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THE GREEN TWIST IN THE BOND MARKET - A PERFORMANCE ANALYSIS OF GREEN AND CONVENTIONAL INDICES

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RESUMO

As obrigações verdes surgiram como um produto inovador de rendimento fixo para mobilizar fundos que promovam a mitigação e adaptação às mudanças climáticas.

O presente estudo tem como objetivo investigar se a integração de obrigações verdes numa carteira de investimentos é rentável para o investidor ou se implica uma escolha entre preocupações ambientais e rentabilidade financeira, com base no estudo de índices obrigacionistas verdes e convencionais.

A análise dos retornos financeiros sugere baixos níveis de volatilidade e por consequência, baixo risco de investimento para os dois tipos de índices. As diferenças entre as médias dos retornos não são estatisticamente significativas o que implica a rejeição de incompatibilidade entre preocupações ambientais e rentabilidade financeira. Dependências de curto-prazo entre índices verdes e índices convencionais obrigacionistas com notações de crédito AAA, AA, A e BBB e de obrigações governamentais foram encontradas.

Através do estudo das relações dinâmicas de longo-prazo, 20 relações de cointegração foram identificadas, das quais apenas 4 demonstraram ser relações de equilíbrio de longo-prazo e 9 revelaram ser de curto-prazo. Evidência de forte exogeneidade foi encontrada em 2 relações. Esta fraca expressão de cointegração de longo-prazo sugere potenciais benefícios associados à diversificação da carteira de investimentos com obrigações verdes.

Palavras-chave: investimento sustentável; mercado obrigacionista; índices verdes obrigacionistas; cointegração

Classificação JEL:

C32 – Multiple or Simultaneous Equation Time-Series Models
G17 – Financial Forecasting and Simulation
Q01 – Sustainable Development

ABSTRACT

Green bonds emerged as an innovative fixed income product with potential to mobilize capital to promote the climate change mitigation or adaptation.

The present study aims to investigate whether the green bonds integration into the investor's portfolio provides superior returns or if it implies a trade-off between sustainability concerns and financial performance, through the analysis of green and conventional bond indices.

The analysis of returns suggests low volatility and consequently, low investment risk for both types of indices. The difference between the means of returns were not statistically significant, implying the rejection of the trade-off theory between sustainability and financial performance. Also, short-run dependencies between green, investment grade (AAA, AA, A e BBB ratings) and conventional governmental-related indices were found.

Through the study of the long-run dynamics 20 cointegration relationships were identified, out of which only 4 showed a long-run equilibrium relationship and 9 revealed a short-run relationship. Evidence of strong exogeneity was found across 2 relationships. This weak expression of long-run cointegration suggests potential for benefits associated to the investment portfolio diversification to green bonds.

Keywords: sustainable investment; bond market; green bond indices; cointegration

JEL Classification:

C32 – Multiple or Simultaneous Equation Time-Series Models

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1. INTRODUCTION

In the last couple of years, an irreversible damage caused by the climate change has been faced. The continuous reduction of natural resources is of utmost importance since it is not only starting to affect the present generation but also impacting the future of the next ones. The activity of economic agents has been negatively affected by the climate change. Gradually, corporates and public institutions are starting to realize the need of adaptation to new climatic conditions, which led to the adoption of environmentally friendly behavior and promotion of socially responsible strategies (Voica, Panait and Radulescu, 2015).

Hence, capital markets needed to intervene to mobilize private funding for climate change mitigation and adaptation projects. Nonetheless, to boost the funds required to contribute to the fight against climate change, investment products needed to be designed to appeal to investors with a significant asset base (Reichelt, 2010). Green bonds emerged as an innovative fixed income product that can pave the way for the next investment products to start mobilizing significant capital to finance the greatest challenge faced by the 21st century.

The investor's social and ecological awareness has been rising and consequently, translated into an increased demand for Green labelled investments. There is a growing evidence that investors are willing to incorporate Environmental, Governance and Social (ESG) factors into their investment decisions, aiming to create portfolios that balance financial returns with their own beliefs and values.

However, Green bonds attract a diversified investor base, encouraging not only socially responsible investors but also investors seeking to diversify their investment portfolio and to reduce their exposure to climate or environmental-related financial risks (Hunt and Weber 2018).

In fact, Green bonds are not different from their conventional peers, offering both a predictable return in the form of a fixed coupon yield in exchange of funding for economic activities. The main difference is in what concerns to the use of proceeds: *"(...) the mission of a Green bond is to finance projects that bring environmental gains, which requires a credible method of assessment over the life of the investment"* (United Nations Framework Convention on Climate Change, 2016)

However, this debt instrument is self-identified by the issuer, which makes market participants concerned about the use of proceeds and questioning the level of transparency. Despite the efforts of some existing frameworks to ensure and evaluate the environmental credentials, clear rules and mandatory standards are yet to be established to ensure the green label correct usage, closely monitoring and reporting of proceeds.

The need of a standardized way to establish what can be labeled as Green did not prevent the Green bonds market from developing over the past years. Despite the divergent opinions on the effect of the ESG integration into the investor's portfolio, Green bonds volume has been growing steadily in recent years.

However, there are still limited articles and studies focused on the Green bonds' financial performance. Due to the Green label nature, which is associated with the funded projects and not with the issuer type, the Green bonds' yield does not rely on the Corporate and Social Performance (CSP) of the issuing firm/institution, which means that to accurately compare Green bond's yield to its conventional peers, it should be considered a similar conventional bond from the same issuer, since their risk characteristics would be identical.

Having said this, the main contribution of the present study is to investigate whether the Green label integration into the investor's portfolio provides superior returns or if it implies a trade-off between sustainability concerns and financial performance, aiming to fill in the missing gaps in the existing literature, since this topic has been rather poorly examined, with limited amount of research made.

This dissertation is the first study, up to the author's best knowledge, that studies the short and long-term dynamics between Green bond indices and their conventional peers, with the aim to capture any common trends between the various indices.

The present study is organized as follows: in the Chapter 2, a brief overview of the Green Finance field is provided, followed by a deep dive on the Green bonds. Including the definition and its typologies, the existing frameworks to ensure transparency and credibility across the Green bonds issuance, monitoring and reporting and the specificities of the Green bond market. Still on the Chapter 2, the literature review on the existing studies on Corporate Social/Environmental Performance and Financial Performance is provided, firstly as a general overview, followed by a deep-dive into the Debt Market and the Green bonds specifically.

In the Chapter 3, the methodology chosen to conduct this study is presented, including the definition of the main objectives of the study, the data and sample selection and a brief empirical theoretical overview to introduce the econometric specifications, tests and procedures that will be applied across the empirical study.

The presentation and analysis of the empirical results take place in the Chapter 4, starting with the analysis of the returns. Firstly, an interpretation of the visual analysis of both prices and returns of bond indices was performed, followed by study of the descriptive statistics of the returns. Then, the results of both parametric and non-parametric tests, which investigated whether exists or not differences in terms of average financial performance in both types of bond indices were presented. The Granger causality tests, performed to study the short-term dynamics between the returns of Green bond indices and its conventional peers under study, were then interpreted.

Afterwards, to analyze the long-run dynamics across the Green bonds indices' prices and its conventional peers, the Johansen cointegration procedure was applied. The Vector Error Correction (VEC) Model was estimated for each cointegration relationship identified, and was followed by the analysis of weak exogeneity tests to trace which Conventional bond indices' prices could or not be used to forecast the Green indices prices in the long-run, since a weak exogeneity implies the absence of significant adjustments in the long-run and, consequently, the preclusion of using the model to forecast the Green bond indices' prices. Lastly, in the Chapter 5, the main conclusions are presented.

2. LITERATURE REVIEW

2.1 GREEN FINANCE: BRIEF OVERVIEW

The impact of economic activity on the environment started to capture attention in the 1960s when global ecological problems first became highly visible. Carson (1962) raised public awareness about the irreversible environmental degradation, which made him known as a catalyst for the environmental movement of the 1960s and 1970s. Firms rapidly became generally perceived as important actors with the reach, resources access, technology, and motivation to help solving environmental and social problems (Hart, 1997).

In the 1970s and 1980s, governments in developed economies introduced environmental regulations aiming to create finance environmental compliance functions, which was not well received by the majority of the companies that faced these new standards as unwarranted impositions on their way to do business (Walley and Whitehead, 1994).

However, as time went by, intermediaries and financial markets started to increasingly contribute to the development of a more environmental and sustainable economy. On the one hand, banks are now developing new financial products and services to provide Green enterprises with an easier access to capital (e.g. preferential banking packages, lower interest rates). On the other hand, the number of business angels (BAs) and venture capitalists (VCs) that consider the capacity of Green projects as adding value to companies is gradually increasing in the financial markets (EIM and Oxford Research, 2011).

According to Wang and Zhi (2016), Green Finance (GF) is a phenomenon that combines both Finance and Business with the Environment. It is an arena for many participants, including individuals and business consumers, producers, investors, and financial institutions. Contrary to the traditional financial activities, Green finance emphasizes more on the ecological benefits and pays more attention to environmental protection.

The inclusion of Environmental, Social and Governance (ESG) criteria into the decision-making process is mainly rooted in ethical and socially responsible investing movements (Falcone, Morone and Sica, 2018). Although, there are various rationales being given for the inclusion of these factors. For instance, from a risk/return perspective, companies that consider investing on ESG practices associated to their business activities are likely to be ahead of their peers[1]. Also, according to Schneider (2011), from an environmental point of view, actively managing a portfolio's footprint may help to decrease exposure to legal and reputational risks and provide a hedge against future regulatory changes.

Moreover, the global commitment on working towards the climate change mitigation has started with its integration as one of the 17 United Nations Sustainable Development Goals (UN SDGs) under the 2030 Agenda agreed by 193 countries in September 2015[2].

These climate pledges, mainly on the greenhouse gas reduction, were emphasized by the world's nations at the 2015 Conference of the Parties (COP21) to the United Nations Framework Convention on Climate Change (UNFCC). Hosted by Paris, this agreement was signed with the aim to limit global warming to 2ºC above the pre-industrialization levels, mainly throughout the commitment on renewables and/or energy efficiency, which is reflected in the IEA's finding that renewables are set to become the leading source of new energy supply from now to 2040 (IEA, 2018).

Under the COP21 agreement[3], developed nations agreed to supply USD$100 billion to fund projects in developing countries and support the transition to a low-carbon footprint. However, in June 2017 U.S. decided to withdraw from the Paris Agreement, which was perceived as a push back on the country's commitment to reach the 2°C target, despite the efforts being made by U.S. to reduce greenhouse gas emissions in the recent years.

This worldwide commitment along with many ambitious emissions reductions' programs coming from many states and cities are certainly helping to spur further interest and growth in GF by highlighting the need for additional green financing initiatives.

Hence, financial instruments are becoming crucial for applying GF into real life and indeed, Green bonds are playing an important role by being able to combine both "bonds" and "Green" features in the same financial instrument. On top of the Green bonds, there are also other products, such as the Social Bonds (funds used to finance projects with a clear social impact) and Sustainable bonds (combination of social and environmental benefits).

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[1] S&P Global Ratings [89]
[2] United Nations [92]
[3] United Nations Framework [93] [94]

2.2 GREEN BONDS

2.2.1 Definition and typologies

In generic terms, Green bonds (or Climate bonds) are a fixed-income asset-class that are similar to the conventional corporate and government bonds regarding pricing and rating, with the peculiarity that their proceeds are earmarked by the issuer for projects with environmental benefits consistent with a climate-resilient economy (Reboredo, 2018).

Hence, the Green label of these vanilla fixed income assets offers a promise to use the proceeds to finance or re-finance, in part or fully, new or existing sustainable projects/activities that promote climate change mitigation or adaptation, or other environmental sustainability purposes, which means that the mission behind the Green bond's issuance is to finance projects that spur renewable energy, energy efficiency, sustainability (e.g. projects leading to reduced carbon emissions), biodiversity and clean infrastructure (Ernst & Young Report, 2016).

International Capital Market Association (ICMA, 2018a) identified 4 types of Green bonds:

1. **Standard Green Use of Proceeds bond:** A standard recourse-to-the-issuer debt obligation aligned with the Green Bonds Principles (GBP);
2. **Green Revenue bond:** A non-recourse-to-the-issuer debt obligation in which the credit exposure in the bond is to the pledged cash flows of the revenue streams, fees, taxes, etc., and the use of proceeds of the bond goes to related or unrelated green projects;
3. **Green Project bond:** A project bond for a single or multiple green project(s) for which the investor has direct exposure to the risk of the project(s) with or without potential recourse to the issuer, and that is aligned with the GBP;
4. **Green Securitized bond:** A bond collateralized by one or more specific Green Project(s), including but not limited to covered bonds, Asset-Backed Securities (ABS), Mortgage-Backed Securities (MBS), and other structures, aligned with the GBP. For instance, this type of bond covers asset-backed securitizations of rooftop solar photovoltaic and/or energy efficiency assets.

Depending on the type of Green bond chosen to invest in, there are different types of risk to which investors may be exposed to. For instance, investing in a Standard Green Use of

Proceeds bond brings the same issuer risk than investing in a regular bond issued by the same issuer. It is also worth noting that due to smaller issuer sizes and an investor base involving mainly Hold-To-Maturity (HTM) investors, Green bonds tend to have lower liquidity than its conventional peers.

Table 1 – Financial risks associated with different Green bond categories

Categories	Issuer Risk	Credit Risk	Market/Liquidity Risk
Standard Green Use of Proceeds	Yes	Issuer default risk	HTM investors and smaller issuer sizes
Green Revenue bond	No	Source of revenue	-
Green Securitized bond	No	Receivables	Non-matured market, lower liquidity
Green Project bond	No	Single specific project	Valuation issues, not priced in Bloomberg

Source: "The 2016 Global Sustainable Investment Review", Global Sustainable Investment Alliance (GSIA)

2.2.2 Green Bonds Principles and Climate Bonds Standard

Green bonds can be issued by any financial institution, government or even by company that want to raise funds for a defined period. However, since these bonds are self-identified by the issuer, market participants require transparency around the use of proceeds and a standardized way to establish what can be labeled as Green.

Therefore, in January 2014, ICMA published the Green Bonds Principles (GBP) to promote integrity across the Green bond's issuance[4] process as well as to support issuers in the transition towards a more sustainable business model. According to ICMA (2018a), "*the principals are voluntary process guidelines that recommend transparency and disclosure and promote integrity in the development of the Green bond Market by clarifying the approach for the issuance of a Green bond*."

Thus, the GBP are not intended to define what Green bonds are neither to narrow down eligible categories to Green bond projects. Rather, they recommend issuers to communicate in a transparent and clear way their use of proceeds so that investors will be better equipped to evaluate the environmental impacts and the consistency with their investment strategy.

[4] The GBP are being used to avoid *Greenwashing* – process of labelling bonds as Green to receive their proceeds without sustainable or environmental purposes or commitment behind

However, the lack of a legal framework aiming to evaluate the compliant issuance of Green bonds and the respective use of proceeds have been raised across the practitioners as a major concern. Some believe that green bonds may merely be a form of *Greenwashing* - "*a few skeptical voices are starting to question the value of this innovation, asking in particular whether green bonds make any real difference or whether they are just another case of greenwashing*" (Financial Times, 2015).

To facilitate greater disclosure and transparency amongst the issuers and to avoid firms to portray an environmentally responsible public image without any commitment[5], GBP are playing a crucial role in the market, by categorizing four components as important fields for Green bonds' issuance: Use of proceeds; Management of proceeds; Process for project evaluation and selection and Reporting:

1. **Use of proceeds:** The eligible green projects should be declared at the beginning, and provide clear environmental benefits, which will be assessed and quantified by the issuer. Examples of eligible green projects are set out in the GBP, including:
    a. Renewable energy (including production, transmission, appliances and products);
    b. Energy efficiency (such as in new and refurbished buildings, energy storage, district heading, smart grids, appliances and products);
    c. Pollution prevention and control (including waste and water treatment, greenhouse gas control, waste reduction/recycling, and soil remediation);
    d. Environmentally sustainable management of living natural resources and land use (including environmentally sustainable agriculture, fishery, forestry, and climate smart farm inputs such as biological crop protection);
    e. Terrestrial and aquatic biodiversity conservation (including the protection of coastal, marine and watershed environments);
    f. Clean transportation (such as electric, hybrid, public, rail, non-motorized transportation and infrastructure for clean energy vehicles);

[5] For further evidence on this topic: Park (2018) – Green bond market and the absence of public laws and regulations [76]

g. Sustainable water management (including sustainable infrastructure for clean water, sustainable urban drainage systems or flooding mitigation);
h. Climate change adaptation (including information support systems, such as climate observation or warning systems);
i. Eco-efficient and/or circular economy adapted products, production technologies and processes (such as resource efficient packaging and distribution and the development of environmentally friendly products);
j. Green buildings which meet regional, national or internationally recognized standards or certifications.

2. **Management of proceeds:** The proceeds should be segregated, or otherwise tracked by the issuer, in a process that should be clearly and publicly disclosed. Information should be made available on eligible instruments in which any unallocated proceeds may be invested. Third party verification of the internal tracking method is desirable;
3. **Process for project evaluation and selection:** The issuer should outline the decision-making process by which the eligible projects were selected (including the type of projects to which the funds will be used), the related eligibility criteria, the environmental sustainability objectives and projects' environmental impact expected. The project evaluation and selection can be supplemented by a third-party revision;
4. **Reporting:** The issuer should report at least annually the green use of proceeds until full allocation, or in the event of new development thereafter, detailing (wherever possible with regards to confidentiality and/or competitive considerations) the specific projects and amounts invested along with the expected environmentally sustainable impact. Quantitative performance indicators are recommended (achieved vs estimated, where feasible).

With these guidelines, investors have at their disposal all the information needed to evaluate the environmental benefits of their Green bond investments. Namely, investors show particular interest in the Reporting as an important instrument not only to ensure issuers' accountability on the environmentally achievements, but also to measure their own investment portfolios in terms of sustainability objectives and performance.

Also, GBP recommend issuers to use external assurance (third-party reviews and certifications, independent audits and ratings) to ensure accuracy and most important, to support investor's decisions towards what a green use of proceeds is.

Due to what environmental sustainability's vast scope encompasses, there is no universal standard to establish what can be labelled as Green. "*Financing of investments through green bonds has grown rapidly in recent years. But definitions of what makes a bond "green" vary. Various certification mechanisms have evolved to allow more granularity as well as continuity in assessment."* (Ehlers and Packer, 2017). Climate Bonds Initiative (CBI) is one example of a non-profit organization that provide bond's databases aligned with the GBP.

CBI finds and quantifies bonds that are being used to finance low carbon and climate-resilient infrastructure: climate-aligned bonds. This includes bonds labelled as Green *"(...) with use of proceeds defined and labelled as green."* (Climate Bonds Initiative, 2018a, 2018c) as well as a larger universe of bonds, the unlabeled climate-aligned bonds which *"(...) do not carry a green label"* (Climate Bonds Initiative, 2018a, 2018c). Together, these two groups make the "climate-aligned" bond universe.

According to CBI report in September 2018, the labelled Green bonds account for 32% (USD$ 389 billion) of the overall climate-aligned bond universe (total of USD$1.45 trillion).

In addition to the CBI framework, other third parties are also available to provide verifications or certifications on green credentials, such as Centre of International Climate and Environmental Research Oslo (CICERO), Moody's Green Bond Assessments, Standard & Poor's Green Evaluations, Vigeo Eiris and Leadership in Energy and Environmental Design (LEED) (*these are neither exclusive nor exhaustive*). For instance, CICERO is a climate research institute based in Oslo, whose evaluations and reviews are based on "Shades of Green" according to the bond's ability to support in the long-run the transition towards a low-carbon economy. These verifications usually happen at the bond's issuance moment, which means that any subsequent change in the bond's impact will no longer be considered.

This effort undertaken by issuers, investors and governments towards transparency on Green credentials, lies in the hope of a convergent worldwide and commonly accepted standard aiming to bring clarity and trust to both Green issuers and Social and Responsible investors.

