A data processing methodology for green bond and climate bond primary and secondary market data[1]

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Abstract

The aim of this paper is to explore challenges for developing a detailed, comprehensive and up-to-date database focusing on the US primary and secondary markets for green bonds and climate bonds. In September 2018, the green and climate bond universe represented USD1.2tn, and included 869 issuers, giving research an opportunity to thoroughly analyze the first financial products to have an extra-financial purpose. This paper first focuses on identifying, acquiring and storing various types of green and climate bond data using available financial databases. It then gives a detailed walk-through on structuring and processing this data. Different data process methodologies result in obtaining various databases on green bonds and climate bonds that can be used to develop a variety of factors that can provide insight on the green bond and climate bond primary and secondary market, as well as obtaining monthly returns for these markets in order to explore the cross-section or times series of green and climate corporate bond returns.

Keywords: Green Bonds; Climate Bonds; Sustainable Finance; Climate Change; Enchanced TRACE Data

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1. Introduction

With the first green bond issuance dating back to 2007, the green bond market is still young. However, since the year 2013, when total issuances grew close to $10 billion worldwide, offerings for green bonds have grown at an increasing rate. In 2019, issuances for the year reached $257.5 billion. This presents not only an opportunity for market practitioners, but for academics as well, as data relative to the primary green bond market starts to accumulate, and the first forms of transaction data relative to the secondary market for these products are starting to emerge.

As one of the first financial products with an extra-financial purpose to reach such a market size, the study of green bonds offers an opportunity to gather interesting and useful insights on the specificities of financial products that do not have a purely financial objective, as well as on the investors that trade these specific securities. However, green bonds are not the only products that have an underlying environmental purpose. Bonds issued by corporations that stream more than 75% of their revenues from climate-aligned activities have been categorized as a specific type of bond. These bonds, referred to as climate bonds, though not officially labeled, can undoubtedly provide further insight on the specificities of environment-related financial products.

However, creating a clean database that has the most detailed, comprehensive and up-to-date data on green and climate bonds presents a series of challenges. This paper focuses on identifying these challenges, and on constructing a robust and practical methodology in order to address them. Setting-up such a database and data treatment methodologies as the green and climate bond markets continue to grow could be useful for academics or practitioners that wish to analyze it, but also to review already existing work and data treatment procedures for the study of corporate bond markets.

Compared to the literature addressing the study of stocks, the literature which deals with the study of corporate bonds is quite recent, and academics in the field have constantly been challenged with issues related to data availability and quality. The primary source of data on the corporate bond market, the Lehman Brothers Fixed Income database closed in 1997, and there was no quality data available on this market until the Mergent Fixed Income Securities Database opened in 2004, and the Trade Reporting and Compliance Engine database (TRACE) was put in place starting in 2002. Furthermore, TRACE data was at first quite unreliable, and required rigorous data treatment that wasn't clearly identified by the literature until 2009. To date, many studies on the subject still do not address some essential steps of this data cleaning procedure which could bias results. In this paper, we create a clear data treatment procedure, applied to a sample of green and climate bonds, to create a framework to study these products using the thorough methodology that needs to be implemented when one studies the corporate bond market.

After explaining the different approaches that are taken on the subject of treatment of corporate bond data in the literature, we develop a methodology specific to green corporate bonds and climate bonds using a variety of different data sources. We use data from Bloomberg to identify green bonds and data provided by the Climate Bond Initiative (CBI)[4] to identify climate bonds. We then extract raw trade-based data from the Enhanced TRACE dataset and develop a data treatment procedure closely following Dick-Nielsen (2009) and Dick-Nielsen (2014), two studies in the literature that address the data treatment procedure for TRACE data in the most detail. Through various steps, this data treatment methodology transforms raw intra-day transaction data into monthly prices, creating different types of databases along the way that can be used for various type of studies on the corporate bond market. Once we obtain monthly prices from the TRACE database, these are merged with monthly prices from Datasteam and Bloomberg. Following the literature, we first use TRACE data for our monthly prices, then, if TRACE data is unavailable, Datastream data is used, followed by Bloomberg. This choice that is put forward by academics in the field, is better understood when we compute correlations between datasets. Datastream data is strongly correlated to TRACE data, with a correlation of 0.93 for green bond data and 0.96 for climate bond data, but Bloomberg has a surprisingly low correlation with TRACE, with a correlation of only 0.28 for our green bond sample and 0.75 for our climate bond sample. This does not only provide insight regarding the quality of data provided by Bloomberg, but also on previous work performed by academics that used Bloomberg data to study the corporate bond market. We also find that Bloomberg data provides very little monthly bond prices to our datasets that is not already provided by either TRACE and Datastream.

