%)	**Technology (multiple choice available)**	Count (N)	Share (%)
<2 Mw	4	10.5%	Wind project (on-shore)	18	30.5%
2 - 6 Mw	2	5.3%	Wind project (off-shore)	12	20.3%
6 - 15 Mw	10	26.3%	Solar project	25	43.1%
16 - 30 Mw	6	15.8%	Geothermal project	1	1.7%
31 - 100 Mw	16	42.1%	Other	3	5.1%
Country	Count (N)	Share (%)	**Cumulative investment**	Count (N)	Share (%)
Austria	1	2.6%	<15 mln euros	4	10.5%
Belgium	1	2.6%	16-100 mln euros	9	23.7%
Croatia	1	2.6%	101- 300 mln euros	7	18.4%
Denmark	2	5.3%	301 - 1000 mln euros	5	13.2%
Finland	1	2.6%	> 1000 mln euros	13	34.2%
France	2	5.3%			
Germany	5	13.2%			
Italy	11	28.9%			
Netherlands	1	2.6%			
Romania	1	2.6%			
Spain	2	7.9%			
United Kingdom	10	26.3%			

Table 12. List of attributes included in the experimental study

Attributes	Description	Level
Return on equity	Expected return on the investment	6% 8% 10% 12%
Differenziated / undifferentiated auction	A tender is differentiated by technology if the total amount of MWs to be installed at each new auction round is defined by technology. (e.g. 100 MW of wind power, 50 MW of solar, etc). Otherwise, the auction is defined as "undifferentiated" .	• Differentiated auctions • Undifferentiated auctions
Auction Schedule (potential project pipelines)	The schedule of next auctions is the following:	• One auction for the same amount of installed capacity (e.g. MW) is scheduled for next year • Auctions for the same amount of installed capacity (e.g. MW) are schedule every year for next 3 years • Auctions for the same amount of installed capacity (e.g. MW) are schedule every year for next 5 years
Bid Bonds	If the bid is successful but the project is not realized, the following penalties apply	• 0.4% of budget costs (0.2% for cooperatives) • 4% of budgeted costs (2% for cooperatives) • No project on the same land can be submitted for the next three auction rounds.
Policy sudden shock (→ transformed into "Timing of investment over Brexit))	Given the recent development, the policy sudden shock has been articulated as the resolution of BREXIT negotiations, i.e. "A definitive agreement on Brexit between EU and the UK will be reached.."	• Negotiations have been concluded entirely and in full agreement between the parties before the auction • 6 months after the auction • 12 months after the auction • 18 months after the auction

3.6.Results

3.6.1. Part-worth utilities

The following tables report the part-worth utilities estimates for our pooled model and, separately, for EU27- and UK-based respondents. The root likelihood (RHL), which ranges from zero to one and it is a measure of goodness of fit of the HB model underlying the utility estimations, suggests a good fit of the different models on the data. The utilities are zero-centered, as such, a negative value associated to one level should not be considered as decreasing overall utility but as less valuable than less negative levels. The zero-centering process also results in having some levels set close (or equal) to zero while others above (or below) this threshold. Therefore, the t-test on whether a given level is significantly different from zero is substituted with a t-test on whether the mean utility for each attribute is statistically higher the utility associated to the preceding (less preferred) level. As such, the number of t-test for each attribute is equal to the number of levels for that attribute less one.

The estimations underline a homogenous direction (or ordering of preference) and relatively similar magnitude of coefficients across all the panels considered except for the attribute “timing of investment over Brexit”. As such, a t-test has been applied to test if the coefficients are statistically different between UK-based respondents and the other European investors included in the sample. The results lead to strongly reject the hypothesis of homogeneity for the attribute “timing over Brexit” and to accept it for all the other attributes considered in the analysis (table A.1). Therefore, the coefficients associated to this attribute should be analyzed bearing in mind the strong and statistically significant difference between the UK- and EU27-based investors. Notably, given the very small sample for UK, model 3 estimates should be considered - at best - indicative.