In a nutshell, market participants are largely finding a common ground on three basic requirements to assign the Green label to bonds:

1. Environmental Social and Governance (ESG) performance of the issuer;
2. Commitment on the use of proceeds towards environmental benefits;
3. Structuring and reporting process in accordance with the GBP.

2.2.3 The Green Bond Market

The first Green bond was issued in 2007 by the European Investment Bank (EIB) for financing renewable energy and energy efficiency improvement projects. At that time, the issuance size was relatively small. Since then, the Green bond market has experienced its initial development stage (2007~2012), and in 2013, the market entered the stage of rapid development. The largest Green bond issued by that time was by a French consumer energy company, the Électricité de France (EDF), for USD$ 1.9 billion[6] which helped to bring the net market size to USD$ 19 million[7] by the end of 2013.

Municipal and local governments have also recognized Green bonds as a way to fund environmental projects. The first Green bond issued by a local authority was by Region of Ile De France in March 2012. By June 2013, the first tax-exempt U.S. municipal Green bond was issued in the form of a general property tax obligation bond by the Commonwealth of Massachusetts. New York, Washington D.C., and California, among others, tapped the market in 2013.

The market started to diversify in terms of issuer type, country of domicile and risk currency. The potential of Green bonds as a new funding source to achieve climate goals started to gain expression by mid-2014 when the market size doubled to USD$ 38 billion[8]. In 2016, an increasing number of financial firms started to enter into the market, showing the increasing popularity of Green bonds in recent years, phenomenon to which Morgan Stanley refers as the "*Green bond boom*" (Morgan Stanley, 2017).

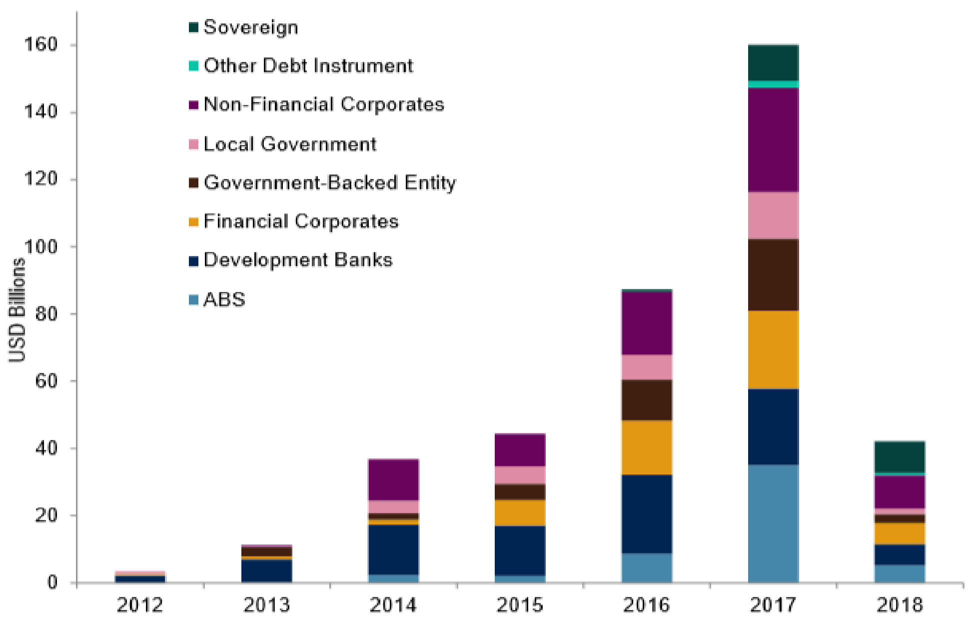
[6] S&P Dow Jones Indices - ESG & Fixed Income Research [87]

[7] Ibid.

[8] S&P Dow Jones Indices - ESG & Fixed Income Research [87]

In 2017, the corporate sector issued USD$49 billion[9] in Green bonds, thanks to corporations that are slowly getting into the market such as Apple and Hyundai. The biggest non-financial issuers as reported by Bloomberg New Energy Finance (2017b) remain the traditional players like the energy companies Southern Powers and Iberdrola. More recently, sovereign issuers entered the market and CBI estimates that this trend will persist. By March 2018, Fijian, Nigerian, Belgium and Indonesian sovereign bonds issuance helped to raise the sovereign Green bonds size to USD$14 billion[10].

Graphic 1 – Green Bond Annual Gross Issuance (in USD billions)



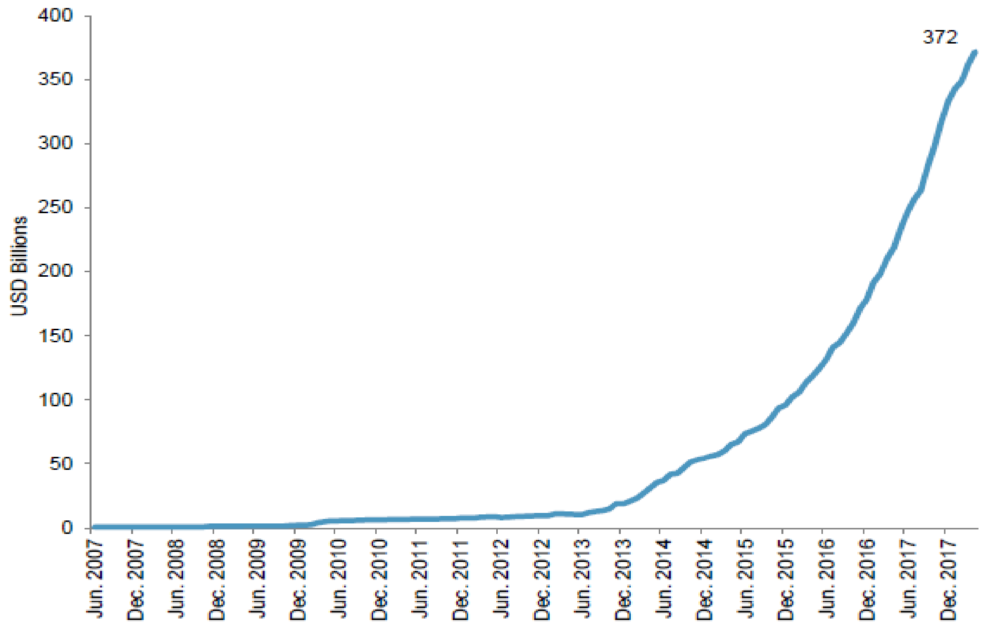
Source: S&P Dow Jones Indices LLC and CBI. Data as of May 9, 2018 (2018 figures are up to May)

It is also worth noting that the expected market growth is more evident for emerging markets, such as China and India (Barclays Credit Research, 2015). Overall, due to the increasing investor's demand, all suggest that the segment's growth will continue to outpace its conventional peers.

[9] This amount was still a small portion of the overall bond market, which size worldwide (based on total debt outstanding) was estimated at USD$ 92.18 trillion in 2016 (SIFMA, 2017) [85]
[10] Climate Bonds Initiative (2017) [15]

The issuance volume of Green bonds shows a clear picture of its potential as the figures have been growing exponentially in the last couple of years, which is easily understood by the graphic presented hereunder.

Graphic 2 – Green Bond Market Size (in USD billions)



Source: S&P Dow Jones Indices LLC and CBI. Data as of April 2018.

The key aspects across the Green bond market development are the scale of increase and the issuer varieties. Distribution scope is expanding from Europe to all over the world specially to developing countries (Wang and Zhi, 2016).

However, the Green bond market is still facing some challenges to its growth and development, namely the lack of commonly accepted green standards and guidelines which may lead issuers to face reputational risks with potential accusations of "*greenwashing*", whenever proceeds are not used for their intended purposes or if issuers are unable to prove the positive impact of the funded projects. To help mitigating these blocking points, OECD suggests that policy markets need to intervene along with market participants to push for standardization and common rules so that the Green bond market can scale up rapidly to raise and finance the debt capital needed to support the low-carbon economy transition.

In the light of these efforts, some improvements have started to be done from Governments, worldwide – for instance, in 2015 Switzerland became the first national Government member of the Climate Bond Partners to support the development of the Climate Bonds Standards (Kidney, 2015); China is developing country-specific Green Bond Guidelines to increase transparency and guide the market as part of the broader green financial reforms (UNEP and PBoC, 2015) and the European Commission has been monitoring, assessing and supporting these developments under the EU Capital Markets Union (EC, 2015).

2.3 EMPIRICAL STUDIES ON CORPORATE SOCIAL/ENVIRONMENTAL PERFORMANCE AND FINANCIAL PERFORMANCE

The relationship between corporate social or environmental performance (CSP) and corporate financial performance (CFP) has been leading to a non-consensual long-standing debate among academics and professionals. According to Orlitzky *et al.* (2003: 403) "(…) *current evidence is too fractured or too variable to draw any generalizable conclusions."* After conducting a meta-analysis study with a total sample size of 33,878 observations, the authors were presented with the following results: (1) CSP is positively correlated with CFP; (2) the relationship tends to be bidirectional and simultaneous and (3) reputation seems to be an important mediator of the relationship alongside with disclosure of CSP and market measure of CFP, which may also impact the relationship, since "*CSP appears to be more highly correlated with accounting-based measures of CFP than with market-based indicators, and CSP reputation indices are more highly correlated with CFP than are other indicators of CSP"* (Orlitzky *et al.*, 2003: 403).

Elsayed and Paton (2004), conducted both static and dynamic panel data analysis of the impact of environmental performance on financial performance, by using Tobin's Q, return on assets (ROA) and return on sales (ROS). The authors based on the sample of UK firms in the Management Today Survey of Britain's Most Admired Companies (BMAC), concluded that environmental performance has a neutral impact on firm's financial performance, which according to them, is consistent with the belief that firms only invest in environmental initiatives until the margin cost of such investments equals the marginal benefit.

Following up on the study conducted by Murphy (2002) which noted a positive relationship between the firm's environmental performance and the overall financial performance, Sharfman and Fernando (2008), examined 267 U.S firms and reached the conclusion that improved environmental risk management is associated with a lower cost of capital. The conventional belief that environmental-conscious activities represented a cost to firms was contradicted by the outcomes that an improved environmental risk management results in a reduction in the cost of equity capital, a shift from equity to debt financing, and higher tax benefits associated with the ability to add debt.

López *et al.* (2007) also examined the relationship between business performance and CSR related initiatives and adoption. To understand so, the authors brought to the analysis some accounting indicators such as ROA, ROE, cost of capital and profit margin and studied whether there are significant performance differences between European firms active towards CSR activities and others who are not – for this purpose, they have chosen a number of companies included in the Dow Jones Sustainability Index (DJSI) and others quoted on the Dow Jones Global Index (DJGI) and not on the DJSI. The main outcome of this study was that in the first years of sustainability strategies implementation (from the group of firms included in the DJSI), a short-term negative relation was spotted in DJSI firms with respect to DJGI ones. However, since the negative relation only occurred during a specific period and was not consistent over time, López *et al.* (2007) did not find evidence that the adoption of sustainability practices has positive repercussions on performance indicators.

From the investor's point of view, is clear that socially/environmentally responsible investors have a better CSP than conventional ones. However, regarding CFP is not clear if sustainability-concerned investors perform better or worse financially.

The majority of Social Responsible Investment (SRI) advocates (Kempf and Osthoff, 2007) strongly believe that socially responsible investing contribute to higher CSP and CFP levels. This so-called outperformance would mean a win-win situation in which sustainability-concerned and conventional investors would have the same profitability. A reason appointed to justify this rationale is the fact that social responsible investors have a much smaller investment universe, and therefore they end up being more selective when investing (striving for the best balance between profit and risk).

To better understand this so-called SRI outperformance, Cortez *et al.* (2009) took 88 European socially responsible funds and analyzed their financial performance compared to conventional and socially responsible benchmark portfolios, through unconditional and conditional models of performance. The outcome was a neutral performance compared to the remaining benchmarks (both conventional and other socially responsible funds), meaning that investors willing to hold European funds may integrate social screens into their portfolios without compromising financial returns.

On the same note, Schröder (2004) also evaluated the performance of SRI funds. Schröder (2004) compared SRI equity investment funds in the United States, Germany and Switzerland to SRI equity indices such as the Domini 400-index, using performance measures (e.g. Jensen's alpha). This study showed that most of the German, Swiss and U.S. SRI funds do not underperform their benchmarks, presenting similar risk-adjusted performance to conventional peers.

However, all these findings are not necessarily applicable to the Debt Market for at least two reasons. Firstly, the payoff of a debtholder may differ from the stockholder, since a bond payoff can be replicated by taking a long position in the firm's assets (i.e. purchase of a stock) and a short position in a call option (i.e. sale of a call option) on the same assets (Merton, 1973). This means that bondholder's potential losses are the entire amount invested while the potential gains are capped (Oikonomou *et al.*, 2014), for bondholders this implies a careful market screening to assess all downside risks, particularly concerning socially responsible investing, even more taking into account that CSP is associated with better credit ratings (Ge and Lui, 2015 and Oikonomou *et al*., 2014). Additionally, as debtholders care primarily about default risk, favorable credit ratings may inspire investor's confidence (Jiraporn *et al*., 2014).

According to Ge and Lui (2015), CSP is also intertwined with lower yield spreads in corporate bonds issuance, which means that, companies with better CSP have easier access to markets and may borrow at a much lower cost. Also, stating Oikonomou *et al.* (2014), companies are more sensitive to the pressure made by bondholders, since they tend to refinance themselves via the Debt Market more frequently than increasing their capital.

The existing studies related to the CSP effect on the bond yields do not present concrete conclusions yet, since the majority of the available research has been focused on the link between CSR and CSP. Only few empirical researches have analyzed the relations between CSR, cost of debt and its relationship with the firm's risk profile.

In what concerns to CSR, risk reduction is seen as one of the potential benefits related to CSR activities. Thus, the expectation is that CSP scores are inversely related to cost of debt. On the one hand, some authors such as Magnanelli and Izzo (2017) conducted a study using 1641 observations from 332 companies and concluded that CSP increases the cost of debt (positive relationship) which strengths the conventional belief that environmental concerns represent an extra cost to firms – *"(...) financial institutions not only seem to avoid applying any risk reduction for CSR activities but also consider them as a waste of resources, which, as a consequence, has a negative impact on the cost of financing."* (Magnanelli and Izzo, 2017: 252). Additionally, Menz (2010) investigated the relationship between CSR and European corporate bonds and given the fact that socially responsible firms are perceived as economically more successful and less risky, they are expected to face lower risk premia. However, this empirical analysis showed that socially responsible firms face higher risk premia than non-socially responsible companies.

On the other hand, some authors such as Oikonomou et al. (2014) and Schneider (2011) analyzed the relationship between CSR and corporate bonds (Oikonomou from a risk point of view and Schneider from the pricing point of view). Oikonomou et al. (2014) showed that good CSR performance can reduce the risk premia associated with corporate bonds and thus, decrease the cost of corporate debt. Also, superior CSP may lead to improved credit quality and lower perceived credit risk.

Schneider (2011) conducted an industry-specific study with a small sample (244 total firm-year observations, 48 firms across two industries), whose results showed that a firm's environmental performance is reflected in its bond pricing. Meaning that, CSP may help to decrease exposure to legal and reputational risks and provide a hedge against future regulatory changes. Additionally, Stellner *et al.* (2015) examined the link between CSR performance and credit risk and found evidence, although weak, that superior CSP reduces credit risk. "*(...) superior CSP is rewarded in countries with above average ESG performance (...) companies benefit from better ratings and lower spreads if their relative ESG performance matches those of the corresponding country.*" (Stellner et al., 2015: 548).

Ge and Liu (2015) focused on CSP disclosure effects on 4,260 public bonds' spreads in the U.S. primary market in the period between 1992–2009. Results showed that firms with better CSR performance are able to issue bonds at a lower cost. Also, bondholders seem to value more CSR performance for financially healthy firms than for financially distressed.

In what concerns to Green bonds, there are few articles published specifically focused on their financial performance and associated cost. Controversially to the studies mentioned above, due to the Green label nature, which is associated to the funded projects and not with the issuer type, the Green bonds' yield does not rely on the CSP of the issuing firm/institution.

Thus, to compare Green bond's yield to its conventional peers, it should be considered a similar bond from the same issuer, to ensure identical risk characteristics – *"(…) while the proceeds from the issuance of a Green bond are earmarked for environmentally friendly projects, Green bonds are serviced from the cash flows of the entire operations of the issuer – not just the green project."* (Ehlers and Packer, 2017: 96).

These specificities impact the Green bonds' pricing and their attractiveness. A premium at issuance for Green bonds would implicitly require a significant demand for this type of bonds over comparable bonds (i.e. investors would need to be willing to acquire Green bonds at an extra cost, meaning accepting a lower spread). At the same time, Green bonds' investors would still be interested in a sufficient financial performance over time.

To analyse the price effect of the Green label, HSBC (2016), Ehlers and Packer (2017) and Climate Bonds Initiative (2016) studied the pricing of bonds (Green and conventional) at issuance by taking the difference between the two yields.

HSBC (2016) considered a sample of 30 Green bonds, Ehlers and Packer (2017) a cross-section of 21 Green bonds and Climate Bonds Initiative (2016) studied 14 Green bonds. HSBC (2016) and Climate Bonds Initiative (2016) did not find any significant differences on the pricing of Green and conventional bonds at issuance in the primary market.

The Climate Bonds Initiative (2016) examined the existence of a "*Greenium*" at issuance (i.e. a persistent negative premium at the Green bonds' issuance) and concluded that it exists only for some bonds. These results were further confirmed on the Climate Bonds Initiative (2018b) report since 2 out of the 21 Green bonds under study exhibited a "*Greenium*" at issuance.

The Climate Bonds Initiative (2016) results are in line with the OECD (2017) and I4CE (2016) reports which support the rationale that investors are not willing to pay a premium at issuance to acquire Green bonds, since Green bonds and conventional bonds' financial characteristics produced by the same issuer are identical on the issue date ("flat pricing"), meaning that investors won't be willing to pay an extra cost (OECD, 2017).

However, Ehlers and Packer (2017) results on 21 Euro- and USD-denominated bonds, issued between 2014 and 2017, showed that Green bond issuers on average have borrowed at lower spreads than they have through conventional bonds. The mean difference found was around 18 basis points, which implies that enough investors have a preference for holding Green bonds over its conventional peers so that the issuance price is impacted.

Nevertheless, the Green premium at issuance will not necessarily mean underperformance in the secondary market trading (Ehlers and Packer, 2017). Natixis (2017) focused on Green bonds issued by the governmental agencies and found that although there is a small price advantage, a "shy" Green premium in the supranational, sub-sovereign, and agency (SSA) primary market, the Green premium on the secondary market is not so clear as it tends to be quite volatile (Natixis, 2017).

Barclays Credit Research (2015) and Bloomberg (2017b) focused on the secondary market and both reports found a negative premium. Barclays Credit Research (2015) study was based on two Indices, the Global Credit Index (multi-currency Index that includes both corporate and government-related issuers) and the Global Green Bond Index. Through an OLS regression of the credit spreads on several market risk factors, a negative premium of -17 basis points was found between March 2014 and August 2015. These results are seen as partly attributable to opportunistic pricing based on the increasing demand for environmentally focused funds. Whereas, Bloomberg (2017b) analyzed 12 Green bonds between March 2014 and December 2016 and found a strong negative premium of -25 basis points on Euro-denominated government-related bonds. However, on USD-denominated and corporate bonds, any premium was observed.

More recently, Hachenberg and Schiereck (2018) also focused on the secondary market, did not find any concrete evidence that Green bonds are priced in a different way compared to similar conventional peers.

The effects of Green bonds issuance were also studied by Flammer (2018) who analyzed 217 corporate Green bonds issued by public companies globally from January 2013 to December 2017. The results pointed for green bonds positive stock market reaction, improvements in long-term value and environmental performance and an increase in green innovations. Also, Tang and Zhang (2018), documented a positive stock market reaction and a greater stock liquidity following Green bond issuance.