We conclude this paper by visualizing monthly returns for our samples of green bonds and climate bonds and find that though climate bond monthly returns and green bonds climate bond returns are strongly correlated overall, these returns vary greatly during the last months of 2016, and correlation is not perfect. From this visualization, we understand that differences exists between these two types of products. Though the precise analysis of these differences is outside the scope of this paper, this provides interesting insight that could prove useful for future research.

The remainder of the paper is structured as follows. Section 2 presents the existing literature related to the study of green and climate bonds as well as the literature on the study of traditional corporate bonds that has led the author to develop such methodology. Section 3 presents the different financial databases that are used as well as their advantages and limitations and the different steps of this data processing methodology. Section 4 describes the resulting datasets we obtain from these methodologies and their applications and the results we obtain for green bonds and climate bonds. Section 5 concludes the study.

2. Literature Review

2.1. The nascent climate-aligned bond literature

The growing number of green bond issuances has led academics to develop an interest in this product. Green bonds are bond products issued in order to specifically finance projects with positive

[4]The Climate Bond Initiative is an international, investor-focused not-for-profit that focuses explosively on the bond market for climate change solutions. The amount of global green bond issuances is monitored on the organization's website. See https://www.climatebonds.net/.

environmental outcomes, and naturally a stem of literature is focused on trying to determine if green bond issuers benefit from a green bond premium given the nature of their project.

However, this initiative has met important challenges. First and foremost, the pricing of bond products is more challenging than that of equity products, given the fact that bonds have multiple specific characteristics that directly impact their pricing, such as coupon rates, credit rating, maturity or size (Zerbib, 2019). Determining if a green bond premium exists would require comparing green bonds with traditional bonds that have precisely the same characteristics, which very rarely exist (Bachelet et al, 2019). In addition to these important limitations, the green bond market represented less than 3.6% of the global bond market issuances[5] in 2019, and issuances are still sporadic throughout the year, which leads both to issues in terms of liquidity, as well as in terms of available data for pricing. Moreover, the academic literature that focuses on studying the corporate bond market refers to one specific transaction-based database to obtain the best quality data on the pricing of corporate bonds – the TRACE database6 – which only applies to US corporate bonds. For the year 2018, Moody's Analytics[7] reported that $1.553 trillion in bonds were issued in the US, while the Climate Bond Initiative reported $34 billion in US green bond emissions (Climate Bond Initiative, 2018). This represents less than 2.2% of US corporate bond emissions, meaning that academics that wish to study this database would have access to too little data to perform robust analyses.

Studies on the pricing of green bonds therefore generally have small samples and must refer to other databases with less precise pricing data, such as dealer quotes provided by market-makers or matrix-prices, which only provide approximations of real prices. To provide an idea of the general ranking of data on corporate bond pricing in terms of quality, Jostova, Nikolova, Philipov and Stahel (2011) built a database of bond returns using the five databases that gave information on corporate pricing and took "the first available return in the following sequence: TRACE, FISD[8], Lehman, Datastream and Bloomberg", clearly giving precedence to trade-based data. Combined, these restrictions in terms of sample size, historical data and pricing data quality results in inconclusive findings concerning the existence of a green bond premium (Hachenberg and Schiereck, 2018; Bachelet et al, 2019; Zerbib, 2019). Similar studies have also focused on the relationship between ESG ratings and corporate bond performance, finding that bonds issued by firms with higher ESG ratings have tighter spreads and outperform peers with lower ESG ratings (Polbennikov, Desclée, Dynkin and Maitra, 2016). Ge and Liu (2015) find that better CSR performance is associated with better credit ratings. In a paper focusing specifically on corporate green bonds, Flammer (2018) finds a positive reaction from stock markets to green bond issuance announcements, that green bond issuers improve their environmental performance