According to estimations for the considered auction design options (nature of bid bonds, duration of the announced auction schedule and type of auction), the highest increase in utility is achieved shifting from non-monetary to moderately large bid-bonds. Interestingly, the bid-bond variable does not improve linearly with the level of financial commitments. In fact, this would require having the preference sorted from the lowest (no financial bid-bonds) to highest bond (4% of budget costs), or vice-versa. Instead, the results suggest a u-shaped preference curve where investors appreciate the presence of financial bid bonds but up to certain threshold located between 0.4% and 4% of projects costs. Overall, the estimates suggest that investors value the presence of financial bid-bonds as an effective tool to discourage under-bidders but these need to be carefully introduced in order to not increase excessively the project costs.

Table 13. Part-worth utility estimations

Attribute	Attribute level	Model 1: Full sample	Model 2: EU27	Model 3: UK
Expected Return on equity	*6%*	-134.79 n.a. (9.025)	-131.01 n.a. (9.999)	-125.59 n.a. (18.742)
	8%	-18.51 *** (2.69)	-19.51 *** (3.416)	-19.69 *** (4.976)
	10%	45.09 *** (3.523)	43.59 *** (4.506)	50.28 *** (3.889)
	12%	108.21 *** (7.591)	106.93 *** (8.124)	94.99 *** (15.59)
Type of auction	*Open to all R.E.T.*	-19.47 n.a. (3.805)	-21.67 n.a. (5.124)	-19.76 n.a. (6.694)
	Technology specific	19.47 *** (3.805)	21.67 *** (5.124)	19.76 *** (6.694)
Auction schedule	*1 year long schedule*	-24.62 n.a. (4.347)	-31.00 n.a. (4.65)	-13.57 n.a. (12.133)
	3 years long schedule	1.86 *** (2.605)	3.86 *** (2.994)	2.36 (5.182)
	5 years long schedule	22.75 *** (3.448)	27.14 *** (3.417)	11.2 *** (11.763)
Bid bond	4% of budgeted costs (2% for cooperatives).	-35.85 n.a. (5.673)	-35.39 n.a. (6.211)	-28.55 n.a. (9.474)
	No project on the same land can be submitted for the next 3 auction rounds.	8.37 *** (3.7)	5.85 *** (4.903)	6.18 ** (3.773)
	0.4% of budget costs (0.2% for cooperatives).	27.48 *** (3.946)	29.53 *** (4.113)	22.36 ** (7.637)
Timing over Brexit Negotiations (*Negotiations will be concluded..)*	*Negotiations concluded*	24.02 *** (4.05)	18.82 *** (4.966)	37.29 ** (4.264)
	12 months after the auction	3.83 *** (2.472)	-1.97 (3.008)	17.47 *** (6.311)
	6 months after the auction	-9.14 ** (2.873)	-12.19 n.a. (3.051)	-1.40 *** (5.655)
	18 months after the auction	-18.71 n.a. (4.073)	-4.66 * (4.884)	-53.36 n.a. (8.637)
Sample size		38	28	10
RHL		0.771	0.764	0.818

Note: *Standard errors in parenthesis. P-values refer to a t-test on whether the mean utility for each level is statistically higher than the mean of the preceding (less preferred) level. ***,**,* respectively means significant at 1%, 5% and 10%. The least preferred level for each attribute is marked as "n.a.".*

As often underlined in the literature, long-term visibility is a key element of a framework conductive to investment, and this seems to apply also to design of auction programs. However, the estimates underline that at least a medium-term schedule should be adopted to have a meaningful impact on the cost of equity. In fact, moving from a *one-off* auction to the introduction of a five years long program leads to an increase in utility equal to 46 points for the pooled model while the utility increase from *one-off* to *three years* is very limited. Finally, bearing in mind all the caveats mentioned for the UK-only model, we highlight how the utility associated to the highest (lowest) levels of this attribute seems to be lower for our UK sample than for model (1) and (2).