Karpf and Mandel (2018) investigated the particular case of the U.S. municipal bond market. Using a sample of 1,880 bonds issued by 189 distinct issuers on the municipal market between 2010 and 2016, they found a positive Green premium in the first 5 years as they were traded at higher yields, whereas in the last 2 years this premium turned negative. Historically, "*Green bonds have been penalized on the municipal market, being traded at lower prices and higher yields than expected by their credit profiles.*" (Karpf and Mandel, 2018: 161). On the contrary, Larcker and Watts (2019) studied 640 pairs of Green and non-Green bonds issued on the same day by the same municipality, with identical maturity and rating, and did not find any evidence of a premium.

Existing research on the Green bonds' performance over its conventional peers is limited when referring to financial returns. Firstly, from an investor perspective the return on a general bond is dependent on the investor's willingness to hold the bond until its maturity, which remains applicable to Green bonds. Moreover, the potential premium at the Green bond's issuance, does not necessarily mean superior performance over time when comparing to its conventional peers.

However, despite divergent opinions on the effect of the ESG integration into the investor's portfolio, Green bonds volume has been growing steadily in recent years which proves its strong demand.

Thus, the main contribution of the present study is to investigate whether the Green label integration into investor's portfolio provides superior returns or if it implies a trade-off between sustainability concerns and financial performance, aiming to fill in the missing gaps in the existing literature.

3. METHODOLOGY

3.1 OBJECTIVES OF THE STUDY

As previously noted, this study aims to analyze whether the Green bonds provide superior returns or if it implies a trade-off between sustainability concerns and financial performance. Hence, this study is divided into three main objectives:

1. Compare the financial performance of both Green bond indices and its conventional peers through the study of their returns' properties;
2. Identify the type of relationship that exist between Green bond indices and their conventional peers by analyzing whether Green bond indices' returns are caused by the traditional bonds Indices returns, and vice-versa;
3. Assess whether exists or not a long-run equilibrium relationship amongst the indices by studying if Green and Conventional bond indices' prices are cointegrated.

3.2 DATA AND SAMPLE SELECTION

To understand if investors face a trade-off between sustainability concerns and financial performance, it is important to take into consideration two important caveats. Being the first, the lack of structured rules on what can be considered Green, which means that Green bonds cannot be unambiguously identified, and the still limited Green bond market size (approximately USD$ 389 billion[11] outstanding) compared to the conventional bond market (USD$ 100 trillion[12]).

However, a good sign of the Green bond market's growing maturity is the launch of several Green bond indices which reveals the need for comparable performance data and benchmarks. These indices are playing an important role for driving Green bonds' demand amongst institutional investors, since they break down the major barriers of this type of bonds (lack of understanding of the concept itself and the implicit risk and performance).

As an index is broadly defined as a metric intended to measure the performance of a specific group of securities, indices are commonly used to manage portfolio's risk and assess investment performance. Moreover, indices require clear rules and guidelines, such as Green

[11] Climate Bonds Initiative (2018a) [12]
[12] SIFMA (2017) [85]

eligibility criteria, inclusion criteria and specific construction rules, which means that to create a Green bond index, an index provider needs as a first step to establish what is the Green label eligibility criteria. Then, it is needed to establish the inclusion criteria (i.e. currency, minimum credit rating, outstanding amount, coupon type and term to maturity). Finally, the construction rules should be set by the index provider (e.g. how can bonds be added or removed from the Index).

Most of the existing Green bond indices are generally based on the ICMA Green Bond Principles (ICMA, 2018b) and besides the fact that Green bond indices vary in terms of methodology to select which bonds should or not be integrated, overall, they act as institutions of certification. They not only ensure consistency with the GBP but also specify additional relevant information such as size, liquidity and the industry sectors for which the financial proceeds are intended to be used.

In this way, Green bond indices are a good starting point to analyse the secondary market performance of Green bonds from an investor's point of view. "*Green bond indices contain a diversified broader portfolio of bonds and thereby provide a good means of comparison with the performance of other bond indices that are suitable for a wide range of investors*" (Ehlers and Packer, 2017: 98). However, it is worth mentioning that Green bond indices tend to differ from other Global bond indices in terms of currency composition, which may impact the relative returns whenever subject to currency movements. Nevertheless, and for the purpose of this study, it is considered the Green bond indices as an accurate representation of the financial characteristics of the Green bond market.

In a nutshell, the Green and Conventional bond indices chosen to be part of this analysis are presented in the table below.

Table 2 – Nature of each Bond Index under study

Bond Indices	Nature of the Index	
	Conventional Indices	**Green Indices**
Bloomberg Barclays Euro Aggregate (Bloomberg.E)	✓	
Bloomberg Barclays US Aggregate (Bloomberg.US)	✓	
Bloomberg Barclays Global Aggregate Bond (Bloomberg)	✓	

Bloomberg Barclays MSCI Euro Green Bond (Bloomberg.E. Green)		✓
Bloomberg Barclays MSCI US Green Bond (Bloomberg.US.Green)		✓
Bloomberg Barclays MSCI Global Green Bond (Bloomberg.Green)		✓
Bloomberg Barclays MSCI Global Green Bond AAA (Bloomberg.Green.AAA)		✓
Bloomberg Barclays MSCI Global Green Bond AA (Bloomberg.Green.AA)		✓
Bloomberg Barclays MSCI Global Green Bond A (Bloomberg.Green.A)		✓
Bloomberg Barclays MSCI Global Green Government (Bloomberg.Green.Gov)		✓
Bank of America Merrill Lynch (BofAML) Global Green Bond (BofAML.Green)		✓
Citi US Broad Invesment Grade (Citi.BIG)	✓	
JP Morgan Government Bond (JPM.Gov)	✓	
Financial Times Stock Exchange (FTSE) Euro Broad Investment-Grade Bond (FTSE.E.BIG)	✓	
FTSE US Broad Investment-Grade Bond (FTSE.US.BIG)	✓	
FTSE World Broad Investment-Grade Bond (FTSE.BIG)	✓	
FTSE World Government Bond (FTSE.Gov)	✓	
Standard & Poor's (S&P) 500 Bond (SP.500)	✓	
S&P Bond AAA (SP.AAA)	✓	
S&P Bond AA (SP.AA)	✓	
S&P Bond A (SP.A)	✓	
S&P Green Bond (SP.Green)		✓
Solactive Green Bond (Solactive.Green)		✓

To conduct the analysis between the Green bond indices and its Conventional peers, the daily closing prices have been collected for both type of bond indices during the period the 7th of January 2015 (date in which the newest index was traded for the first time) to the 16th of May 2019 (total of 1084 observations). The data was gathered from a Bloomberg terminal.

To give a brief overview about the Green bond indices under study, the Solactive Green bond index was the first Green bond index to be launched back in March 2014. Then, in July S&P created the S&P Green Bond index and the S&P Green Project Bond index. Bank of America Merrill Lynch (BAML) launched their index in October 2014 and finally in November 2014, MSCI in collaboration with Barclays launched the family of Green bond related indices.

In terms of key characteristics, the Bloomberg Barclays MSCI Green Bond index is a multi-currency benchmark that the debt markets tracked by the Barclays Global Aggregate index. Whilst, BAML Green Bond index is designed to track the performance of debt issued by quasi-governments and corporations where the proceeds are used solely for projects and activities that promote climate or environmental sustainability purposes.

The S&P Green Bond index is also a multi-currency benchmark that includes bonds issued by multilateral, government and corporate issuers. The S&P Green Bond index was developed collaboratively by S&P Dow Jones indices and Infrastructure Credit Alpha Group LLC. The Solactive Green Bond index is a rules-based, market value weighted index engineered to mirror the Green bond market.

It is interesting to note that each of the indices have a slightly different criteria for Green bonds inclusion (be it issuer eligibility criteria, reliance on third party assessment, self-labelling, etc.) and this may facilitate or form part of an investor's investment criteria. For instance, the Green eligibility criteria of Solactive Green Bond index and the S&P Green Bond indices require that Green bonds are aligned with the CBI. However, this does not mean that all Green bonds identified by the CBI are included in the index (e.g. bonds classified as Green by the CBI may be excluded due to inclusion criteria, such as minimum issue size or currency). Bloomberg Barclays MSCI Green Bond index's eligibility criteria require that a bond's use of proceeds fall within one of six MSCI-defined categories[13] and that the bond meet the four principles set out by the GBP. For the Band of America Merrill Lynch Green Bond index, bonds to be marked as Green need to have a clearly designated use of proceeds that is solely applied to projects or activities that promote climate change mitigation or adaptation or other environmentally sustainable purposes (ICMA, 2018b).

In what concerns to the Conventional indices, as they are all well known, they do not require further contextualization. However, to justify the selection it is worth mentioning that the main rationale was the alignment in terms currency, credit quality and composition (sector).

[13] The six categories are alternative energy, energy efficiency, pollution prevention, sustainable water, green building, and climate adaptation - Bloomberg Barclays MSCI Green Bond Index Consultation (2017) [4]

According to the Climate Bonds Initiative (2018a), Europe has the highest volume of outstanding Green bonds (USD$145 billion[14] of labelled Green bonds), for instance France has a volume of USD$ 44 billion[15] Green bonds, but the largest amount of labelled Green bonds outstanding is denominated in USD[16]. In terms of quality, Green bonds present well distributed ratings, with an approximately equal percentage of Green bonds AAA-rated, AA-rated and A-rated (each of them counting around 20% for the overall volume outstanding). With around 80% of the overall Green universe being Investment Grade, making it important to include Investment Grade and Global conventional indices in the study.

Lastly, in what concerns to composition, taking for instance the Bloomberg Barclays MSCI Global Green Bond index as an example, by analyzing its composition (61% of are Government-related Green bonds, 31.3% Corporate, 6.8% Treasury and 0.9% Securitized (Bloomberg Barclays Green indices, 2017)), it is clear the relative weight of Government-related Green bonds in the overall universe.

This type of bonds is a growing segment along with the sovereign Green bonds that *"(...) are increasingly seen as a key tool for governments to raise capital to implement infrastructure plans to meet the Paris agreement targets and the Sustainable Development Goals*" (Climate Bonds Initiative, 2018a). In total, USD$ 21billion of sovereign Green bonds have been issued in 2018 (Climate Bonds Initiative, 2017). Thus, it was considered relevant to include sovereign and governmental-related indices to closely capture these securities in the analysis.

[14] Climate Bonds Initiative (2018a) [12]
[15] Ibid.
[16] Ibid.

3.3 EMPIRICAL THEORETICAL OVERVIEW

3.3.1 Jarque-Bera normality test

The empirical analysis started with a visual inspection of bonds indices daily prices (in levels) and was followed by the analysis of the descriptive statistics of returns, including the Jarque-Bera normality test.

The Jarque-Bera test is a type of Lagrange multiplier test for testing the errors' normality, which is an assumption that supports all statistical inference in the linear regression model. This test is valid for big samples and it is based on the estimates for the coefficients of skewness and kurtosis.

To measure the skewness and kurtosis of a random variable distribution with mean μ and standard deviation σ, two coefficients are computed based on the third and fourth moments about the mean:

$$S(X) = E\left[\frac{(X-\mu)^3}{\sigma^3}\right] = \frac{E\,(X-\mu)^3}{\sigma^3} = \frac{\mu_3}{\sigma^3} = \frac{\mu_3}{(\mu_2)^{3/2}} \quad (1)$$

and,

$$K(X) = E\left[\frac{(X-\mu)^4}{\sigma^4}\right] = \frac{E\,(X-\mu)^4}{\sigma^4} = \frac{\mu_4}{\sigma^4} = \frac{\mu_4}{(\mu_2^2)}\ (^{17}) \quad (2)$$

Under a normal distribution (symmetric, as the Gaussian), the moments about the mean are all zero, which implies a skewness equal to zero: S(X) = 0. If the distribution is asymmetric positive, the skewness is positive and if the distribution is asymmetric negative, the skewness is negative. Related to the kurtosis, under a normal distribution: $\mu_4 = 3\sigma^4 = 3\mu_2^2$, if $\sigma = 1$, the kurtosis of a standard normal distribution is 3: K(X) = 3. Whenever, the probability mass on the distribution's tails is greater than the mass of the normal distribution, the kurtosis is higher than 3 (called a *leptokurtic* distribution), if the opposite holds, meaning the kurtosis being lower than 3, the distribution is called *platikurtic*.

Thus, the statistic of the Jarque-Bera test is:

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[17] To remove the effect of variables units of measure, the moments are divided by a scale parameter, resulting in the third and fourth normalized moments (Pinto and Curto, 2010) [78]

$$JB = n\left\{\frac{\widehat{S(X)}^2}{6} + \frac{\left[\widehat{K(X)} - 3\right]^2}{24}\right\} \sim \chi^2_{(2)} \quad (3)$$

The normality hypothesis is rejected if: JB > $\chi^2_{(2)}(\alpha)$. If the variable under the normality test is the Ordinary Least Squares (OLS) residuals from a regression model, *n* should be replaced by *n* – *k*, being *k* the number of parameters to estimate (Diebold, 2004).

3.3.2 Parametric and non-parametric tests

The next step was the performance of parametric tests to compare the average financial performance of both types of indices (Green and conventional). According to Pinto and Curto (2010), the Analysis of Variance (ANOVA) is a parametric test used to test the equality of means $(\mu_1, \mu_2, \ldots, \mu_k)$ of the same variable, named dependent variable (*Y*), in two or more populations and based on the same number of samples.

Thus, null hypothesis assumes the equality of means and in the alternative hypothesis there are at least two populations with different means:

$$H_0: \mu_1 = \mu_2 = \ldots = \mu_k$$
$$H_1: \mu_i \neq \mu_j, with\ i \neq j$$

This hypothesis that the sample come from populations with the same mean, only holds if the following assumptions are verified:

1. The elements of the sample are randomly selected and the samples under consideration are independent from each other;
2. The dependent variable must follow a Gaussian distribution in each of the populations considered (this condition is not mandatory for big samples, more than 30 observations);
3. The populations considered have all equal variances: σ^2.

Focusing on the last assumption, the decision relies on the comparison of 2 estimates for the populations' variance: an estimate resulting from the variation among the sample mean (S_B^2); and an estimate resulting from the variation of the dependent variable within each group (S_W^2). These estimates are computed as follows:

$$\hat{\sigma}_1^2 = S_B^2 = \frac{\sum_{j=1}^{k} n_j (\bar{Y}_j - \bar{Y})^2}{k-1},$$
$$\hat{\sigma}_2^2 = S_W^2 = \frac{\sum_{j=1}^{k} \sum_{i=1}^{n_j} n_j (\bar{Y}_{ji} - \bar{Y})^2}{n-k}, \tag{4}$$

where:

- k is the number of samples or groups[18];
- n_j is the number of the dependent variable observations in the sample j;
- $\bar{Y}_J$ is the mean of the dependent variable in the sample j;
- Y_{ji} is the observation i of the dependent variable in the sample j;
- $\bar{Y}$ is the overall mean of the dependent variable;
- n is the total number of observations (considering all samples).

If k samples with n_j (j = 1, …, k) observations are randomly collected from k normal populations with equal variances and in case the equality of means assumption holds, then the ratio between the two estimators for the variance of the population has a F-Snedecor distribution with k – 1 and n – k degrees of freedom:

$$F = \frac{S_B^2}{S_W^2} \sim F_{(\mathrm{k-1;\, n-k})} \tag{5}$$

Regarding the non-parametric Kruskall-Wallis test, it should only be used when the ANOVA's assumptions do not hold or if the data under analysis follows an ordinal scale.

The hypotheses of the Kruskall-Wallis test are:

H_0: The populations follow the same distribution

H_1: The populations do not follow the same distribution

Since this test is a non-parametric test, it ends up being less powerful. The statistic of the Kruskall-Wallis test is as follows:

$$H = \frac{SST}{\frac{SSB}{n-1}} \sim \chi^2_{k-1} \tag{6}$$

where, the Sum of Squares Total (SST) and the Sum of Squares Between (SSB) are calculated based on the ranked values. Thus, r_{ji} represents the rank (amongst all observations) of observation i from the group j:

[18] A group of observations is defined by each category of the explanatory variable

$$SST = \sum_{j=1}^{k} \sum_{i=1}^{n_j} (r_{ji} - \bar{r})^2$$
$$SSB = \sum_{j=1}^{k} n_j (\bar{r}_j - \bar{r})^2, \quad (7)$$

3.3.3 Pairwise Granger Causality

Then, to identify the short-term relationships between the returns of Green bond and Conventional indices and to understand if the Conventional indices' returns influence the Green bond indices' behavior, and vice-versa, the Pairwise Granger Causality test was conducted.

According to Granger (1969), the concept of Granger causality suggests that if *x* implies *y*, then, changes of *x* happened first and were followed by changes of *y*. In other words, *y* is said to be Granger-caused by *x* if *x* helps in the prediction of *y* (i.e. *x* Granger-causes *y* if, *ceteris paribus*, the past values of *x* help to improve the current forecast of *y*).

It may also occur the two-way causation, meaning that *x* Granger-causes *y* and *y* Granger-causes *x* which implies a feedback effect between the two variables. Whenever, there is just one unidirectional causal relationship, then one indices' returns can effectively influence the other returns, but the reverse is not true. In case the null hypothesis is not rejected in both cases, then there is no causal relationship between the underlying indices' returns.

The hypotheses under the Granger Causality test are as follows:

$$H_0: \beta_1 = \beta_2 = \ldots = \beta_k = 0$$
$$H_1: \exists\, \beta_j \neq 0$$

For all possible pairs of (*x*, *y*) series in a certain group, the bivariate regressions are as follows:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \ldots + \alpha_k y_{t-k} + \beta_1 x_{t-1} + \ldots + \beta_k x_{t-k} + \varepsilon_t \,, \quad (6)$$
$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \ldots + \alpha_k x_{t-k} + \beta_1 y_{t-1} + \ldots + \beta_k y_{t-k} + \varepsilon_t \,, \quad (7)$$

where *k* represents the lag length of the model estimation. This lag suggests the time over which one variable can help to predict the other, i.e. when a time series *x* Granger-causes *y*, the patterns observed in *x* are approximately repeated in *y* after some time lag. The lag length is often obtained through an Information Criteria.

Hence, the hypotheses under the above-mentioned regressions are as follows:

Regression (8):

$H_0: x\ does\ not\ Granger - causes\ y$

$H_1: x\ Granger - causes\ y$

Regression (9):

$H_0: y\ does\ not\ Granger - causes\ x$

$H_1: y\ Granger - causes\ x$

Thus, it is possible to distinguish between four causality types: **(i) Unidirectional causality**, where *x* Granger-causes y, when the null hypothesis is rejected in the first regression (8) and it is not in the second one (9); **(ii) Unidirectional causality**, where *y* Granger-causes *x*, when the null hypothesis is not rejected in the first regression (8) but it is rejected in the second one (9); **(iii) Bilateral causality** (feedback effect) when the null hypothesis is rejected in both regressions (8) and (9), meaning that *x* Granger-causes *y* and *y* Granger-causes *x*; **(iv) Independence**, when the null is not rejected in both regressions (8) and (9), showing that *x* does not Granger-causes *y* and *y* does not Granger-causes *x*.

3.3.4 Unit root tests

As the last step was the investigation of long-run equilibrium relationships amongst the Green and the Conventional indices' prices, the Unit root tests need to be performed to study the non-stationarity condition.

As the largest majority of economic and financial time series are non-stationary (time varying mean and variances) meaning that they exhibit a trending behavior around the mean, a spurious regression may arise depending on whether the trend is deterministic or stochastic (Granger and Newbold, 1974). In other words, when a random walk is regressed on another independent random walk, making a linear combination of first-order integrated variables, a first-order integrated residual variable will be produced. Under these circumstances, both *t* and *F* tests carried out on the Ordinary Least Squares (OLS) estimates do not follow, respectively, the *t* and *F* distributions and therefore, are meaningless (Phillips, 1986).

In this case, if for instance, the objective was to trace long-term relationships between the variables, the model would be capturing a common stochastic trend between the variables (in levels) instead of the relationship of causality as it was supposed. Thereby, the time series would not be related in the long-run although they may be related in the short-run (frequent between two random walks).