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[5] Global bond issuances in 2019 amounted to $7.148 trillion. See https://www.dealogic.com/insight/dcm-highlights-full-year-2019/

[6] As TRACE transaction data is the main source of data for this paper, more information is provided in section 4 of this paper on the specificities of this database

[7] See https://www.moodysanalytics.com/-/media/article/2019/weekly-market-outlook-corporate-bond-issuance-reflects-business-activitys-heightened-to-rates.pdf

[8] When referring to FISD, the authors referred to the NAIC databases which complements the FISD database, which itself only provides information on characteristic data of US bonds. The NAIC database provides transaction data on corporate bonds issued and traded by US insurance companies.

after the issuance, and that they experience increase in ownership by long-term and green investors. To date and to the author's knowledge, there is no academic literature focusing on empirical studies of climate bonds.

2.2. Recent studies on the corporate bonds market

Looking at the progress that has been made relative to the study of traditional bonds can help us understand what research questions and possible results can be applied and obtained when focusing more specifically on green and climate bonds. This is quite understandable, as green bonds only differ from traditional bonds in the fact that they have been labelled as being green and are financial tools used to finance environmental projects, and climate bonds, which have only recently been identified by the Climate Bonds Initiative (CBI, 2018), are traditional bonds that finance firms that are considered to positively - or at least not negatively - affect climate change. In addition, looking at the young literature that focuses specifically on green bonds and climate bonds can help us identify the first research questions that have been applied, and results that have been obtained, on these specific bond markets, and understand how our work can benefit to this literature.

There is an important literature focusing on liquidity-related issues on the traditional corporate bond market. Acharya et al. (2013) show that the pricing of liquidity risk in the bond market is conditional to the state of the economy, and that liquidity risk is more important in times of financial and economic distress. Focusing on bond-specific liquidity measures, Chen et al. (2007) find that liquidity is priced in corporate bond yield spreads and Lin et al (2011) investigate corporate bond expected returns and find that these are partly explained by liquidity risk. Using transaction data similar to ours, Bao et al (2011) shows that illiquidity in corporate bonds is substantial and significantly greater that what can be explained by bid-ask spreads. The authors establish a strong link between illiquidity and bond prices. Two years later, Bao et al (2013) find that empirical volatilities of corporate bond returns are higher than implied by equity return volatilities and the Merton model due to illiquidity.

Focusing more specifically on traditional bond returns, DeCosta (2017) find that investment-grade bonds with short-maturity perform better than similar bonds with longer maturities. These results are attributable in part to the insurance companies' trading behavior, as insurance-company purchases create a strong demand for long-term bonds. By examining underpricing of initial public offerings (IPOs) and seasoned offerings in the corporate bond market, Cai et al. (2007) investigate whether underpricing results from an information problem or a liquidity problem and find that issues related to information cause underpricing. On a similar note, Liu et al. (2014) try to understand the relationship between information risk and the underpricing of newly issued corporate bonds and find that information risk is associated with higher underpricing for these products.

Studies on the effects of increased transparency on corporate bond markets - mostly due to improved trade reporting - have also emerged. On this subject, Bessembinder et al. (2006) find that improved trade reporting in the corporate bond market lowered trade execution costs, also showing that better pricing information regarding some bonds also improves valuation and execution cost monitoring for related bonds and find no evidence that market quality deteriorated in other dimensions. Adding to this work, Edwards et al. (2007), using a record of US over-the-counter (OTC) secondary trades in corporate bonds, find that transactions costs decrease significantly with trade size, and that costs lower for bonds with transparent trade prices, suggesting that public traders benefit significantly from price transparency. Finally, Goldstein et al. (2007) find that adding transparency has either a neutral or a positive effect on liquidity, and that transparency is not associated with greater trading volume. The authors conclude that observed decreases in transaction costs illustrate the investors' ability to negotiate better terms once they have access to better data.