The third largest increase is given by adopting technology-specific instead of technology-open auctions (+39 utility points in panel 1 and 3 and +43 according to estimates based on EU27-based respondents). Overall, shifting from open to technological specific auctions seems to be an effective tool in reducing investment risks. Importantly, policy makers should carefully consider the potential trade-off between least-cost and lower capital costs that this choice entails. In fact, while it is true that organizing technology-specific auction is probably an effective tool to decreasie the business risk, and therefore the cost of capital, it may well be possible that the higher competition brought by an open auction may result in lower overall costs. By the same token, technology-specific auctions can be more effective from a dynamic perspective if the targeted technologies exhibit faster learning curves.

The interpretation of the coefficients associated to the last attribute, "timing of investment over Brexit", is affected by numerous issues. In fact, the pooled estimates (model 1) appear to be highly driven by the significantly higher impact on investment decision of the timing over Brexit for UK based investors. Overall, this segment of respondents may be seen almost as behaving as "outliers" inflating the pooled estimates (model 1). This is especially true for the utility associated to the level *18 months before Brexit*. By the same token, also the sub-groups estimates appear to be not robust. In fact, the t-test performed does not allow to be statistically confident about the ordering of preference of EU investors. More precisely, while the level *12 months* appears to be preferred to *18 months* and, in turn, this is preferred to *6 months*, the lack of significance of these estimates suggest extreme caution in interpreting them (Table 2). Instead, as per the other attributes, model 3 estimates should be considered at best indicative the given the very small sample for UK.

Given the need to cautiously interpret the coefficients associated this attribute, we limit this discussion to underline two key conclusions. First of all, as often discussed in the literature, investors' utility function put a prize on an investment environment characterized by a lack of policy uncertainty. This nature emerges also in our analysis where a strong preference for having a policy environment characterized by an agreement on Brexit is confirmed across all panels. Secondly, estimations across all the samples underline how investors seem to consider the period closer to the end of the negotiations as highly turbulent and to agree on the higher utility provided by locking-in their investment during the central stage of this process (12 months). The extremely limited number of respondents based in UK suggests caution in discussing further difference between the two groups and we limit this analysis to underlining the weak evidence of an inversion in ordering for the least preferred level between the two sub-panels.

The average importance score, based on eq. 1, are shown in table 4. The overall range for each attribute is relatively similar, thus leading to an overall similar importance scores within each panel. The only exception is the expected return on the investment that naturally emerges as the leading driver of the investment decision. As for the single utility levels, the importance scores appear homogenous across the various panels, except for the Brexit attribute. Also in this case, a t-test strongly leads to reject the hypothesis of equality of the importance score between UK and EU27 respondents only for this attribute (i.e.“ Timing over from Brexit”) (table A2). Overall, the importance score provides some weak evidence of a much higher relevance of the timing (setting aside the outcomes) of negotiations on Brexit for English investors rather than those based in EU27