Thus, the Unit root tests should always be the first step of a cointegration study, since economic and finance theory often suggests the existence of long-run equilibrium relationships among non-stationary time series variables. In case, the variables are found to non-stationary and *I(1)*, then cointegration is the right tool to model these long-run relationships.

One of the most famous unit root tests to study the stochastic non-stationarity is the one proposed by Dickey and Fuller (1981), the Augmented Dickey-Fuller (ADF) test, which relies on the following regression model:

$$\Delta x_{it} = \mu_0 + \mu_1 t + (\rho - 1)x_{i,t-1} + \sum_{k=1}^{p} \gamma_k \Delta x_{i,t-k} + e_t \tag{10}$$

where:

- μ_0 is a constant term;
- μ_t represents a linear deterministic trend;
- $(\rho - 1)x_{i,t-1}$ is the corresponding stochastic trend;
- $e_t \sim NID(0, \sigma^2)$, meaning that the residuals are normally and independently distributed with mean 0 and variance σ^2.

Also, the Δ symbol indicates first difference and the summation term aims to capture any potential autocorrelation. The null hypothesis is $\rho = 1$ implies non-stationarity (stochastic trend) and the alternative is $|\rho| < 1$, implies a deterministic linear trend, meaning that the variable is stationary. The critical values were proposed by MacKinnon (MacKinnon, 1996).

Besides its popularity, the ADF test suffers from low power problems when the process is stationary with roots close to one (Blough, 1992), which leads to the need of performing another unit root test. The joint conduction of unit root tests and stationarity tests is called confirmatory data analysis.

The most commonly used alternative unit root test is the KPSS test (Kwaitkowski *et al*,. 1992), whose null hypothesis assumes that the time series is stationary around a deterministic trend. This test is based on the following regressions:

$$\begin{aligned} x_{it} &= \mu_t + z_t + u_t \\ z_t &= z_{t-1} + e_t \end{aligned} \tag{8}$$

where:

- x_{it} represents the sum of a deterministic trend (μ_t), a random walk (z_t) and a stationary residual variable (u_t);
- $e_t \sim NID(0, \sigma^2)$

The KPSS test statistic is a Lagrange Multiplier where the numerator is the sum of squared residuals obtained from regressing x_{it} on a constant and a deterministic trend and the denominator is an estimator of the variance of the residuals u_t. The null hypothesis of stationarity is given by Ω = 0 in which the initial value (z_0) is a constant. As μ_t is a stationary residual variable, x_{it} is a trend stationary process (TSP).

In a nutshell, the non-stationary unit root tests present the non-stationarity condition in the null hypothesis, whereas the stationarity tests have the stationarity condition under the null. Having said this, in case of a time series being non-stationary or *I(0),* the ADF test should has its null hypothesis rejected and the KPSS test should not reject the null hypothesis (i.e. stationarity condition holds), meaning that the respective null and alternative hypotheses of both ADF and KPSS are as follows:

ADF Test:
$H_0: x_t \sim I(1)$

$H_1: x_t \sim I(0)$

KPSS Test:
$H_0: x_t \sim I(0)$

$H_1: x_t \sim I(1)$

Thus, there are 4 possible results: (1) Reject H_0 and Do not Reject H_0; (2) Do not Reject H_0 and Reject H_0; (3) Reject H_0 and Reject H_0 and (4) Do not Reject H_0 and Do not Reject H_0. For both tests to be aligned and ensure consistent and strong conclusions, the results should fall under (1) or (2), pointing both for stationary or non-stationary time series, respectively.

3.3.5 Cointegration and VEC Model

Cointegration was introduced by Granger (1981) and further developed by Engle and Granger (1987), whose main concept lies in the fact that a linear combination of two or more non-stationary time series may be stationary. Thus, if such stationary linear combination exists, the non-stationary time series are said to be cointegrated.

Cointegration is known as a robust way to trace stable long-run relationships between the variables. Thus, this analysis was conducted to identify long-term relationships between the Green and conventional bond indices' prices under study.

The present study was based on the Johansen (1991, 1995) methodology, which relies on a vector autoregressive (VAR) system to investigate whether non-stationary time series are cointegrated. Being $y_t = (y_{1t}, y_{2t}, \ldots, y_{kt})'$ a *k*-vector of non-stationary *I(1)* variables and y_t has been generated by an unrestricted p^{th} order vector autoregression in the levels of the variables, then:

$$y_t = \Pi_1 y_{t-1} + \Pi_2 y_{t-2} + \ldots + \Pi_p y_{t-p} + \Phi y_t + \varepsilon_t \qquad (11)$$

where $\Pi_1, \Pi_2, \ldots, \Pi_p$ and Φ are matrices of coefficients to be estimated and ε_t is a vector of innovations.

The Johansen (1991, 1995) methodology, implies a VAR system of equations in error correction form (application of the Error Correction Model - ECM) as follows:

$$\Delta y_t = c + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \ldots + \Gamma_{p-1} \Delta y_{t-p+1} + \Pi y_{t-p} + \varepsilon_t, \qquad (12)$$

where Δ is the first difference operator and $\Gamma_i = \Pi_1 + \Pi_2 + \ldots + \Pi_i - I$, for $i = 1, 2, \ldots, p-1$, and $\Pi = \sum_{i=1}^{p} \Pi_i - I$.

Then, Π represents the long-run "level solution" for the VAR model application (11).

If y_t is a vector of *I(1)* variables, then the elements $\Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \ldots + \Gamma_{p-1} \Delta y_{t-p+1}$ are *I(0)* and the last element is a linear combination of *I(1)* variables. In case the variables are cointegrated, this last element must also be *I(0)*: $\Pi y_{t-p} \sim I(0)$. This means that either y_t contains a number of cointegrated vectors or Π is a matrix of zeros.

The rank of Π, r, indicates the number of linear combinations of y_t that are stationary. Meaning that, whenever $r = k$, the variables in levels are stationary and if $r = 0$ so that $\Pi = 0$, none of the linear combinations are stationary. However, if $0 < r < k$, there are r cointegration vectors or r stationary linear combinations of y_t. In this case, one can factorize Π: $-\Pi = \alpha\beta'$, where both α and β are $(k \times r)$ matrices, and β comprises the cointegration vectors (the error correcting mechanism in the system) and α the factor loadings.

There are two asymptotically equivalent tests based on the Johansen methodology for testing cointegration: Trace test and maximum Eigenvalue test, whose test statistics are computed as follows:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{g} ln(1-\hat{\lambda}_i) \quad (13)$$

$$\lambda_{max}(r, r+1) = -Tln(1-\hat{\lambda}_{r+1}) \quad (14)$$

where r is the number of cointegrated vectors under the null hypothesis and $\hat{\lambda}_i$ is the estimated value of the i^{th} ordered eigenvalues from the Π matrix. Both tests are calculated by looking at the rank of the Π matrix considering its eigenvalues (the rank of a matrix is equal to the number of its characteristics roots – eigenvalues – that are different from zero). Also, each eigenvalue has associated a different cointegrating vector – the eigenvectors. A significantly non-zero eigenvalues points for a significant cointegrating vector.

If the variables are not cointegrated, the rank of Π will not be significantly different from zero, so $\lambda_i \approx 0, \forall i$. The test statistics take into account the $ln(1-\lambda_i)$ rather than the λ_i themselves, but when $\lambda_i = 0$, then $ln(1-\lambda_i) = 0$. Also, the larger the $\hat{\lambda}_i$, the larger and more negative the $ln(1-\lambda_i)$ will be and therefore, the larger the test statistic will be.

Specifically to each test, the $\lambda_{trace}(r)$ is a joint test in which the null hypothesis is that the number of cointegrating vectors is less than or equal to r against an unspecified or general alternative that there is more than r (null hypothesis of no cointegrating vectors, implying a 0 rank of Π). It starts with g eigenvalues, and then successively the largest is removed, $\lambda_{trace}(r) = 0$ when all the $\lambda_i = 0$, for $i = 1, 2, \ldots, g$.

On the opposite, the $\lambda_{max}(r, r+1)$ conducts an individual test for each variable. The null hypothesis states that the number of cointegrating vectors is r against an alternative or $r + 1$.

Critical values for both statistics' tests were provided by Johansen and Juselius (1990). These critical values are relying on the value of $g - r$, the number of non-stationary components and whether constants are included in each of the equations. If the test statistic is greater than the critical value, then the null hypothesis of $r + 1$ (for λ_{trace}) or more than r (for λ_{max}) is rejected. The test is conducted in a sequence under the null, $r = 0, 1, \ldots, g - 1$ so that the hypothesis for λ_{max} are:

$$H_0\text{: r} = 0 \text{ versus } H_1\text{: } 0 < r \le g$$

$$H_0\text{: r} = 1 \text{ versus } H_1\text{: } 1 < r \le g$$

$$H_0\text{: r} = 2 \text{ versus } H_1\text{: } 2 < r \le g$$

...

$$H_0\text{: r } = g - 1 \text{ versus } H_1: r = g$$

The first involves a null hypothesis of no cointegrating vectors (corresponding Π having 0 rank). If the null is not rejected, then there are no cointegrating vectors and the test is completed. However, if the null $H_0\text{: r} = 0$ is rejected, the null that assumes one cointegrating vector (i.e. $H_0\text{: r} = 1$) would be tested and this process will continue until the null is no longer rejected.

As previously mentioned, r represents the rank of Π. In case Π is full rank (g), this would imply the original series (y_t) being stationarity. However, if Π has 0 rank, by taking the univariate case, Δy_t would only depend on Δy_{t-i} and not on y_{t-p} which would mean that there is no long-run relationship between the elements of y_{t-p} (i.e. no cointegration). For 1< rank(Π) < g, there are r cointegrating vectors, since Π would be defined as the product of two matrices, α and β', of dimension (g × r) and (r × g), respectively (Π = αβ').

The matrix β provides the cointegrating vectors whilst the α provides the amount of each cointegrating vector entering each equation of the VEC (Vector Error Correction) Model, also known as the "adjustment parameters".

The VEC Model presented in (12) describes the relationship between prices and returns in a given market, making the current returns or price changes a linear function of previous returns or price changes and historical prices. These historical prices represent the long-run or equilibrium relationship, in which the variables considered co-move over time independently of the existence of stochastic trends in each of them, i.e. ensuring a stable difference.

Thus, the long-run residuals measure the distance of the system to the equilibrium at each moment t (due to the impossibility of economic agents to adjust immediately to new information or to the short-run dynamics also present in the data considered). Thereby, when the variables are cointegrated, there is a complex adjustment process involving short-run and long-run dynamics.

3.3.6 Exogeneity test

According to Johansen (1992), the weak exogeneity is a relevant condition to apply to the conditional model for the estimation of the long-run parameters. The concept of weak exogeneity was introduced to justify considering some variables as given (exogenous) in the analysis of other (endogenous) variables.

Pacheco (2010) explained these concepts, with two variables y_t and x_t. If y_t is regressed on x_t. one can say that x_t is weakly exogenous if y_t does not explain x_t. On the other hand, x_t is said to be strongly exogenous if current and lagged y values do not explain x_t (i.e. no feedback relationship). Also, x_t is said to be super-exogenous if the parameters values in the regression of y on x are invariant to changes in the values of x.

In other words, Dwivedi (2015) clarified that economic variables may be classified as endogenous and exogenous, in which an endogenous variable is one whose value is determined within the model under analysis (i.e. is the equivalent of the dependent variable in a single-equation regression model) while an exogenous variable is determined outside the model (i.e. is the equivalent of the n variables, or regressors, in such a model, provided the variables are uncorrelated with the error term in that equation).

Also, according to Johansen and Juselius (1990), the factor loadings α are of the most interest as they contain information about exogeneity, and therefore about price leadership. If a row in α contains only zeros (or if one element in a column vector), the price under analysis will be weakly exogenous, i.e. determined outside of the system.

Hence, if the factor loading parameter in the equation for a Green bond index is zero, it means that the Green bond index prices are determined outside of the system. Thus, if the factor loading parameter associated with one of the bond index prices is zero, this index will be determined outside of the system, and therefore it would be the bond index leader. Also, according to Johansen and Juselius (1990), with one cointegration vector, at least one factor loading parameter must be different from zero.

To test weak exogeneity, the matrix α which contains information on the dynamic adjustment of the long run relationships, is used. Hence, to test if the price of product i drives the price of product j in a bivariate cointegrating relationship, a test under the null hypothesis of α_{i1} =

0 (*i* =1, 2) needs to be employed. Then, if the null hypothesis is not rejected, the endogenous variable *i* is weakly exogenous with respect to the parameters β (Johansen, 1991). This test follows a χ^2 distribution with one degree of freedom.

However, if any of the endogenous variables under study are considered to be weakly exogenous, the strong exogeneity through the Granger causality principle will be analyzed. According to Ericsson et al (1998), a Granger non-causality is one of the conditions required for strong exogeneity, as it implies the absence of feedback. It is commonly agreed that Granger non-causality is neither necessary nor sufficient for weak exogeneity. However, Granger non-causality combined with weak exogeneity defines strong exogeneity.

4. PRSENTATION AND ANALYSIS OF RESULTS

4.1 VISUAL ANALYSIS

As previously mentioned, this empirical study started with the observation of the graphical representation of both Conventional and Green bond indices daily closing prices (levels) of each variable, from the period of 7th of January 2015 to 16th of May 2019, presented in the Appendix A (Charts 1 and 2).

The graphical representations of both bond indices show various increasing and decreasing trends, which reveals a non-constant behavior in terms of variance and mean across the time. This trending behavior around the mean was expected since the majority of economic and financial time series are non-stationary[19] (time varying mean and variances).

Thus, to accurately analyse the financial performance of the variables under study, the bond indices' continuously compounded percentage rate of returns was computed by taking the first differences of the logarithm of the daily prices, as the follows:

$$r_{jt} = 100*[\ln(P_{jt}) - \ln(P_{jt-1})] \quad (16)$$

where P_{jt} represents the daily closing price for each bond index j at the time t.

Despite the noticeable volatility clustering, the graphical representations of the daily returns seem to be now stationary[22] (see Appendix B, Charts 3 and 4) showing a more stable behavior around the mean. Thus, if the daily prices charts are compared to the daily returns for each time series, despite the existence of some outliers, such as the SP.500, SP.AA, SP.A and BofAML.Green (see Appendix B, Charts 3 and 4), it is possible to conclude that the first differences time series show a more constant behavior around the mean.

To better investigate the bond indices returns' statistical properties, this introductory analysis was followed by descriptive statistical properties of returns, including mean, median, maximum, minimum, standard deviation, skewness, kurtosis and the Jarque-Bera normality test.

[19] The stationarity of the logarithm of daily prices and returns will be further assessed in this study

4.2 DESCRIPTIVE STATISTICS

As per the table below (Table 3), the means of the daily returns are almost all negative but very close to zero. As the SP.500 bond index shows a positive mean of return, the sum of the means of returns of Conventional bond indices are higher than the Green ones (0.00046 and -0.00071, respectively).

In what concerns to volatility, by analyzing the standard deviation it is possible to conclude that both Conventional and Green bond indices present similarly low levels of volatility (excluding SP.500 in the Conventional bond indices that shows a higher value for the standard deviation measure). Thus, the returns of both types of indices under study almost do not vary from the average, which indicates low volatility and consequently, low investment risk.

Regarding skewness and kurtosis, the positive skewness estimates indicate that the empirical distribution of the returns of both Conventional and Green bond indices is asymmetric positive (positively skewed distribution). This means that the distribution of the returns shows an asymmetric tail extending towards more positive values, making abnormal positive returns more likely to happen than negative occurrences.

The kurtosis is always higher than 3 (expected value for a Gaussian distribution), which means that there is excess kurtosis and therefore, the probability of an extreme return (extremely high or extremely low outlier) is higher than what would be in a normal distribution, causing the "fat tails" when compared to the bell-shaped distribution curve. For instance, when comparing the SP.500 (kurtosis of 1040.22) to the Bloomberg.Green (kurtosis of 4.77), the SP.500 by presenting an extremely higher kurtosis will have more instances of extreme returns than the Bloomberg.Green.

Lastly, the Jarque-Bera test was computed to reinforce the previous conclusion from the skewness and kurtosis analysis. As all probabilities associated to the Jarque-Bera test are lower than the significance level (considering a 5% significance level), the hypothesis that all empirical returns' distribution follow a Gaussian distribution is rejected (i.e. normality assumption is rejected).

Table 3 – Daily returns descriptive statistics (see Appendix C)

	Bond Indices	Mean	Median	Max.	Min.	Standard Deviation	Skewness	Kurtosis	Jarque-Bera test	P-value
Conventional Bond Indices	SP.500	0.00138	-0.00037	1.86750	-0.03829	0.05731	31.92896	1040.2170	48730352	0.00
	SP.AAA	-0.00005	-0.00019	0.01924	-0.01181	0.00289	0.32438	5.2293	243	0.00
	SP.AA	-0.00006	-0.00030	0.14800	-0.00854	0.00513	22.26324	642.6121	18550269	0.00
	SP.A	-0.00006	-0.00024	0.13740	-0.00808	0.00479	21.94522	630.3052	17844146	0.00
	Bloomberg	-0.00009	-0.00017	0.01652	-0.01526	0.00294	0.12646	5.7167	336	0.00
	Citi.BIG	-0.00009	-0.00015	0.00935	-0.00787	0.00185	0.19928	4.1432	66	0.00
	JPM.Gov	-0.00005	-0.00015	0.02671	-0.03462	0.00563	0.10058	5.5518	296	0.00
	FTSE.Gov	-0.00009	-0.00011	0.01938	-0.01805	0.00357	0.10479	5.6306	314	0.00
	FTSE.BIG	-0.00009	-0.00015	0.01518	-0.01429	0.00291	0.15635	5.3223	248	0.00
	FTSE.E.BIG	-0.00010	-0.00027	0.02628	-0.02402	0.00516	0.07393	4.6718	127	0.00
	FTSE.US.BIG	-0.00009	-0.00015	0.00935	-0.00787	0.00185	0.19928	4.1438	66	0.00
	Bloomberg.E	-0.00006	-0.00016	0.01107	-0.00611	0.00179	0.80311	6.9731	829	0.00
	Bloomberg.US	-0.00008	-0.00014	0.00982	-0.00825	0.00198	0.21946	4.0175	55	0.00
Green Bond Indices	Bloomberg.Green	-0.00008	-0.00010	0.01601	-0.01597	0.00336	0.17315	4.7705	147	0.00
	Bloomberg.E. Green	-0.00012	-0.00012	0.02633	-0.02424	0.00539	0.09096	5.0625	193	0.00
	Bloomberg.US. Green	-0.00008	-0.00003	0.01002	-0.01031	0.00181	0.13581	5.3947	262	0.00
	Solactive.Green	-0.00004	-0.00009	0.01646	-0.01667	0.00347	0.20567	5.0540	198	0.00
	SP.Green	-0.00009	-0.00007	0.01383	-0.01403	0.00300	0.17854	5.0266	191	0.00
	Bloomberg.Green. Gov	-0.00007	-0.00003	0.01700	-0.01704	0.00343	0.15682	5.2422	231	0.00
	Bloomberg.Green. AAA	-0.00002	-0.00002	0.00576	-0.00449	0.00119	0.19739	4.2157	74	0.00
	Bloomberg.Green. AA	-0.00009	-0.00011	0.01011	-0.00837	0.00243	0.32897	4.1836	83	0.00
	Bloomberg.Green. A	-0.00006	-0.00007	0.00911	-0.00688	0.00174	0.69576	6.2824	574	0.00
	BofAML.Green	-0.00006	-0.00009	0.10690	-0.00681	0.00363	23.58399	694.1458	21655816	0.00

4.3 COMPARISON OF BOND INDICES PERFORMANCE

To understand whether investing in Green bond indices is more, less or equally profitable than investing in its Conventional peers, a dedicated analysis of variance was performed.

The one-way analysis of variance (ANOVA) was intended to determine whether there are any statistically significant differences between the sample means of returns of Conventional and Green bond indices. However, to apply this test there are three conditions that needed to be verified:

1. The elements of the sample are randomly selected and the samples under consideration are independent from each other;

2. The dependent variable must follow a Gaussian distribution in each of the populations considered (this condition is not mandatory for big samples, more than 30 observations);
3. The populations considered have all equal variances: σ^2.