The study of the relationships between equity characteristics and corporate bond characteristics has also stimulated the interest of some academics. In their paper, Chordia et al. (2017) tell us "although it stands to reason that corporate bonds are not as sensitive to firm outcomes as equities, corporate bond return volatility is still material, at about a third of that of equities for junk bonds and about a fifth for investment-grade bonds". The authors estimate that uncertainty in cash flow resulting from credit risk could have similarities with equities. Risk-based factors and possible investor biases that apply in equity markets might also apply to the credit risk sector. In a similar manner, De Jong et al. (2007) study the liquidity risk premia in corporate bonds and equity markets and find that corporate bond returns are sensitive to fluctuations in liquidity of the Treasury and equity markets.

In the asset pricing literature, the behavior of bond returns has also tried to be identified using a variety of factors. This was initiated by Fama and French (1993) when the authors identified five risk factors that were common to the returns of stocks and corporate bonds. Since then, the study of the cross-section of corporate bond returns has created interest in the asset pricing literature. Academics that focused on this subject mostly developed factors using either stock-level data, treasury bond data and macroeconomic data. This is the case for the long-established Fama-French (1993) factors composed of the market risk factor (Mm-Rf), the size factor (SMB) and the book-to-market factor (HML) that originate from stock data and treasury bond data, and the term spread (TERM) and default spread (DEF) factors that originate from treasury bond data and government bond data[9]. Other factors that have complemented Fama and French's work, such as the liquidity (LIQ) factor (Pastor and Stambaugh, 2003), momentum (MOM) factor (Carhart, 1997), and more recently, the investment (CMA) and profitability (RMW) factors (Fama and French, 2015) all originate from stock-level data. Realizing that these factors performed poorly in their ability to explain industry-sorted and size/maturity sorted portfolios of US corporate bonds, Bai, Bali and Wen (2019) introduced new bond-implied risk factors based on characteristics specific to corporate bonds.

The study of the dense corporate bond literature allows us to understand the wide array of possible studies that could be applied to a dataset of green bonds and climate bonds. Whether we chose to focus on liquidity, performance, increased transparency, the equity-bond relationships that can exist within firms or markets, or the more general asset pricing literature that is starting to focus more specifically on the study of the corporate bond market, the fact that these climate-aligned products are just traditional

[9] In order to compute the default factor, a market portfolio of long-term corporate bonds was also required, and the data needed to compute such portfolio return could for the most part only be accessed through Ibbotson Associates, a private investment advisory firm.

corporate bonds with an underlying climate objective is a an important opportunity to discover whether these products behave differently. However, before being able to perform such analyses, academics need to face an important challenge related to the quality of available data, and the different data treatment procedures that need to be taken care of before being able to obtain robust results.

2.3. The corporate bond data challenge

As this paper focuses on a data processing methodology for green and climate bonds, we study the traditional bond literature to understand what databases are used, how data is treated and more importantly for what purpose. Research on traditional bonds relies on six financial databases, each providing different types of data, on different markets. Some of the data provided by the databases overlap, and the literature also provides a ranking on the most qualitative data sources depending on the data types that are provided. The main databases are Mergent's Fixed Income Securities Database (FISD), the Trade Reporting and Compliance Engine (TRACE) database, the National Association of Insurance Commissioners Database (NAIC), DataStream, Bloomberg, and the Lehman Brothers Fixed Income Database. (Jostova, et al, 2013; Chordia et al., 2017). As the Lehman Brothers Fixed Income Database provides data from January 1973 to March 1998, we exclude it from our analysis, as our dataset spans from January 2013 to July 2019. We explore these databases in detail in Section 3.

In addition to providing us with explicit details on the advantages and limitations of each financial database that provides information on traditional bonds, the literature also gives precedence to specific databases depending on the types of data they provide. Each database can provide information on the characteristics of bonds, information on trades and transactions that have been on the secondary bond market, and information on the bonds prices on the primary bond market. Regarding data on the characteristics of bonds, precedence is given to FISD over Bloomberg, these two financial databases being the only ones that offer such types of data10. This is justified by the fact that FISD is recognized as the most comprehensive database on bonds, but also due to the fact that Bloomberg offers only a limited amount of data extractions. As aforementioned, regarding data on bond prices, the literature differentiates dealer-quote data provided by Datastream and Bloomberg from transaction data provided by TRACE and NAIC. Precedence is given to transaction data (Jostova et al., 2013). TRACE transaction data is preferred to NAIC transaction data given the fact that NAIC data only provides information relative to insurance companies. Datastream quote-based data is preferred to Bloomberg quote-based data since it gives no restriction on data extractions. The data selection sequence regarding bond prices is therefore the following: TRACE, NAIC, Datastream, Bloomberg.