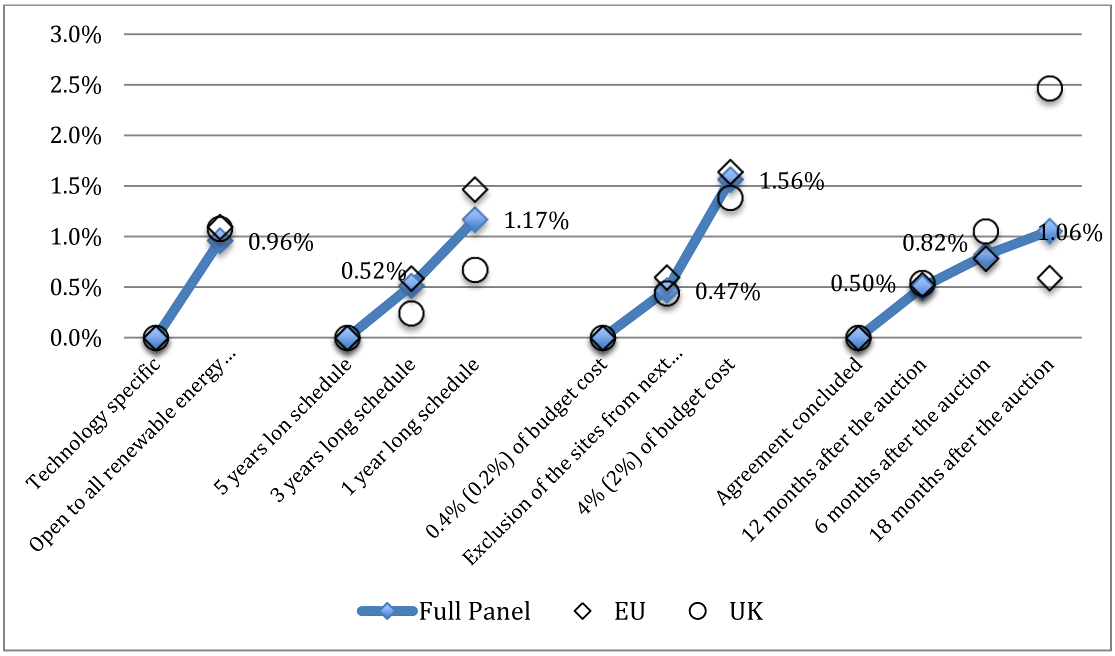
Table 14. Relative importance score

Attribute	Full-Panel	EU27	UK
Expected return on equity	50.2%	48.8%	45.9%
Type of auction	9.8%	11.1%	10.2%
Auction schedule	12.2%	13.0%	13.4%
Bid bond	15.0%	15.6%	11.4%
Timing over Brexit negotiations	12.8%	11.5%	19.1%

3.6.2. Investors implicit willingness-to-pay

As a next step, in order to facilitate interpretation of our most robust results, the investors' willingness-to-accept (WTA) certain auction framework design options is estimated using Eq. 2 following the approach discussed on Luthi and Wüstenhagen (2012) on energy economics. Results are presented in Fig. 2 and briefly discussed below. Note that the simulations below are based on the preference data estimated out of the entire sample to increase their robustness. However, as discussed before, the estimations are remarkably similar across all sub-panels for the considered auction design features.

Figure 7. Willingness-to-accept certain policy risks.



Overall, auction design can lead to improvement in financing costs by lowering the cost of equity between 0.5% and 1.5% (Figure 2). Mirroring previous discussion, the adoption of moderate financial bid-bonds leads to the highest improvement in overall financing costs (-1.5%). Instead, the adoption of non-financial bid-bonds or requiring high(er) financial deposits will instead lead investors to seek higher return on their invested capital in order either to compensate for the higher financial cost or for the larger risk of under-bidding by competitors. Fig. 2 shows that every two-year increase in the duration of planned auctions can lead to half a percentage point decrease in the cost of equity. This improvement is probably driven by the possibility of participating and recalibrating bids for next auction rounds, if the first bid round is unsuccessful. Notably, as previously discussed, the adoption of longer schedule seems to have a lower utility, and therefore to lead to a lower decrease in equity cost, for UK-based developers compared to EU27. However, all the discussed caveats for this sample apply. Finally, the results suggest that adopting open auctions will lead to an increase in the cost of capital of less than one percentage point (0.9%). The calculations for the Brexit attribute are reported but not discussed here given the lack of significance of the estimated coefficients.

3.7.Conclusions

Our main research question is how policy-induced uncertainty affects the risk-return profile of investments in renewable energy. From this standpoint, this paper aims at complementing the existing literature by opening the "black-box" of auction design and at shedding some light on its impact on the cost of capital for renewable energy project. In addition, the effect of on-going Brexit negotiations, as a potential driver of policy induced uncertainty, is considered. As in previous studies, we assume that each policy framework is composed by different attributes, whose levels affect the uncertainty faced by investors.

After an in-depth review of auction design options in Europe, three auction design features have been selected for our experiment. The results show that the three considered attributes can lead to a moderate improvement in financing costs by lowering the cost of equity between 0.5% and 1.5%. The largest decrease is provided by the adoption of moderate financial bid-bonds. Captivatingly, the estimates suggest an u-shaped preference curve where investors appreciate the presence of financial bid bonds but up to certain threshold located between 0.4% and 4% of projects costs. The analysis also underlines how long-term auction programs strengthen the cost reduction effects typical of tendering competition. Interestingly, the results show that the adoption of a five year long auction schedule characterized by one auction round per year can already lead to meaningful capital cost reduction. Finally, the adoption of technology specific auction leads to lower business risks and, therefore, a willingness to accept lower returns on equity.