The first and second conditions were assumed but the third condition did not hold true. To analyse if both Conventional bond indices and Green bond indices had the equal variances, the Levene test was performed. This test considers the homogeneity of variances in the null (meaning that the variances are equal across the groups/samples).

Levene (1960) proposed a test for homogeneity of variance in k groups which relies on the ANOVA statistic applied to absolute deviations of observations from the corresponding group mean. However, for the purpose of this study, an extended Levene test version by Brown and Forsythe (1974) was performed (see Appendix D). In this version, the group mean is replaced by the group median[20].

As the hypothesis of homogeneity of variances was rejected (probability associated to the Levene test was lower than the significance level – considering a significance level of 5%), the ANOVA test should not be used. Thus, a non-parametric alternative (Kruskal-Wallis test) needed to be performed.

Table 4 – Kruskall-Wallis test (see Appendix E)

Kruskal-Wallis	
Test statistic	P-value
5.09660	0.02397

According to the results of the Table 4, the Kruskal-Wallis test, that compares the empirical distribution of the bond indices, led to the rejection of the null hypothesis (probability of the test was lower than the significance level – considering a significance level of 5%). Therefore, the difference between the distributions of the returns of the 23 bond indices under study is considered to be statistically significant between 08/01/2015 and 16/05/2019. In

[20] Brown and Forsythe (1974) defended that the median performed best when the underlying data followed skewed distribution [8]

other words, at a 5% significance level, it is possible to conclude that Conventional bond indices and Green bond indices have *nonidentical* distributions.

Thus, Green bonds indices showed to have significantly different distributions of returns than its conventional peers (which may impact positively or negatively bondholder's financial performance). Hence, and besides the rejection of one ANOVA assumption, to better understand the potential investor's trade-off between sustainability concerns and financial performance, the ANOVA test was still computed.

Table 5 – ANOVA test (see Appendix F)

ANOVA	
F-Test	P-value
0.547	0.46

As per the Table 5, the result of the ANOVA test led to the non-rejection of the null hypothesis, as 0.46 > 0.05 (considering a significance level of 5%). Thus, the difference in the sample means of returns from the Green and Conventional bond indices under study is not statistically significant, which may be connected to the fact that there are companies belonging to different indices simultaneously.

That being said, it is not possible to affirm that investing in Green bond indices bring superior returns, but it is indeed possible to affirm that it does not prejudices the investor financial performance. Thus, and according to the ANOVA test, investors who want to invest in Green bond indices do not seem to face a trade-off between sustainability and financial performance.

4.4 SHORT-TERM DYNAMICS

The Granger causality study was performed to investigate the existence of short-term dependences on returns, in other words: if Conventional Bond Indices returns Granger-cause Green bond indices returns and vice-verse.

The first hypothesis to be tested was that: Conventional Bond Indices Granger-cause Green Bond Indices (with 2 lags), meaning that the independent variables (columns in Table 4) are the Conventional Bond Indices and the dependent variables the Green (rows in Table 4). The results are presented in the table below (Table 4).

Table 4 – Granger Causality test (see Appendix G)

		Independent variables - Conventional Bond Indices												
		SP.500	SP.AAA	SP.AA	SP.A	Bloomberg	Citi.BIG	JPM.Gov	FTSE.Gov	FTSE.BIG	FTSE.E.BIG	FTSE.US.BIG	Bloomberg.E	Bloomberg.US
Dependent variables - Green Bond Indices	Bloomberg.Green	0.9341	0.5627	**0.0098***	**0.0150***	0.0684	**0.0000***	0.9032	**0.0000***	**0.0000***	**0.0000***	**0.0000***	0.8725	0.3705
	Bloomberg.E.Green	0.9941	0.7588	**0.0006***	**0.0008***	0.2500	**0.0000***	0.9040	**0.0000***	**0.0000***	**0.0000***	**0.0000***	0.9004	0.6641
	Bloomberg.US.Green	0.1832	0.0596	0.8794	0.9281	**0.0000***	**0.0000***	0.7086	**0.0001***	**0.0000***	**0.0425***	**0.0000***	0.5709	0.0509
	Solactive.Green	0.8299	0.1056	0.1703	0.1832	0.2187	**0.0297***	0.9364	0.3514	0.2431	0.5419	**0.0298***	0.7290	0.4136
	SP.Green	0.8231	0.7739	0.1576	0.1754	**0.0468***	**0.0000***	0.1679	**0.0000***	**0.0183***	**0.0000***	**0.0000***	0.1974	0.6997
	Bloomberg.Green.Gov	0.9282	0.5999	**0.0019***	**0.0032***	0.0606	**0.0000***	0.8969	**0.0000***	**0.0000***	**0.0000***	**0.0000***	0.8933	0.3929
	Bloomberg.Green.AAA	0.4293	0.3091	0.7865	0.8832	0.0933	**0.0000***	0.3695	**0.0003***	**0.0000***	0.1075	**0.0000***	0.7980	0.1881
	Bloomberg.Green.AA	0.8067	0.5017	0.8950	0.9562	0.2688	**0.0000***	0.4205	**0.0000***	**0.0000***	**0.0421***	**0.0000***	0.4935	0.1003
	Bloomberg.Green.A	0.5278	0.3069	0.7062	0.5636	0.2372	**0.0000***	0.1057	**0.0153***	**0.0016***	0.4265	**0.0000***	0.5404	0.0809
	BofAML.Green	0.4655	0.2514	0.7670	0.7498	0.5882	0.4406	0.8472	0.8956	0.4915	0.5968	0.4404	0.9582	0.7775

As per the Table 4, under the null hypothesis "Conventional bond indices do not Granger cause Green bond indices", the probabilities revealing Granger causality effects are highlighted (*). These probabilities (lower than the significance level – considering a significance level of 5%) reveal that Citi.BIG Granger-causes all the Green bond indices under study (exception of the the BofAML.Green). Also, FTSE.US.BIG Granger-causes all the Green Bond Indices (exception of the BofAML.Green). The same behavior is observed in the FTSE.Gov and FTSE.BIG which Granger-cause all Green bond indices, with exception of the Solactive.Green and the BofAML.Green. The FTSE.E.BIG Granger-causes 6 Green bond indices out of 10 considered in the study. Similarly, SP.AA and SP.A Granger-cause Bloomberg.Green, Bloomberg.E.Green and Bloomberg.Green.Gov. Lastly, Bloomberg Granger-causes both Bloomberg.US.Green and SP.Green.

In a nutshell, as the lag considered for this analysis was 2, it is possible to conclude that the returns of the previously mentioned Conventional bond indices from *t-2* and *t-1* impact the Green bond indices' returns at time *t*. Thus, Green bond indices (exception of the BofAML.Green) show a significant short-term dependency with the Conventional peers.

Afterwards, the reverse hypothesis "Green bond indices do not Granger-cause Conventional bond indices" (with 2 lags) was tested and the results are presented in the table below (Table

5), with independent variables being now the Green bond indices (columns in Table 5) and the dependent the Conventional ones (rows in Table 5).

Table 5 – Granger Causality test (see Appendix H)

Bond Indices		Independent variables - Green Bond Indices									
		Bloomberg. Green	Bloomberg. E.Green	Bloomberg. US.Green	Solactive. Green	SP.Green	Bloomberg. Green.Gov	Bloomberg. Green.AAA	Bloomberg. Green.AA	Bloomberg. Green.A	BofAML. Green
Dependent variables - Conventional Bond Indices	SP.500	0.7832	0.8375	0.7536	0.9679	0.9191	0.7727	0.2926	0.2925	0.3444	**0.0000***
	SP.AAA	0.2973	0.2382	0.7882	**0.0039***	0.6322	0.2483	0.9861	0.9914	0.9746	0.7383
	SP.AA	0.0594	**0.0215***	0.6468	0.2440	**0.0000***	**0.0257***	0.8479	0.8275	0.5462	0.8429
	SP.A	**0.0419***	**0.0165***	0.5403	0.2102	**0.0000***	**0.0186***	0.8792	0.8562	0.5264	0.8539
	Bloomberg	**0.0019***	**0.0236***	**0.0099***	**0.0477***	**0.0000***	**0.0021***	**0.0420***	0.3051	0.0965	0.4570
	Citi.BIG	0.9286	0.8352	0.3906	0.2456	**0.0009***	0.8751	0.6520	0.8794	0.9875	0.7430
	JPM.Gov	**0.0000***	**0.0000***	**0.0001***	0.5019	**0.0004***	**0.0000***	**0.0052***	**0.0074***	**0.0471***	0.8715
	FTSE.Gov	0.0635	**0.0343***	0.7478	0.7057	0.7315	0.0600	0.1880	0.1760	0.0859	0.4524
	FTSE.BIG	0.8686	0.9075	0.3403	0.0553	**0.0329***	0.8060	0.3636	0.2061	0.4514	0.5372
	FTSE.E.BIG	**0.0269***	**0.0174***	0.1396	0.7311	0.5784	**0.0259***	0.0685	**0.0426***	**0.0158***	0.7861
	FTSE.US.BIG	0.9291	0.8353	0.3898	0.2449	**0.0009***	0.8757	0.6515	0.8787	0.9878	0.7429
	Bloomberg.E	0.6395	0.6668	0.8585	0.1560	0.8313	0.5768	0.9379	0.9394	0.7067	0.6239
	Bloomberg.US	0.3256	0.2669	0.8465	**0.0000***	0.5800	0.2844	0.9985	0.8066	0.8114	0.8099

In this case, the SP.Green is the index that Granger-causes the highest number of Conventional bond indices, followed by the Bloomberg.E.Green and the Bloomberg.Green.Gov. Also, Bloomberg.Green Granger-causes 4 Conventional peers and with less expression, Bloomberg.US.Green, Solactive.Green, Bloomberg.Green.AAA, Bloomberg.Green.AA, Bloomberg.Green.A and BofAML.Green Granger-cause at least 1 Conventional bond index.

Thus, as the lag considered was 2, it is possible to conclude that the returns of the previously mentioned Green bond indices from *t-2* and *t-1* impact the Conventional bond indices' returns at time *t*.

Moreover, there are certain indices in which Granger causality runs two-ways (feedback effect), being those: Bloomberg.Green that shows a feedback effect with both SP.A and FTSE.E.BIG; Bloomberg.E.Green with SP.A, SP.AA, SP.AAA, FTSE.Gov and FTSE.E.BIG; Bloomberg.US.Green and SP.Green showing both feedback effect with Bloomberg; Morever, SP.Green also showing with Citi.BIG, FTSE.BIG and FTSE.US.BIG.

Bloomberg.Green.Gov showing with SP.AA, SP.A and FTSE.E.BIG. Lastly, Bloomberg.Green.AA reveals feedback effect with FTSE.E.BIG.

For all these indices mentioned above, there is a feedback effect between Green and Conventional bond indices (considering a significance level of 5%).

4.5 LONG-TERM RELATIONSHIPS

As previously mentioned, in order to understand if the Green bond indices' prices are related in the long-run with the Conventional peers, a Cointegration analysis was conducted. The first step was the investigation of whether time series (in levels) are nonstationary and integrated of the same order, for that Unit Root tests were applied to each variable (ADF and KPSS tests).

Afterwards, for the nonstationary time series of order one the Bivariate Johansen Cointegration test was performed, as the main objective is to understand if the Conventional bond indices prices are cointegrated with Green bond indices under study. This test is performed for each two variables system, allowing a one by one analysis and identification of those relationships. Lastly, the Vector Error Correction Model (VECM) was estimated for each cointegration relationship identified.

4.5.1 Non-stationarity

For cointegration purposes, the first step consists of applying Unit Root tests in each index (by using the natural logarithm of the closing daily prices). Afterwards, the Unit Root tests should be performed on the indices' returns, and if the residuals are found to be stationary, the cointegration tests can be performed.
The Unit Root tests used were the ADF and KPSS as presented in the table below:

Table 6 – Unit Root tests applied to Log(Prices) (see Appendices I and J)

	Bond Indices	Log (Prices)			
		ADF		KPSS	
		Lags	Test statistic[21]	Lags	Test statistic[22]
Conventional Bond Indices	SP.500	1	-2.8474	7	1.3572
	SP.AAA	1	-0.5836	7	1.7125
	SP.AA	1	-2.7020	7	0.6131
	SP.A	1	-2.8327	7	0.4989
	Bloomberg	1	-2.1065	7	0.7773
	Citi.BIG	1	-2.4169	7	0.9759
	JPM.Gov	1	-1.8905	7	1.1723
	FTSE.Gov	1	-2.0853	7	0.7673
	FTSE.BIG	1	-2.1379	7	0.7464
	FTSE.E.BIG	1	-2.3599	7	0.7356
	FTSE.US.BIG	1	-2.4169	7	0.9759
	Bloomberg.E	1	-2.4679	7	0.7979
	Bloomberg.US	1	-2.5727	7	0.8869
Green Bond Indices	Bloomberg.Green	1	-2.2101	7	0.7119
	Bloomberg.E.Green	1	-2.3307	7	0.7633
	Bloomberg.US.Green	1	-2.5503	7	0.7094
	Solactive.Green	1	-1.7495	7	0.7521
	SP.Green	1	-2.1071	7	0.7336
	Bloomberg.Green.Gov	1	-2.3713	7	0.6214
	Bloomberg.Green.AAA	1	-2.3115	7	1.2583
	Bloomberg.Green.AA	1	-2.9108	7	0.4542
	Bloomberg.Green.A	1	-1.9579	7	1.3065
	BofAML.Green	1	-2.6382	7	1.8626

Starting with the ADF test (whose null hypothesis admits the existence of a unit root – non-stationarity), as one can see in the Appendices I and J, to conduct this test in R some function inputs needed to be defined, including the type and number of lags. For the lags, an automatic lag length selection was conducted through the selection of the Bayesian Information Criteria (BIC). For the type, given the nature of the variables (natural logarithm of the indices' closing daily prices), the "*trend*" option was chosen to allow for the inclusion of both an intercept and a deterministic trend in the test regression. The same rationale was applied to define the KPSS function inputs (whose null hypothesis points for stationarity), including both deterministic trend and intercept. The lag length was automatically chosen by R.

As per the Table 6, while the ADF null hypothesis was not rejected, the KPSS stationarity hypothesis was rejected for all the series of logarithm prices (levels) which means that both Conventional and Green bond indices prices (in logarithms) are non-stationary. Then, it is

[21] The ADF critical value at 5% significance level is -3.41
[22] The KPSS critical value at 5% significance level is 0.146

needed to check if they are integrated of order one, using the daily returns instead of the daily prices (Table 7).

Table 7 – Unit Root tests applied to returns (see Appendices K and L)

	Bond Indices	Returns			
		ADF		KPSS	
		Lags	Test statistic[23]	Lags	Test statistic[24]
Conventional Bond Indices	SP.500	1	-23.4512	7	0.2453
	SP.AAA	1	-23.2807	7	0.2702
	SP.AA	1	-24.7289	7	0.0819
	SP.A	1	-24.6226	7	0.0737
	Bloomberg	1	-22.8219	7	0.0614
	Citi.BIG	1	-24.2248	7	0.1185
	JPM.Gov	1	-22.1172	7	0.0984
	FTSE.Gov	1	-22.7706	7	0.0663
	FTSE.BIG	1	-22.9515	7	0.0589
	FTSE.E.BIG	1	-22.7748	7	0.0736
	FTSE.US.BIG	1	-24.2260	7	0.1185
	Bloomberg.E	1	-23.0111	7	0.0785
	Bloomberg.US	1	-24.2819	7	0.1226
Green Bond Indices	Bloomberg.Green	1	-23.1502	7	0.0574
	Bloomberg.E.Green	1	-23.3845	7	0.0654
	Bloomberg.US.Green	1	-24.0632	7	0.1422
	Solactive.Green	1	-22.6315	7	0.1175
	SP.Green	1	-22.6661	7	0.0592
	Bloomberg.Green.Gov	1	-23.1849	7	0.0530
	Bloomberg.Green.AAA	1	-22.8577	7	0.1233
	Bloomberg.Green.AA	1	-22.9934	7	0.1231
	Bloomberg.Green.A	1	-23.6147	7	0.1387
	BofAML.Green	1	-23.8267	7	0.1677

As previously, the ADF and KPSS test's inputs needed to be defined and this time for both tests only the intercept was taken into the analysis, since now the expectations point for stationary returns and therefore, a deterministic trend is not expected. Also, the same Information Criteria for the lag length selection was chosen.

As per the results described in the Table 7 (see Appendices K and L), the conclusions are consistent across ADF and KPSS tests. The ADF null hypothesis was rejected for all indices while the KPSS null hypothesis was not rejected, indicating that both Conventional and Green bond indices' returns series are stationary.

That being said, the logarithm of the indices' prices are non-stationary and integrated of order one, *I(1)*, whilst the indices' returns are *I(0)*. The fact that all bond indices under analysis (in

[23] The ADF critical value at 5% significance level is -2.86
[24] The KPSS critical value at 5% significance level is 0.463

natural logarithms) are first-difference stationary, allowed to proceed with the cointegration analysis.

4.5.2 Cointegration tests

To address the last objective of this empirical analysis – investigation of the bivariate cointegration relationships between each Green bond index under analysis and its Conventional peers – the methodology considered was the VAR-based cointegration tests developed by Johansen (Johansen and Juselius, 1990).

As a first step, the R function *VARselect()* was applied to get the optimal lag length according to the available information criteria. In order to avoid over-parameterizing the models, the VAR lag length was investigated until a maximum of 10 lags.

The information criteria chosen was the Akaike Information Criterion (AIC) and the Final Prediction Error (FPE), since they were both in accordance across the entire analysis. The optimum lag length selection is presented in the Appendix M.

Next, another input that needs to be considered when computing cointegration tests is the "*ecdet*" – character – which presents three different options: "*none*" for no intercept in cointegration, "*const*" for constant term in cointegration and "*trend*" for deterministic trending variable in cointegration. For practical purposes and since cointegration means that the linear combination of unit root processes is a stationary process, the "*const*" option was chosen. It is usually assumed that this stationary process has zero mean, however the possibility of a non-zero mean and the consequent trend is acknowledged.

Given the definition of the function inputs, the cointegration ranks were obtained through the Trace and Maximum Eigenvalue tests. Both tests have non-standard distributions and their critical values have been tabulated by Johansen in 1988.