As FISD, NAIC and TRACE data only provide information on the US bond market, we understand that we can only apply the most qualitative analyses to the United States market. The study of other geographical markets will be both limited by Bloomberg data extractions for bond characteristics, and by the fact that transaction data is not available for academics. Therefore, in this paper, we choose to focus specifically on the US market.

[10] Regarding data on characteristics, Datastream only provides us with issuers identification and currency used for the issuance, and TRACE and NAIC with issuer identification and information that is specific to each transaction individually.

Having developed a clear understanding of the general scope of available bond data that can be used to analyze traditional bonds on financial databases, we use the literature to differentiate data treatment processes that are applied to these datasets. In this paper, we differentiate two types of research designs that require distinct data treatment processes: cross-sectional studies and event studies. Two main differences distinguish these approaches. In a majority of cases, cross-sectional studies can be performed using monthly bond prices while it has been demonstrated that event studies perform better when using daily transaction data. Furthermore, it is recommended that noninstitutional trades below $100,000 be eliminated in the case of event studies. (Bessembinder et al., 2009). Regardless of these two approaches, much like it is the case for research on equity markets, most research on traditional bonds focus on bond returns, whether monthly returns for cross-sectional studies, and daily returns for event studies. We give further detail on the specific data processing procedures to obtain daily and monthly green bond and climate bond returns for both approaches in the following section.

3. Data and Methodology

3.1. Databases of the corporate bond market

To date, there are five distinct sources to find financial data relative to US green bonds and climate bonds. For the purpose of our database, it is important to differentiate three types of data that are important to obtain to study these bonds. Firstly, data on bond characteristics is essential. This includes information on bond issuance dates, maturities, currency, ratings, industry, and any form of information that can help us identify bonds and group them by specific categories. Other types of data include historical prices, whether this regards daily, weekly or monthly prices provided by either quote-based databases or trade-based databases. As previously mentioned, the literature gives precedence to trade-based databases, as these are regarded as giving higher quality data on corporate bond prices. Each of the following databases gives different types of data that we must categorize in order to develop our data processing algorithms. Table 1 summarizes the different used databases, the types of data that they provide as well as the markets they describe.

The Mergent Fixed Income Securities Database (FISD) is considered the most comprehensive database regarding the characteristics of publicly offered U.S. bonds. It contains information on more than 140,000 corporate bonds, medium term notes, supranational or US Agency and Treasury debt products. It provides information both on issuers and on specific issues. The FISD database is composed of a series of datasets that focus on specific characteristics of bond issuers and issuances. In the context of this paper, we focus on the datasets that provide information on issues, issuers, agents, coupons, industry codes and ratings. The FISD database provides us with all necessary information relative to bond characteristics for US green bonds and climate bonds.

Table 1

Database Comparison

Database	Type of Data	Advantages	Limitations
FISD	Characteristics	Most comprehensive database on US Bonds	Limited to the US
Bloomberg	Characteristics, Quote-Based Prices	Provides the list of green bonds. Provides characteristics and historical prices. Is the most comprehensive database overall.	Limited Extractions. Characteristics data on Bonds is less precise than FISD. Quote-based prices are less precise than trade-based prices.
TRACE	Transaction Data	Provides transaction data on US Bond market	Limited to the US
Datastream	Quote-Based Prices	Provides historical prices for all bonds	Quote-based prices are less precise than trade-based prices.

Considered as a dataset contained within the FISD database, we consider the National Association of Insurance Commissioners Database (NAIC) independently from the FISD database, as it provides a different type of data, in a different form, for a different purpose. NAIC data represents bond sales and purchases by US insurance companies and contains bond transactions in more than 79,000 unique issues for almost 8,000 issuers from 1994 onwards.