Notably, auction design is likely to involve various trade-offs between different policy objectives and needs to be carefully assessed. For instance, while moderate financial bid-bonds emerge to be the favorite design option for the investors included in our sample, non-financial bid-bonds are likely to favor the participation of small players. As such, if the policy planner is interested in increasing the participation of local residents (e.g. through cooperatives or SMEs) in the development of domestic resources, then accepting the higher costs delivered by non-financial bid-bonds may be an interesting option. By the same token, technology-specific auctions can sensibly decrease the investment risk faced by investors and promote technology learning with positive effect over time. However, a technology-neutral design promotes competition and therefore is more likely to meet the least *overall* cost criteria in a static context.

In addition to policy design features, this study attempts to evaluate the impact of the uncertainty brought by the Brexit process on investment in renewables. However, given the need to cautiously interpret the coefficients associated to this attribute, we limit this discussion to underline how estimations across all the samples suggest that investors seem to consider the period closer to the end of the negotiations as highly turbulent and to agree on the higher utility provided by locking-in their investment during the central stage of the negotiation process (12 months) or once the negotiations are concluded. In addition, the estimates provide weak evidence of a higher relevance of the timing (setting aside the outcome) of the negotiations on future relations between the UK and EU for English investors rather than for those based in EU27. The extremely limited number of respondents based in UK suggests caution in discussing further difference between the UK- and EU27-based respondents.

Importantly, the conclusions of this paper are limited to the attributes considered in the experiment. However, numerous other auction features may have a positive (or negative) impact on equity costs. For instance, frequency of auctions or penalties for delays, as discussed in the review section, may help further lowering the cost of investment and be the object of further studies.

Table A1. T-test on equality of level utility estimates.

Average Utilities (Zero-Centered Diffs)	EU27	UK	P-value Ho: $\beta_{EU,l} = \beta_{UK,l}$
6%	-131.01 (9.999)	-125.59 (18.742)	**0.80**
8%	-19.51 (3.416)	-19.69 (4.976)	**0.98**
10%	43.59 (4.506)	50.28 (3.889)	**0.27**
12%	106.93 (8.124)	94.99 (15.59)	**0.51**
Technology specific	-21.67 (5.124)	-19.76 (6.694)	**0.82**
Open to all renewable energy technologies	21.67 (5.124)	19.76 (6.694)	**0.82**
1 year long schedule	-31.00 (4.65)	-13.57 (12.133)	**0.21**
3 years long schedule	3.86 (2.994)	2.36 (5.182)	**0.81**
5 year long schedule	27.14 (3.417)	11.2 (11.763)	**0.22**
4% of budgeted costs (2% for cooperatives).	-35.39 (6.211)	-28.55 (9.474)	**0.55**
No project on the same land can be submitted for the next 3 auction rounds.	5.85 (4.903)	6.18 (3.773)	**0.96**
0.4% of budget costs (0.2% for cooperatives).	29.53 (4.113)	22.36 (7.637)	**0.42**
BREXIT1	18.82 (4.966)	37.29 (4.264)	**0.01**
6 months after the auction	-1.97 (3.008)	17.47 (6.311)	**0.11**
12 months after the auction	-12.19 (3.051)	-1.40 (5.655)	**0.02**
18 months after the auction	-4.66 (4.884)	-53.36 (8.637)	**0.00**

Table A2. T-test on equality of average importance scores estimates.

Attribute	**EU27**	**UK**	P-value Ho: $\beta_{EU,l} = \beta_{UK,l}$
Expected return on equity	48.8%	45.9%	0.66
Type of Auction	11.1%	10.2%	0.69
Auction schedule	13.0%	13.4%	0.89
Bid Bonds	15.6%	11.4%	0.23
Distance from Brexit agreement	11.5%	19.1%	0.01

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