Table 8 – Bivariate Johansen test for Cointegration (see Appendix N)

	Bond Indices	Rank	Max. Eigenvalue Test	Trace Test
Bloomberg.Green	Bloomberg.Green - SP.500	r = 0	11.388	13.233
		r <= 1	1.845	1.845
	Bloomberg.Green - SP.AAA	r = 0	2.728	4.066
		r <= 1	1.338	1.338
	Bloomberg.Green - SP.AA	r = 0	7.674	10.858
		r <= 1	3.184	3.184
	Bloomberg.Green - SP.A	r = 0	8.460	11.538
		r <= 1	3.077	3.077
	Bloomberg.Green - Bloomberg	r = 0	2.904	5.148
		r <= 1	2.244	2.244
		r = 0	9.894	12.131

	Bond Indices	Rank	Max. Eigenvalue Test	Trace Test
Bloomberg.E.Green	Bloomberg.E.Green - SP.500	r = 0	10.930	12.695
		r <= 1	1.765	1.765
	Bloomberg.E.Green - SP.AAA	r = 0	2.224	3.532
		r <= 1	1.308	1.308
	Bloomberg.E.Green - SP.AA	r = 0	7.632	10.256
		r <= 1	2.624	2.624
	Bloomberg.E.Green - SP.A	r = 0	8.266	10.760
		r <= 1	2.494	2.494
	Bloomberg.E.Green – Bloomberg	r = 0	4.267	6.350
		r <= 1	2.083	2.083
		r = 0	10.383	12.297

	Bloomberg.Green - Citi.BIG	r <= 1	2.237	2.237
	Bloomberg.Green - JPM.Gov	r = 0	4.988	7.193
		r <= 1	2.205	2.205
	Bloomberg.Green - FTSE.Gov	r = 0	2.504	4.599
		r <= 1	2.096	2.096
	Bloomberg.Green - FTSE.BIG	r = 0	3.076	5.400
		r <= 1	2.323	2.323
	Bloomberg.Green - FTSE.E.BIG	r = 0	**19.4181***	**21.2615***
		r <= 1	1.843	1.843
	Bloomberg.Green - FTSE.US.BIG	r = 0	9.894	12.131
		r <= 1	2.237	2.237
	Bloomberg.Green - Bloomberg.E	r = 0	9.438	13.946
		r <= 1	4.508	4.508
	Bloomberg.Green - Bloomberg.US	r = 0	9.977	14.780
		r <= 1	4.804	4.804
Bloomberg.US.Green	Bloomberg.US.Green - SP.500	r = 0	**16.9266***	**20.1027***
		r <= 1	3.176	3.176
	Bloomberg.US.Green - SP.AAA	r = 0	10.437	12.122
		r <= 1	1.685	1.685
	Bloomberg.US.Green - SP.AA	r = 0	10.943	18.691
		r <= 1	7.748	7.748
	Bloomberg.US.Green - SP.A	r = 0	12.222	**20.2539***
		r <= 1	8.032	8.032
	Bloomberg.US.Green - Bloomberg	r = 0	**19.2037***	**21.4055***
		r <= 1	2.202	2.202
	Bloomberg.US.Green - Citi.BIG	r = 0	**18.5095***	**22.7012***
		r <= 1	4.192	4.192
	Bloomberg.US.Green - JPM.Gov	r = 0	14.539	16.889
		r <= 1	2.350	2.350
	Bloomberg.US.Green - FTSE.Gov	r = 0	15.248	17.648
		r <= 1	2.400	2.400
	Bloomberg.US.Green - FTSE.BIG	r = 0	**19.2755***	**21.3912***
		r <= 1	2.116	2.116
	Bloomberg.US.Green - FTSE.E.BIG	r = 0	15.361	17.570
		r <= 1	2.209	2.209
	Bloomberg.US.Green - FTSE.US.BIG	r = 0	**18.5079***	**22.6990***
		r <= 1	4.191	4.191
	Bloomberg.US.Green - Bloomberg.E	r = 0	**32.1855***	**37.4975***
		r <= 1	5.312	5.312
	Bloomberg.US.Green - Bloomberg.US	r = 0	**42.1463***	**48.8273***
		r <= 1	6.681	6.681
SP.Green.Green	SP.Green - SP.500	r = 0	11.449	13.133
		r <= 1	1.683	1.683
	SP.Green - SP.AAA	r = 0	2.647	3.945
		r <= 1	1.298	1.298
	SP.Green - SP.AA	r = 0	9.497	12.933
		r <= 1	3.436	3.436
	SP.Green - SP.A	r = 0	10.322	13.669
		r <= 1	3.346	3.346
	SP.Green - Bloomberg	r = 0	3.561	5.570
		r <= 1	2.009	2.009
	SP.Green - Citi.BIG	r = 0	10.920	13.207
		r <= 1	2.287	2.287
	SP.Green - JPM.Gov	r = 0	6.272	8.715
		r <= 1	2.443	2.443
	SP.Green - FTSE.Gov	r = 0	3.576	5.625
		r <= 1	2.049	2.049
	SP.Green - FTSE.BIG	r = 0	3.731	5.982
		r <= 1	2.251	2.251
	SP.Green - FTSE.E.BIG	r = 0	7.027	9.720
		r <= 1	2.693	2.693
	SP.Green - FTSE.US.BIG	r = 0	10.919	13.206
		r <= 1	2.287	2.287
	SP.Green - Bloomberg.E	r = 0	8.425	12.289
		r <= 1	3.865	3.865
	SP.Green - Bloomberg.US	r = 0	10.704	14.881
		r <= 1	4.177	4.177
Bloomberg.Green.AAA	Bloomberg.Green.AAA - SP.500	r = 0	13.386	18.348
		r <= 1	4.962	4.962
	Bloomberg.Green.AAA - SP.AAA	r = 0	**23.6205***	**25.6597***
		r <= 1	2.039	2.039
	Bloomberg.Green.AAA - SP.AA	r = 0	10.583	15.706
		r <= 1	5.123	5.123
	Bloomberg.Green.AAA - SP.A	r = 0	10.729	16.417
		r <= 1	5.688	5.688
	Bloomberg.Green.AAA - Bloomberg	r = 0	7.138	8.470
		r <= 1	1.332	1.332
	Bloomberg.Green.AAA - Citi.BIG	r = 0	14.184	16.078
		r <= 1	1.894	1.894
	Bloomberg.Green.AAA - JPM.Gov	r = 0	7.867	11.252
		r <= 1	3.384	3.384
	Bloomberg.Green.AAA - FTSE.Gov	r = 0	6.002	7.927
		r <= 1	1.925	1.925
	Bloomberg.Green.AAA - FTSE.BIG	r = 0	6.848	8.327
		r <= 1	1.478	1.478
	Bloomberg.Green.AAA - FTSE.E.BIG	r = 0	6.493	8.694
		r <= 1	2.201	2.201

	Bloomberg.E.Green - Citi.BIG	r <= 1	1.915	1.915
	Bloomberg.E.Green - JPM.Gov	r = 0	4.303	6.309
		r <= 1	2.006	2.006
	Bloomberg.E.Green - FTSE.Gov	r = 0	3.221	4.856
		r <= 1	1.635	1.635
	Bloomberg.E.Green - FTSE.BIG	r = 0	5.074	6.909
		r <= 1	1.836	1.836
	Bloomberg.E.Green - FTSE.E.BIG	r = 0	**17.0125***	**18.8567***
		r <= 1	1.844	1.844
	Bloomberg.E.Green - FTSE.US.BIG	r = 0	10.382	12.297
		r <= 1	1.915	1.915
	Bloomberg.E.Green - Bloomberg.E	r = 0	9.403	13.345
		r <= 1	3.943	3.943
	Bloomberg.E.Green - Bloomberg.US	r = 0	10.395	14.430
		r <= 1	4.035	4.035
Solactive.Green	Solactive.Green - SP.500	r = 0	11.133	13.627
		r <= 1	2.494	2.494
	Solactive.Green - SP.AAA	r = 0	7.781	9.213
		r <= 1	1.433	1.433
	Solactive.Green - SP.AA	r = 0	10.180	13.261
		r <= 1	3.081	3.081
	Solactive.Green - SP.A	r = 0	10.983	13.990
		r <= 1	3.006	3.006
	Solactive.Green - Bloomberg	r = 0	**19.8981***	**24.3362***
		r <= 1	4.438	4.438
	Solactive.Green - Citi.BIG	r = 0	**17.3247***	**21.5343***
		r <= 1	4.210	4.210
	Solactive.Green - JPM.Gov	r = 0	26.669	29.986
		r <= 1	3.317	3.317
	Solactive.Green - FTSE.Gov	r = 0	14.983	18.808
		r <= 1	3.825	3.825
	Solactive.Green - FTSE.BIG	r = 0	**22.6894***	**26.2429***
		r <= 1	3.553	3.553
	Solactive.Green - FTSE.E.BIG	r = 0	**29.5349***	**32.7530***
		r <= 1	3.218	3.218
	Solactive.Green - FTSE.US.BIG	r = 0	**17.3257***	**21.5354***
		r <= 1	4.210	4.210
	Solactive.Green - Bloomberg.E	r = 0	8.287	11.400
		r <= 1	3.113	3.113
	Solactive.Green - Bloomberg.US	r = 0	13.529	16.622
		r <= 1	3.093	3.093
Bloomberg.Green.Gov	Bloomberg.Green.Gov - SP.500	r = 0	10.987	13.550
		r <= 1	2.563	2.563
	Bloomberg.Green.Gov - SP.AAA	r = 0	3.460	4.943
		r <= 1	1.484	1.484
	Bloomberg.Green.Gov - SP.AA	r = 0	7.527	11.342
		r <= 1	3.814	3.814
	Bloomberg.Green.Gov - SP.A	r = 0	8.305	12.018
		r <= 1	3.713	3.713
	Bloomberg.Green.Gov - Bloomberg	r = 0	4.502	7.481
		r <= 1	2.980	2.980
	Bloomberg.Green.Gov - Citi.BIG	r = 0	9.905	12.892
		r <= 1	2.987	2.987
	Bloomberg.Green.Gov - JPM.Gov	r = 0	5.043	7.196
		r <= 1	2.153	2.153
	Bloomberg.Green.Gov - FTSE.Gov	r = 0	3.409	5.821
		r <= 1	2.412	2.412
	Bloomberg.Green.Gov - FTSE.BIG	r = 0	5.265	8.125
		r <= 1	2.860	2.860
	Bloomberg.Green.Gov - FTSE.E.BIG	r = 0	**18.8465***	**20.8099***
		r <= 1	1.963	1.963
	Bloomberg.Green.Gov - FTSE.US.BIG	r = 0	9.905	12.892
		r <= 1	2.987	2.987
	Bloomberg.Green.Gov - Bloomberg.E	r = 0	10.150	15.109
		r <= 1	4.959	4.959
	Bloomberg.Green.Gov - Bloomberg.US	r = 0	9.941	15.704
		r <= 1	5.763	5.763
Bloomberg.Green.AA	Bloomberg.Green.AA - SP.500	r = 0	13.966	17.349
		r <= 1	3.384	3.384
	Bloomberg.Green.AA - SP.AAA	r = 0	6.537	7.792
		r <= 1	1.255	1.255
	Bloomberg.Green.AA - SP.AA	r = 0	10.853	18.129
		r <= 1	7.275	7.275
	Bloomberg.Green.AA - SP.A	r = 0	11.088	18.569
		r <= 1	7.481	7.481
	Bloomberg.Green.AA - Bloomberg	r = 0	12.698	15.911
		r <= 1	3.213	3.213
	Bloomberg.Green.AA - Citi.BIG	r = 0	7.129	12.305
		r <= 1	5.175	5.175
	Bloomberg.Green.AA - JPM.Gov	r = 0	11.090	13.398
		r <= 1	2.308	2.308
	Bloomberg.Green.AA - FTSE.Gov	r = 0	10.085	13.809
		r <= 1	3.724	3.724
	Bloomberg.Green.AA - FTSE.BIG	r = 0	11.996	15.188
		r <= 1	3.191	3.191
	Bloomberg.Green.AA - FTSE.E.BIG	r = 0	**15.6877***	18.432
		r <= 1	2.744	2.744

	Bloomberg.Green.AAA - FTSE.US.BIG	r = 0	14.186	16.080
		r <= 1	1.894	1.894
	Bloomberg.Green.AAA - Bloomberg.E	r = 0	14.906	**21.6182***
		r <= 1	6.712	6.712
	Bloomberg.Green.AAA - Bloomberg.US	r = 0	13.871	18.604
		r <= 1	4.734	4.734
Bloomberg.Green.A	Bloomberg.Green.A - SP.500	r = 0	15.343	17.856
		r <= 1	2.513	2.513
	Bloomberg.Green.A - SP.AAA	r = 0	5.055	6.422
		r <= 1	1.367	1.367
	Bloomberg.Green.A - SP.AA	r = 0	10.278	16.680
		r <= 1	6.403	6.403
	Bloomberg.Green.A - SP.A	r = 0	11.212	17.559
		r <= 1	6.348	6.348
	Bloomberg.Green.A - Bloomberg	r = 0	8.584	12.125
		r <= 1	3.541	3.541
	Bloomberg.Green.A - Citi.BIG	r = 0	11.867	15.626
		r <= 1	3.759	3.759
	Bloomberg.Green.A - JPM.Gov	r = 0	10.806	13.027
		r <= 1	2.221	2.221
	Bloomberg.Green.A - FTSE.Gov	r = 0	8.387	12.451
		r <= 1	4.064	4.064
	Bloomberg.Green.A - FTSE.BIG	r = 0	8.086	11.594
		r <= 1	3.508	3.508
	Bloomberg.Green.A - FTSE.E.BIG	r = 0	10.760	13.260
		r <= 1	2.499	2.499
	Bloomberg.Green.A - FTSE.US.BIG	r = 0	11.866	15.625
		r <= 1	3.759	3.759
	Bloomberg.Green.A - Bloomberg.E	r = 0	**45.7858***	**51.0738***
		r <= 1	5.288	5.288
	Bloomberg.Green.A - Bloomberg.US	r = 0	**21.1682***	**28.8488***
		r <= 1	7.681	7.681

	Bloomberg.Green.AA - FTSE.US.BIG	r = 0	7.129	12.305
		r <= 1	5.175	5.175
	Bloomberg.Green.AA - Bloomberg.E	r = 0	**45.1876***	**50.5919***
		r <= 1	5.404	5.404
	Bloomberg.Green.AA - Bloomberg.US	r = 0	**25.2755***	**32.6099***
		r <= 1	7.334	7.334
BofAML.Green	BofAML.Green - SP.500	r = 0	11.973	17.120
		r <= 1	5.147	5.147
	BofAML.Green - SP.AAA	r = 0	10.913	12.667
		r <= 1	1.753	1.753
	BofAML.Green - SP.AA	r = 0	9.095	16.342
		r <= 1	7.247	7.247
	BofAML.Green - SP.A	r = 0	9.689	16.615
		r <= 1	6.926	6.926
	BofAML.Green - Bloomberg	r = 0	10.097	12.330
		r <= 1	2.232	2.232
	BofAML.Green - Citi.BIG	r = 0	15.339	18.582
		r <= 1	3.243	3.243
	BofAML.Green - JPM.Gov	r = 0	8.571	10.940
		r <= 1	2.369	2.369
	BofAML.Green - FTSE.Gov	r = 0	10.312	12.398
		r <= 1	2.086	2.086
	BofAML.Green - FTSE.BIG	r = 0	10.155	12.293
		r <= 1	2.138	2.138
	BofAML.Green - FTSE.E.BIG	r = 0	9.515	11.779
		r <= 1	2.264	2.264
	BofAML.Green - FTSE.US.BIG	r = 0	15.339	18.582
		r <= 1	3.243	3.243
	BofAML.Green - Bloomberg.E	r = 0	11.203	14.964
		r <= 1	3.761	3.761
	BofAML.Green - Bloomberg.US	r = 0	12.807	16.187
		r <= 1	3.380	3.380

The column Rank "***r = p***" denotes the null hypothesis under each cointegration test, being "***r = 0***" the hypothesis which assumes that there are no cointegrating vectors and "***r ≤ 1***" the hypothesis that assumes there is at most 1 cointegrating vector.

Considering the 5% significance level, both Trace and Maximum Eigenvalue statistics simultaneously reject the null of no cointegration (***r = 0***) in 20 Bond Indices out of the 130 relationships analyzed (the variables in which the null of no cointegration was rejected are highlighted (*) in the Table 8). Then, for those cointegration relationships identified, the results point for 1 cointegration equation (since the "***r ≤ 1***" hypothesis failed to be rejected).

However, if we consider 1% significance level, both Trace and Maximum Eigenvalue statistics only simultaneously reject the null of no cointegration in 10 observations and for 10% significance level, the same observations (only 10) are verified for the simultaneously rejection of the no cointegration null hypothesis in both tests.

The weak expression of bivariate cointegrated variables suggests that Green bond indices do not tend to have a strong long-run linkage to their Conventional peers, which means that they might diverge without bound. However, for each cointegration relationships found based on the Johansen tests, the Vector Error Correction (VEC) Model was estimated.

4.5.3 VEC Model estimation

According to the bivariate cointegration analysis (Table 8) and considering the 5% significance level conclusions, a long-run relationship is only verified across 20 series of logs. For each of them, the VEC Model was estimated, considering the lag length already applied to the cointegration tests (Appendix M). The following estimated equations are based on the R outputs presented in the Appendix O.

1. Bloomberg.Green - FTSE.E.BIG:

$$\Delta(\text{LogBloomberg.Green}_t) = -0.039791\Delta(\text{LogBloomberg.Green}_{t-1}) + 0.0348421\Delta(\text{LogFTSE.E.BIG}_{t-1}) - 0.2658052\Delta(\text{LogBloomberg.Green}_{t-2}) + 0.1594165\Delta(\text{LogFTSE.E.BIG}_{t-2}) - 0.2564654\Delta(\text{LogBloomberg.Green}_{t-3}) + 0.1982266\Delta(\text{LogFTSE.E.BIG}_{t-3}) - 0.2019117\Delta(\text{LogBloomberg.Green}_{t-4}) + 0.2809723\Delta(\text{LogFTSE.E.BIG}_{t-4}) - 0.1707408\Delta(\text{LogBloomberg.Green}_{t-5}) + 0.1381597\Delta(\text{LogFTSE.E.BIG}_{t-5}) - 0.1048291\Delta(\text{LogBloomberg.Green}_{t-6}) + 0.1592205\Delta(\text{LogFTSE.E.BIG}_{t-6}) - 0.0580270\Delta(\text{LogBloomberg.Green}_{t-7}) + 0.0988203\Delta(\text{LogFTSE.E.BIG}_{t-7}) - 0.0005376\Delta(\text{LogBloomberg.Green}_{t-8}) + 0.1090615\Delta(\text{LogFTSE.E.BIG}_{t-8}) - 0.0402721\Delta(\text{LogBloomberg.Green}_{t-9}) + 0.0414184\Delta(\text{LogFTSE.E.BIG}_{t-9}) - 0.0582484(\text{LogBloomberg.Green}_{t-1} - 0.004883194\text{LogFTSE.E.BIG}_{t-1} - 0.5834122\,constant_{t-1})$$

2. Bloomberg.US.Green - SP.500:

$$\Delta(\text{LogBloomberg.US.Green}_t) = -0.095199928\Delta(\text{LogBloomberg.US.Green}_{t-1}) - 0.001379213\Delta(\text{LogSP.500}_{t-1}) - 0.001138369(\text{LogBloomberg.US.Green}_{t-1} - 0.233100\text{LogSP.500}_{t-1} - 2.881125\,constant_{t-1})$$

3. Bloomberg.US.Green – Bloomberg:

$$\Delta(\text{LogBloomberg.US.Green}_t) = -0.20309461\Delta(\text{LogBloomberg.US.Green}_{t-1}) + 0.11245411\Delta(\text{LogBloomberg}_{t-1}) - 0.02141133(\text{LogBloomberg.US.Green}_{t-1} - 0.5421736\text{LogBloomberg}_{t-1} - 1.3692153\,constant_{t-1})$$

4. Bloomberg.US.Green – Citi.BIG:

$$\Delta(\text{LogBloomberg.US.Green}_t) = -0.350112729\Delta(\text{LogBloomberg.US.Green}_{t-1}) + 0.167832730\Delta(\text{LogCiti.BIG}_{t-1}) - 0.258282399\Delta(\text{LogBloomberg.US.Green}_{t-2}) + 0.218035488\Delta(\text{LogCiti.BIG}_{t-2}) - 0.173047371\Delta(\text{LogBloomberg.US.Green}_{t-3}) + 0.330994493\Delta(\text{LogCiti.BIG}_{t-3}) - 0.117693848\Delta(\text{LogBloomberg.US.Green}_{t-4}) + 0.443398243\Delta(\text{LogCiti.BIG}_{t-4}) - 0.102900033(\text{LogBloomberg.US.Green}_{t-5}) + 0.212810815\Delta(\text{LogCiti.BIG}_{t-5}) - 0.006695446\Delta(\text{LogBloomberg.US.Green}_{t-6}) + 0.144238521\Delta(\text{LogCiti.BIG}_{t-6}) + 0.010428636\Delta(\text{LogBloomberg.US.Green}_{t-7}) +$$

$0.075290148\Delta(LogCiti.BIG_{t-7}) - 0.048999274(LogBloomberg.US.Green_{t-1} - 0.8539163LogCiti.BIG_{t-1} + 1.6169700\textit{constant}_{t-1})$