Since July 2002, all corporate bond transactions in the secondary market have been made available with the TRACE system through the Trade Reporting Compliance Engine. Before this new dataset was made available, most studies that focused on the corporate bond market only used daily quotes and matrix prices for corporate bonds, which could bias results. In their paper on the subject, Sarig and Warga (1989) explore the fact that there can be liquidity-driven noise errors in daily prices for corporate bonds since daily prices are given even on days when bonds have not been traded for multiple days. When this is the case, brokers set matrix prices based on similar bonds issued by issuers with similar characteristics, which creates bias. More recently, Dick-Nielsen et al. (2009) show that this bias still exists with prices from Datastream. This gives TRACE data a considerable edge when focusing on daily prices that can be used for microstructure research such as event studies, as well as an edge for weekly and monthly prices. Important changes have been made to the TRACE database from 2002 to 2012, however since our database spans from January 2013 to June 2018, only the latest version of TRACE needs to be considered for our data processing methodology. Two distinct versions of TRACE exist: the standard TRACE data that censors trading volumes that are greater than $5 million for investment grade bonds and greater than $1 million for speculative grade bonds and that usually has a three-month lag for the availability of data, and the enhanced TRACE data, that has information on all transaction volumes but has an 18 month lag for the availability of data. We use TRACE data conjointly with NAIC data to compute trade-based data for our database.

The last two databases are Bloomberg and Datastream. Datastream provide us with corporate bond prices, while Bloomberg offers both data on bond characteristics and on prices. However, Bloomberg has limited monthly extractions, which is quite an important constraint when considering the sizes of the samples we wish to focus on. It is interesting to note that data from Datastream is preferred to Bloomberg by academics that focus on the corporate bond market.

3.2. Data Processing Methodology

3.2.1. Obtaining a sample of US Green Corporate Bonds

Amongst the different databases available, Bloomberg is the only one that clearly identifies green bonds. As aforementioned, Bloomberg provides two types of information on green bonds: information on bond characteristics, and monthly quote-based prices for each bond since its month of issuance. As information of bond characteristics in more precise when referring to the FISD database, we only extract monthly prices from Bloomberg and information relative to the identification of each bond. We can then use this information to identify green bonds on the FISD database.

Bloomberg provides two types of identification information on bonds: a CUSIP number, a unique identification number assigned to US and Canada stock and bonds, and an ISIN number, which similarly identifies any specific securities issue throughout the world. Either can be used to obtain a list of green bonds in the FISD database. We identify 2015 green bond instruments on Bloomberg from January 2013 to June 2018. This number represents the total number of bonds, regardless of the types of issuers, geographies or the types of bonds issued. Using bond CUSIPs, we identify 253 US green bonds on FISD.

We then select only U.S. Corporate Debentures (bond type = CDEB) and U.S. Corporate Bank Notes (bond type = USBN), filtering out of our dataset bonds issued by government agencies, medium-term notes or bonds issued in a foreign currency following the literature (Bessembinder et al, 2018). This further reduces our sample to 49 US corporate bonds. Finally, we follow Jostova et al (2011) and exclude non-U.S. dollar denominated bonds, bonds with unusual coupons (e.g., step-up, increasing-rate, pay-in-kind, and split-coupons), mortgage backed or asset-backed bonds, convertible bonds, bonds with warrants, and bonds part of unit deals from our sample. This only reduces our sample by two additional bonds. Our final sample for green bonds is composed of 47 US green corporate bonds, out of the global sample of 2015 green bond instruments for the period 2013 to December 2018.

3.2.2. Obtaining a sample of US Climate Bonds

In order to identify US climate bonds, we use a list of climate bond issuers provided directly by the Climate Bond Initiative (CBI) research team. This list was used by CBI in their study on the climate bond market (Climate Bond Initiative, 2018). To identify climate bonds, CBI identified issuers that originated at least 75% of their revenues from green business lines in either clean energy, low-carbon buildings and transport, water and waste management and sustainable land use. Climate bonds were included if they were issued after the 1st of January 2005 and before the end of Q2 2018. Therefore, we use the list of issuers provided by the Climate Bond Initiative to identify climate bonds in the FISD database.

Using the same approach that was used on green bond data, we identify 332 US climate bond issuances in the FISD database between 2005 and December 2018 out of a total of 424 global climate bond issuers globally.