5. Bloomberg.US.Green - FTSE.BIG:

$$\Delta(LogBloomberg.US.Green_{t}) = -0.14046652\Delta(LogBloomberg.US.Green_{t-1}) + 0.05484561\Delta(LogFTSE.BIG_{t-1}) - 0.03782795\Delta(LogBloomberg.US.Green_{t-2}) + 0.08980342\Delta(LogFTSE.BIG_{t-2}) - 0.00122979\Delta(LogBloomberg.US.Green_{t-3}) + 0.04801041\Delta(LogFTSE.BIG_{t-3}) - 0.01531654\Delta(LogBloomberg.US.Green_{t-4}) + 0.04262503\Delta(LogFTSE.BIG_{t-4}) - 0.05552621(LogBloomberg.US.Green_{t-5}) + 0.12198375\Delta(LogFTSE.BIG_{t-5}) - 0.02222632(LogBloomberg.US.Green_{t-1} - 0.5580296LogFTSE.BIG_{t-1} - 1.7048217\textit{constant}_{t-1})$$

6. Bloomberg.US.Green - FTSE.US.BIG:

$$\Delta(LogBloomberg.US.Green_{t}) = -0.350124251\Delta(LogBloomberg.US.Green_{t-1}) + 0.167842208\Delta(LogFTSE.US.BIG_{t-1}) - 0.258299184\Delta(LogBloomberg.US.Green_{t-2}) + 0.218053038\Delta(LogFTSE.US.BIG_{t-2}) - 0.173078477\Delta(LogBloomberg.US.Green_{t-3}) + 0.331017263\Delta(LogFTSE.US.BIG_{t-3}) - 0.117729653\Delta(LogBloomberg.US.Green_{t-4}) + 0.443416421\Delta(LogFTSE.US.BIG_{t-4}) - 0.102925499(LogBloomberg.US.Green_{t-5}) + 0.212871270\Delta(LogFTSE.US.BIG_{t-5}) - 0.006721708\Delta(LogBloomberg.US.Green_{t-6}) + 0.144239392\Delta(LogFTSE.US.BIG_{t-6}) + 0.010427551\Delta(LogBloomberg.US.Green_{t-7}) + 0.075326382\Delta(LogFTSE.US.BIG_{t-7}) - 0.048990458(LogBloomberg.US.Green_{t-1} - 0.8539069LogFTSE.US.BIG_{t-1} + 1.6169004\textit{constant}_{t-1})$$

7. Bloomberg.US.Green - Bloomberg.E:

$$\Delta(LogBloomberg.US.Green_{t}) = -0.094026963\Delta(LogBloomberg.US.Green_{t-1}) + 0.005929654\Delta(LogBloomberg.E_{t-1}) - 0.025657617(LogBloomberg.US.Green_{t-1} - 0.9595594LogBloomberg.E_{t-1} + 0.5804804\textit{constant}_{t-1})$$

8. Bloomberg.US.Green - Bloomberg.US:

$$\Delta(LogBloomberg.US.Green_{t}) = -0.08883057\Delta(LogBloomberg.US.Green_{t-1}) + 0.02127899\Delta(LogBloomberg.US_{t-1}) - 0.04186962(LogBloomberg.US.Green_{t-1} - 0.8316853LogBloomberg.US_{t-1} + 1.6161456\textit{constant}_{t-1})$$

9. Bloomberg.Green.AAA - SP.AAA:

$$\Delta(LogBloomberg.Green.AAA_{t}) = 0.03183638\Delta(LogBloomberg.Green.AAA_{t-1}) + 0.01068493\Delta(LogSP.AAA_{t-1}) - 0.02246927(LogBloomberg.Green.AAA_{t-1} - 0.3013599LogSP.AAA_{t-1} + 3.2479914\textit{constant}_{t-1})$$

10. Bloomberg.Green.A - Bloomberg.E:

$\Delta(LogBloomberg.Green.A_t) = 0.02299011\Delta(LogBloomberg.Green.A_{t-1}) - 0.02971724\Delta(LogBloomberg.E_{t-1}) - 0.03832859(LogBloomberg.Green.A_{t-1} - 1.135378LogBloomberg.E_{t-1} + 1.491885constant_{t-1})$

11. Bloomberg.Green.A - Bloomberg.US:

$\Delta(LogBloomberg.Green.A_t) = 0.03257393\Delta(LogBloomberg.Green.A_{t-1}) - 0.02823449\Delta(LogBloomberg.US_{t-1}) - 0.02472177(LogBloomberg.Green.A_{t-1} - 0.9508543LogBloomberg.US_{t-1} + 2.4661008constant_{t-1})$

12. Bloomberg.E.Green - FTSE.E.BIG:

$\Delta(LogBloomberg.E.Green_t) = -0.400138642\Delta(LogBloomberg.E.Green_{t-1}) + 0.040160464\Delta(LogFTSE.E.BIG_{t-1}) - 0.344406519\ \Delta(LogBloomberg.E.Green_{t-2}) + 0.262493690\Delta(LogFTSE.E.BIG_{t-2}) - 0.341966272\Delta(LogBloomberg.E.Green_{t-3}) + 0.362494729\Delta(LogFTSE.E.BIG_{t-3}) - 0.279331003\Delta(LogBloomberg.E.Green_{t-4}) + 0.514496417\Delta(LogFTSE.E.BIG_{t-4}) - 0.207146132\Delta(LogBloomberg.E.Green_{t-5}) + 0.309370791\Delta(LogFTSE.E.BIG_{t-5}) - 0.134501262\Delta(LogBloomberg.E.Green_{t-6}) + 0.323349294\Delta(LogFTSE.E.BIG_{t-6}) - 0.079824841\Delta(LogBloomberg.E.Green_{t-7}) + 0.206836665\Delta(LogFTSE.E.BIG_{t-7}) - 0.006766672\Delta(LogBloomberg.E.Green_{t-8}) + 0.218540907\Delta(LogFTSE.E.BIG_{t-8}) - 0.028603863\Delta(LogBloomberg.E.Green_{t-9}) + 0.090344373\Delta(LogFTSE.E.BIG_{t-9}) - 0.068914144(LogBloomberg.E.Green_{t-1} - 1.124972LogFTSE.E.BIG_{t-1} - 1.696374constant_{t-1})$

13. Bloomberg.Green.Gov - FTSE.E.BIG:

$\Delta(LogBloomberg.Green.Gov_t) = -0.329681774\Delta(LogBloomberg.Green.Gov_{t-1}) + 0.026902824\Delta(LogFTSE.E.BIG_{t-1}) - 0.283896848\ \Delta(LogBloomberg.Green.Gov_{t-2}) + 0.155691140\Delta(LogFTSE.E.BIG_{t-2}) - 0.267240238\Delta(LogBloomberg.Green.Gov_{t-3}) + 0.212033382\Delta(LogFTSE.E.BIG_{t-3}) - 0.212230907\Delta(LogBloomberg.Green.Gov_{t-4}) + 0.308617695\Delta(LogFTSE.E.BIG_{t-4}) - 0.176501092\Delta(LogBloomberg.Green.Gov_{t-5}) + 0.159473893\Delta(LogFTSE.E.BIG_{t-5}) - 0.102062005\Delta(LogBloomberg.Green.Gov_{t-6}) + 0.175929844\Delta(LogFTSE.E.BIG_{t-6}) - 0.062276538\Delta(LogBloomberg.Green.Gov_{t-7}) + 0.110692821\Delta(LogFTSE.E.BIG_{t-7}) + 0.008174149\Delta(LogBloomberg.Green.Gov_{t-8}) + 0.116780962\Delta(LogFTSE.E.BIG_{t-8}) - 0.032610650\Delta(LogBloomberg.Green.Gov_{t-9}) + 0.045644982\Delta(LogFTSE.E.BIG_{t-9}) - 0.061705283(LogBloomberg.Green.Gov_{t-1} - 0.5892981LogFTSE.E.BIG_{t-1} - 1.2890919constant_{t-1})$

14. Bloomberg.Green.AA - Bloomberg.E:

$\Delta(LogBloomberg.Green.AA_t) = 0.02212309\Delta(LogBloomberg.Green.AA_{t-1}) - 0.03283600\Delta(LogBloomberg.E_{t-1}) - 0.03438382(LogBloomberg.Green.AA_{t-1} - 1.444501LogBloomberg.E_{t-1} + 3.196941constant_{t-1})$

15. Solactive.Green – Bloomberg:

$\Delta(LogSolactive.Green_{t}) = -0.043414823\Delta(LogSolactive.Green_{t-1}) + 0.051127208\Delta(LogBloomberg_{t-1}) + 0.004021005(LogSolactive.Green_{t-1} - 1.1446242LogBloomberg_{t-1} + 0.1697754constant_{t-1})$

16. Solactive.Green - Citi.BIG:

$\Delta(LogSolactive.Green_{t}) = -0.043469635\Delta(LogSolactive.Green_{t-1}) + 0.113126848\Delta(LogCiti.BIG_{t-1}) + 0.035789462\ \Delta(LogSolactive.Green_{t-2}) + 0.119975269\Delta(LogCiti.BIG_{t-2}) - 0.074439854\Delta(LogSolactive.Green_{t-3}) + 0.130228805\Delta(LogCiti.BIG_{t-3}) + 0.001851612(LogSolactive.Green_{t-1} - 1.952964LogCiti.BIG_{t-1} + 7.583104constant_{t-1})$

17. Solactive.Green - FTSE.BIG:

$\Delta(LogSolactive.Green_{t}) = -0.040347828\Delta(LogSolactive.Green_{t-1}) + 0.006470144\Delta(LogFTSE.BIG_{t-1}) + 0.002173272(LogSolactive.Green_{t-1} - 1.1513402LogFTSE.BIG_{t-1} - 0.6816462constant_{t-1})$

18. Solactive.Green - FTSE.US.BIG:

$\Delta(LogSolactive.Green_{t}) = -0.043469078\Delta(LogSolactive.Green_{t-1}) + 0.113167836\Delta(LogFTSE.US.BIG_{t-1}) + 0.035789550\ \Delta(LogSolactive.Green_{t-2}) + 0.119876089\Delta(LogFTSE.US.BIG_{t-2}) - 0.074443027\Delta(LogSolactive.Green_{t-3}) + 0.130311141\Delta(LogFTSE.US.BIG_{t-3}) + 0.001851688(LogSolactive.Green_{t-1} - 1.952969LogFTSE.US.BIG_{t-1} + 7.583139constant_{t-1})$

19. Solactive.Green - FTSE.E.BIG:

$\Delta(LogSolactive.Green_{t}) = -0.032706830\Delta(LogSolactive.Green_{t-1}) + 0.020889522\Delta(LogFTSE.E.BIG_{t-1}) + 0.040694121\ \Delta(LogSolactive.Green_{t-2}) - 0.003649205\Delta(LogFTSE.E.BIG_{t-2}) - 0.072137741\Delta(LogSolactive.Green_{t-3}) + 0.041883654\Delta(LogFTSE.E.BIG_{t-3}) - 0.001121863(LogSolactive.Green_{t-1} - 0.7528685LogFTSE.E.BIG_{t-1} - 2.6806873constant_{t-1})$

20. Bloomberg.Green.AA - Bloomberg.US:

$\Delta(LogBloomberg.Green.AA_{t}) = 0.03293740\Delta(LogBloomberg.Green.AA_{t-1}) + 0.03591902\Delta(LogBloomberg.US_{t-1}) - 0.02676498(LogBloomberg.Green.AA_{t-1} - 1.156896LogBloomberg.US_{t-1} + 4.035834constant_{t-1})$

By analyzing the estimates for the Error Correction term (ECT), which indicate the speed of adjustment towards equilibrium, it is possible to see that the largest majority have a negative sign and are significantly different from zero to 5% (see Appendix O) which demonstrates equilibrium correction mechanism. However, there are few exceptions, such as the Solactive.Green - Bloomberg; Solactive.Green - Citi.BIG; Solactive.Green - FTSE.BIG; Solactive.Green - FTSE.E.BIG and Solactive.Green - FTSE.US.BIG (see Appendix O).

These 5 bivariate equations (all considering the Solactive.Green bond index) pointed to have a cointegration relationship according to the Johansen tests results. However, since their estimates for the ECT were not statistically significant, it is not possible to conclude about their long-run cointegration relationship and therefore, they were excluded from further analysis.

For the remaining cointegration relationships, all coefficients β of the long-term relationship equation, which explain the long-run gravitation towards the equilibrium relationship between each pair of indices, are significantly different from zero to 5%. Thus, on average, an increase in the above-mentioned Conventional bond indices' daily prices promotes a decrease (negative coefficient) in the variation of the Green indices daily prices, *ceteris paribus*. However, there are some cases in which the equilibrium coefficient is very close to 0, meaning that the disequilibrium between the two series has little impact on the Green indices' prices forecast.

Regarding the α coefficients, which are the short-term adjustment coefficients[25], it is possible to find some short-term deviations not statistically significant, for instance in the relationship (2) between Bloomberg.US.Green - SP.500, the estimate -0.001379213 is not statistically significant, considering a significance level of 5% (see Appendix O). These not significant lagged changes indicate that on each one of these bivariate equations there is not a long-term relationship between one of these variables and the Green bond index under equation. Thus, these results indicate that these variables should be exogenous and the remaining endogenous, which will be study through weak exogeneity tests in the next section.

4.5.4 Exogeneity

The weak exogeneity condition implies the absence of significant adjustment in the long-run relationship of the corresponding VECM. In other words, this test allows to conclude if any

[25] The adjustment coefficients show the short-term deviations around the long-run equilibrium

of the considered price series are price leaders, finding which price adjusts to maintain the long-run equilibrium.

A weak exogeneity test was performed to each cointegration relationship previously found, aiming to test every element of the adjustment matrix coefficient against zero. This test follows a χ^2 distribution with degrees of freedom equal to the number of cointegrating vectors.

Table 9 – Weak Exogeneity test (see Appendix P)

Cointegration relationships	P-value	Result
Bloomberg.Green - FTSE.E.BIG	0.85	Do not reject
Bloomberg.US.Green - SP.500	0.01	Reject
Bloomberg.US.Green – Bloomberg	0.19	Do not reject
Bloomberg.US.Green – Citi.BIG	0.02	Reject
Bloomberg.US.Green - FTSE.BIG	0.28	Do not reject
Bloomberg.US.Green - FTSE.US.BIG	0.02	Reject
Bloomberg.US.Green - Bloomberg.E	0.66	Do not reject
Bloomberg.US.Green - Bloomberg.US	0.39	Do not reject
Bloomberg.Green.AAA - SP.AAA	0.16	Do not reject
Bloomberg.Green.A - Bloomberg.E	0.63	Do not reject
Bloomberg.Green.A - Bloomberg.US	0.26	Do not reject
Bloomberg.E.Green - FTSE.E.BIG	0.34	Do not reject
Bloomberg.Green.Gov - FTSE.E.BIG	0.02	Reject
Bloomberg.Green.AA - Bloomberg.E	0.72	Do not reject
Bloomberg.Green.AA - Bloomberg.US	0.88	Do not reject

According to the results (see Appendix P), it is possible to conclude that the null hypothesis that supports the existence of weak exogeneity could be rejected for the following 4 cointegration relationships (probability associated to the test was lower than the significance level, considering a 5% significance level):

- Bloomberg.US.Green - SP.500
- Bloomberg.US.Green - Citi.BIG
- Bloomberg.US.Green - FTSE.US.BIG
- Bloomberg.Green.Gov - FTSE.E.BIG

Thus, the Bloomberg.US.Green index shows a long-run relationship with both SP.500, Citi.BIG and FTSE.US.BIG. Meaning that, the variation in the prices of the

Bloomberg.US.Green may be forecasted by using the SP.500, Citi.BIG and FTSE.US.BIG indices prices in the long-run (*ceteris paribus*). Similarly, the Bloomberg.Green.Gov also showed a long-run relationship with the FTSE.E.BIG and therefore, the variation of its prices may be forecasted using the FTSE.E.BIG index prices in the long-run (*ceteris paribus*).

For the remaining 11 cointegration relationships, the null hypothesis was not rejected which indicates weak exogeneity. As weak exogeneity implies an absence of significant adjustment in the long-run relationship of the corresponding VEC Model, for these 11 weak exogenous variables only a short-term relationship remains with the respective Green bond index.

This fact also implies that it is not possible to use the Conventional bond indices under these 11 relationships to forecast the respective Green bond index in the long-run. For this to be also the case in the short-run, these 11 Conventional bond indices need to be strongly exogeneous (i.e. not impacted by the short-run movements of the respective Green Bond Index pair). Thus, for these weakly exogenous bond indices, the strong exogeneity through the Granger causality principle was analyzed.

As per the Granger Causality outputs (which now considered the natural logarithm of the closing daily prices[26] – see Appendix Q), a non-causal relationship was indeed found, for two pairs: Bloomberg – Bloomberg.US.Green and FTSE.E.BIG – Bloomberg.E.Green. Thus, it is possible to say that the Bloomberg bond index and the FTSE.E.BIG bond index, in which evidence of strong exogeneity was found, do not have neither a long-term nor a short-term relationship with Bloomberg.US.Green and Bloomberg.E.Green, respectively.

It is worth noting that in the first case, between the Bloomberg (Bloomberg Barclays Global Aggregate Bond Index) and the Bloomberg Barclays MSCI US Green Bond (Bloomberg.US.Green) is clear the evidence of both being part of the Bloomberg Barclays spectrum of bond indices. However, the Bloomberg is a multi-currency global index and the Bloomberg.US.Green is only focused on US. Dollar-denominated Green bonds. One possible reason to explain the strong exogeneity of the Bloomberg index could be the currency

[26] The null hypothesis is X_{jt} is not Granger cause of Y_t (Conventional bond index ~ Green bond index)

composition of both indices, which may impact the relative returns whenever subject to currency movements.

Also, the strict criteria used by Bloomberg, Barclays and MSCI to bring greater transparency to the Green bond markets, may turn the number of Green bond issuers and sectors included quite restricted and therefore, may diverge from the Bloomberg index.

Also, the still limited Green bond market in the United States which may impact the volume of US. Dollar-denominated Green bonds outstanding and may influence its demand, since the Green bond issuance from North America reached USD$ 14.7bn[27] in Q1 2019 (considering United States and Canada), but US. issuance alone was around USD$ 11.5bn[28] as of April 2019, comparing to the Bloomberg Barclays Global Aggregate Bond Index market value of USD$54.6 trillion[29] (as of June 2019), so also the liquidity in the market is expected to be different.

Regarding the strong exogeneity of the Financial Times Stock Exchange Euro Broad Investment-Grade Bond (FTSE.E.BIG), this time both indices are EUR-denominated, since Bloomberg Barclays MSCI Euro Green Bond (Bloomberg.E.Green) is also targeting only Green bonds issued in EUR.

One possible reason to explain the strong exogeneity may be connected to the liquidity of both indices in the market, due to its structure (time-to-maturity, credit quality, size of bonds) which can impact the investor's demand. However, regarding the credit quality, FTSE.E.BIG only covers Investment-Grade bonds and the largest amount of Green bonds outstanding are also Investment-Grade (around 80% of the overall Green bond universe[30]), but still they may diverge in terms of issuers and sectors (taking into consideration once again, the strict criteria used by Bloomberg, Barclays and MSCI to include Green bonds into their indices).

[27] Climate Bonds Initiative (2019) [11]
[28] Ibid.
[29] Bloomberg Barclays Indices (2019) [3]
[30] Climate Bonds Initiative (2018a) [12]

5. SUMMARY AND CONCLUSIONS

The present dissertation aimed to analyse whether the Green bonds provide superior returns when comparing to its Conventional peers, or if there is a trade-off between sustainability concerns and financial performance. Hence, this study was divided into three main objectives: (i) compare the financial performance of Green bond indices returns and its conventional peers throughout the study of their returns properties; (ii) identify the type of relationship that exist between Green bond indices returns and their conventional peers by analyzing whether Green bond Indices returns are caused by the Conventional bond indices returns, and vice-versa; (iii) assess whether exists or not a long-run equilibrium relationship amongst the bond indices prices by studying if Green and Conventional bond indices are cointegrated.

To achieve the proposed objectives and understand if investors face a trade-off between sustainability concerns and financial performance, it was important to take into consideration two important caveats: (i) the lack of agreement and mandatory guidelines on what can be considered Green, which means that Green bonds cannot be unambiguously identified and (ii) the limited Green bond market size (approximately USD$ 389 billion[31] outstanding) compared to the Conventional bond market (approximately USD$ 100 trillion[32]) which may impact the liquidity of the Green bonds in the market and affect the results.

However, the Green bond has been giving proofs of its growing maturity, namely with the launch of several Green bond indices. These indices are playing an important role for driving Green bonds' demand amongst institutional investors, since they break down the major barriers of this new type of bonds (the lack of understanding of the implicit risk and performance). Moreover, as they are considered to be a good starting point to analyse the secondary market performance, several Green and Conventional bond indices were chosen to conduct this empirical study.

[31] Climate Bonds Initiative (2018a) [12]

[32] SIFMA (2017) [85]

The Green bond indices chosen were Bloomberg Barclays MSCI Indices (Global, EUR and USD-Denominated, Government-related, Investment-Grade); Bank of America Merrill Lynch (Global); S&P 500 (Global) and Solactive (Global).

The set of Conventional bond Indices were also Bloomberg Barclays (Global, EUR and USD-denominated); Citi (Broad Investment-Grade); JP Morgan (Governmental-related); FTSE (Global, EUR and USD Broad Investment-Grade; Government-related); S&P 500 (Global; Investment-Grade).

To perform the present study, the daily closing prices have been collected for both type of bond indices during the period the 7th of January 2015 (date in which the newest Index was traded for the first time) to the 16th of May 2019.

To address the first objective of this study, the descriptive statistics of the bond Indices' returns were analyzed. In what concerns to volatility, the analysis of the Standard Deviation of both types of indices, led to conclude similarly low levels of risk. Thus, the returns of the indices under study almost did not vary from the average return, which indicates low volatility and consequently, low investment risk.

Then, both parametric and non-parametric tests were applied to the indices' returns, to investigate whether exists differences in terms of financial performance. The results point for statistically significant differences between the distributions of the Green and Conventional returns, but when the ANOVA test was applied, the difference between the samples means of returns were not statistically significant.

Thus, it is not possible to affirm that investing in Green bond indices bring superior returns, but it is indeed possible to affirm that it does not prejudices the investor financial performance This conclusion may be connected to the fact that there are companies belonging to different indices simultaneously. According to these last results, the theory of a trade-off between sustainability and financial performance was rejected.

The short-term dynamics of the indices' returns were also studied through the Granger causality tests, and it was observed a feedback causality effect between Bloomberg.Green and SP.A; Bloomberg.Green and FTSE.E.BIG; Bloomberg.E.Green and SP.A;

Bloomberg.E.Green and SP.AAA; Bloomberg.E.Green and SP.AA; Bloomberg.E.Green and FTSE.Gov; Bloomberg.E.Green and FTSE.E.BIG; Bloomberg.US.Green and Bloomberg; SP.Green and Bloomberg; SP.Green and Citi.BIG; SP.500 and FTSE.BIG; SP.Green and FTSE.US.BIG; Bloomberg.Green.Gov and SP.AA; Bloomberg.Green.Gov and SP.A; Bloomberg.Green.Gov and FTSE.E.BIG; Bloomberg.Green.AA and FTSE.E.BIG. By analyzing these relationships, it is possible to see a Granger causality tendency between Green and Investment Grade and Governmental-related conventional indices.

Finally, to study the long-term dynamics of the indices' prices and meet the last objective, it was needed to (i) analyse the non-stationarity and first-order integration of each time series under study; (ii) test the cointegration between Green and Conventional Bond indices; (iii) estimate the Vector Error Correction Model (VECM) for each cointegration relationship identified; (iv) analyse the weak exogeneity that trace which Conventional Bond indices' prices could be used to forecast Green indices' prices in the long-run.

All time series under study were indeed non-stationary and integrated of order one, which led to the inclusion of all variables in the cointegration analysis. The bivariate cointegration Johansen tests noted a long-run relationship across 20 pairs (out of 130 relationships analyzed), allowing for the VECM estimation for each relationship identified.

As some bivariate equations indicated signals of exogeneity, the weak exogeneity test was performed. The weak exogeneity implies the absence of significant adjustment in the long-run relationship of the corresponding VECM, allowing to identify which index actually adjusts to maintain the long-run equilibrium.

The null hypothesis that supports the existence of weak exogeneity could be rejected for 4 cointegration relationships: Bloomberg.US.Green - SP.500; Bloomberg.US.Green - Citi.BIG; Bloomberg.US.Green - FTSE.US.BIG and Bloomberg.Green.Gov - FTSE.E.BIG. Thus, the Bloomberg.US.Green may be forecasted by using the SP.500, Citi.BIG and FTSE.US.BIG indices' prices in the long-run (*ceteris paribus*). Similarly, Bloomberg.Green.Gov prices may be forecasted by using the FTSE.E.BIG index prices in the long-run (*ceteris paribus*).

For the remaining 11 cointegration relationships, the null hypothesis was not rejected which indicates weak exogeneity and therefore, for those variables only a short-term relationship remains. This fact also implies that it is not possible to use the Conventional bond indices to forecast the respective Green bond index in the long-run. For this to be also the case in the short-run, these 11 Conventional bond indices need to be strongly exogeneous.

To assess the strong exogeneity of those exogeneous variables, the Granger causality test was applied. As per the Granger Causality outputs (now considering the natural logarithm of the closing daily prices), a non-causal relationship was found for Bloomberg – Bloomberg.US.Green and FTSE.E.BIG – Bloomberg.E.Green. Thus, the Bloomberg and the FTSE.E.BIG bond indices, in which evidence of strong exogeneity was found, do not have neither a long-term nor a short-term relationship with the respective Green bond index.

This strong exogeneity may be connected to differences in terms of currency composition between the two indices, which may impact the relative returns whenever subject to currency movements. Also, the strict criteria used by Bloomberg, Barclays and MSCI to bring greater transparency to the Green bond markets, may turn the number of Green bond issuers and sectors included quite restricted and therefore, may diverge from the Conventional index.

Also, due to smaller issuer sizes and an investor base involving mainly Hold-To-Maturity (HTM) investors, Green bonds tend to have lower liquidity than its conventional peers, which affects the investor demand.

It is important to note that as the majority of the indices shown not to be cointegrated, having their yields not moving together over time, may increase the potential benefits associated to the investment portfolio diversification to Green bonds. On the other way, as no significant differences were found in terms of returns properties and risk profile, it is not certain that for those indices that did not show any cointegration relationship, there is any long-run diversification benefit granted. The only certain benefit associated is the help to decrease exposure to legal and reputational risks, by providing a hedge against future regulatory changes on environmental-related issues.

Moreover, the information on this financial innovation, its effectiveness in terms of financial and environmental performance is still very limited. With the development and increasing maturity of the market, clear regulation and standards for the “Green label” will be required and harmonization and consistency will finally be reached.

Meanwhile, emerging markets are starting to gain some expression, with the Governments and regulators from predominantly emerging and Asian countries, such as China, Hong Kong, India, Indonesia, Japan, Malaysia and Singapore, being proactively contributing to the development of clear guidelines and policies for defining what is Green and therefore building the foundations for their Green bond market. Thus, as future research, since the emerging markets were out of the scope of this study, one suggestion would be to incorporate those in the study and to compare them to the developed ones.

Additionally, as Green bond Indices tend to differ from other bond indices in terms of currency composition this was one limitation in this study that could have impacted the relative returns. To offset this limitation, the currency exposure could have been hedged. Also, the potential differences in terms of liquidity (e.g. in terms of EUR and USD-denominated bonds, Governmental-related or Investment-Grande) may have also impacted the underlying volatility with the inclusion of short-term shocks. Thus, as further research, the study of structural breaks could be incorporated to offset the short-term shocks.

Another limitation faced in this study was due to the quite recent nature of Green bond indices. Considering the date in which the newest index was traded for the first time (7^{th} of January 2015) to the present 16^{th} of May 2019, only few years were under analysis, which might have captured some shocks not significant in the long-run. Thus, as further research, it might be interesting to repeat this analysis in some years when the market will be more mature.

In a nutshell, according to this empirical study, Green bonds did not show any potential damage to the investor’s portfolio and with the right application of their use of proceeds, they could serve as a successful and powerful tool to support the transition towards a low-carbon economy.

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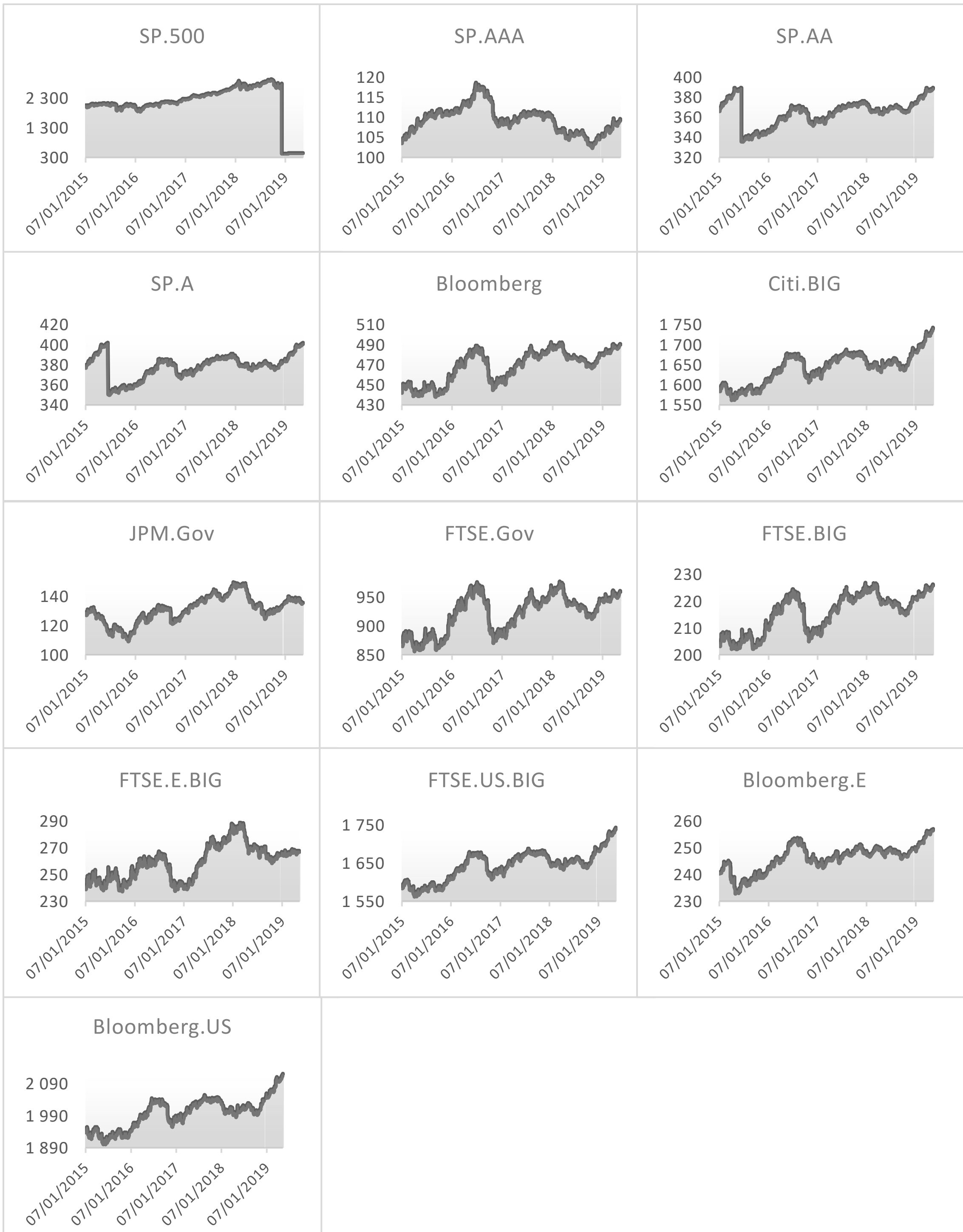
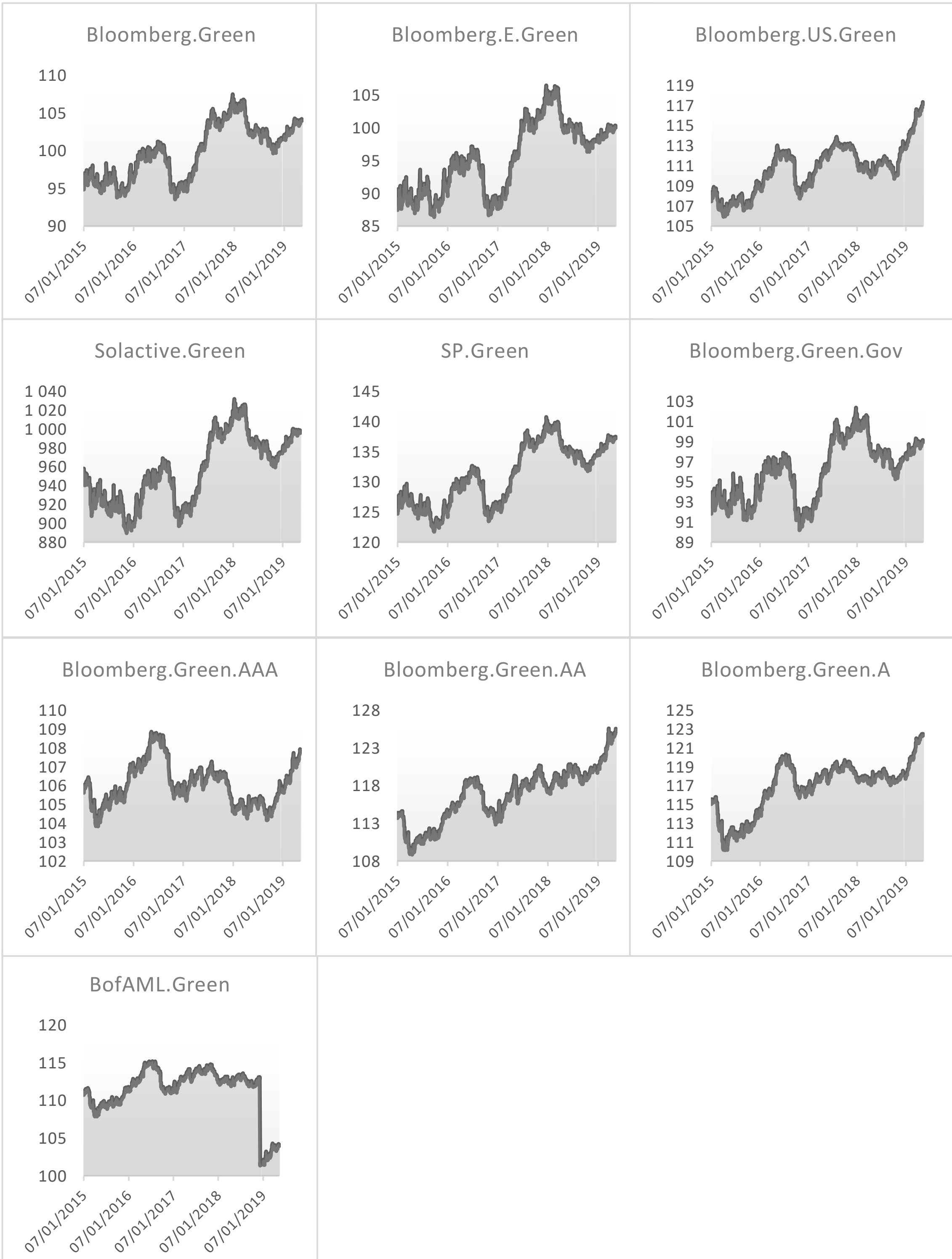
7. APPENDIX[33]

A. Daily prices of Conventional and Green Bond Indices



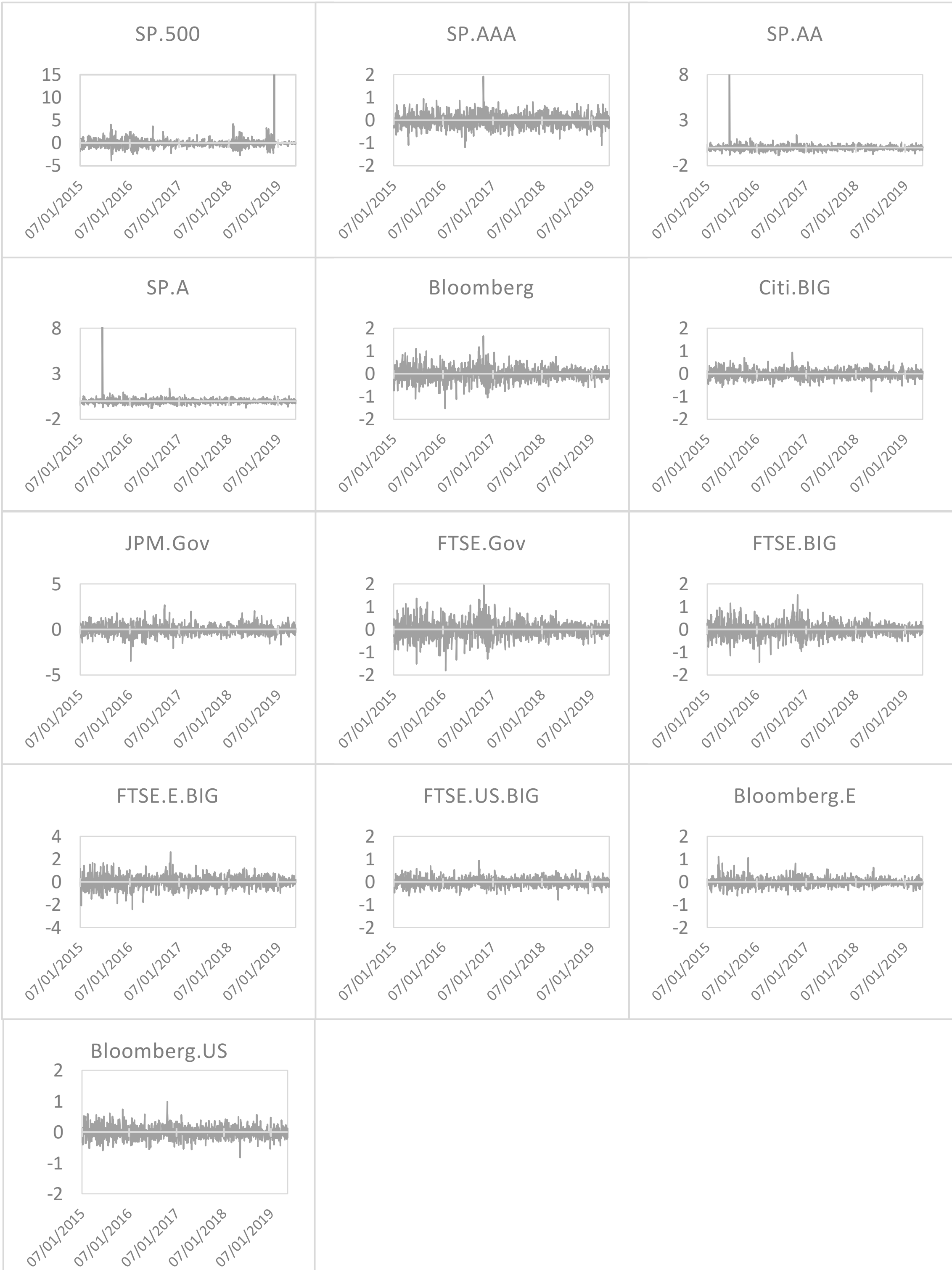
Charts 1: Daily prices (in levels) of Conventional Bond Indices, between 07/01/2015 and 16/05/2019

[33] For fully access to the Appendix, please contact: iagte@iscte-iul.pt



Charts 2: Daily prices (in levels) of Green Bond Indices, between 07/01/2015 and 16/05/2019

B. Daily returns of Conventional and Green Bond Indices



Charts 3: Daily returns of Conventional Bond Indices, between 08/01/2015 and 16/05/2019

Charts 4: Daily returns of Green Bond Indices, between 08/01/2015 and 16/05/2019