3.2.3. *Obtaining Enhanced TRACE data*

As aforementioned, there are two distinct disseminated TRACE datasets. The original dataset has a 6-month lag compared to the market and does not offer specific information regarding the volumes of transactions that are superior to $1 million (marked as 1MM+) and transactions that are superior to $5 million (marked as 5MM+). The enhanced TRACE dataset has an 18-month lag compared to the market but gives information on volumes that are superior to $1 million.

By using the list of CUSIP numbers we obtain from FISD, we extract 107,848 observations for our green bond dataset and 755,847 observations for our climate bond dataset from the enhanced TRACE database spanning from 01/01/2013 to 09/30/2019[11]. It is important to note that according to Dick-Nielsen (2014), the filters that need to be applied to on the enhanced dataset filter around 35% of observations. Enhanced TRACE data contains information relative to each transaction, providing identification data (CUSIP, TRACE Bond Symbol and Company Symbol), data relative to the time and date of each transaction, as well as data relative to volume and price of the transaction. Furthermore, various data on both the buyer and seller in each transaction is provided.

3.2.4. *Developing the Enhanced TRACE data filter*

The enhanced TRACE dataset contain a certain amount of reporting errors that need to be identified and deleted. These errors have been made by agents as they were reporting transactions and corrected at a later date through another report. In addition, some transactions are reported multiple times since dealers and agencies that trade for final customers have to report the same trade to TRACE. This can have implications in terms of computing both liquidity and price from the TRACE dataset, and therefore needs to be corrected.

In the literature, two different approaches are used to clean TRACE data. One follows the Dick-Nielsen (2009) procedure, and the other one refers to Bessembinder et al (2009). However, the enhanced TRACE dataset did not yet exist as these papers were being written, and Dick-Nielsen later wrote a paper in which he adapts his filter to enhanced TRACE data more specifically (Dick-Nielsen, 2014). I chose to refer to this most recent approach in this work. The cleaning procedure for reporting errors goes as follows:

1. Delete cancelled reports. These are reports that are later marked as cancelled by the reporting agent and need to be taken out of the dataset. In order to do this, the reporting agent files a report that consists in canceling the original report that needs to be canceled. This report (marked with an “X” in the Trading Status) and the corresponding original report (that have a similar Sequence Number and that are marked with a regular “T” in the Trading Status) both need to be taken out of the dataset.

[11] At this study is being performed, this sample is composed only of bonds issued before the 31st of December of 2018, as the author does not have access to FISD 2019 data.

2. Delete corrected reports. These are reports that contain a mistake that needs to be corrected. In order to do this, the reporting agent files two additional reports. One consists in indicating that the original report contains a mistake and needs to be corrected, and the other consists in providing the new information for the report containing the corrected data. The report that indicates a correction needs to be made (marked with a "C" in the Trading Status) and the corresponding original report (that have a similar Sequence Number and that are marked with a regular "T" in the Trading Status) are taken out of the dataset. The last report that contains the corrected information needs to be kept in the dataset (marked with an "R" in the Trading Status and has a similar sequence number).

3. Delete reversals. These are reports that have been marked as being cancelled at a much later date. Overall, the procedure is similar than for cancelled reports. Reversal reports (that are marked with an "R" in the "As Of" column and a "Y" in the "Trading Status" column) as well as their corresponding original reports (that have a corresponding Sequence Number and that are marked with a regular "T" in the Trading Status) need to be taken out of the dataset.

Once our error filter is applied, we also need to create an agency filter. Still following Dick-Nielsen (2014), we perform the following steps:

1. Delete agency transactions. Agency transactions occur when a broker acts on behalf of a customer and transacts with an executive broker. When this occurs, three reports are made in TRACE which correspond to the same transaction. In most cases, the broker acting on behalf of a client charges a commission, and therefore the price reported by the customer does not reflect the real market price of the bond. In these cases, we must take the original transaction reported by the customer (market with a "C" in Contra Party) out of the dataset.

2. Delete one of the reports of each inter-dealer pair. Once the original customer transaction has been taken out of the sample, we must choose to keep one of the remaining two reports on the same transaction. We follow Dick-Nielsen (2014) and keep information from the buyer (marked with a B in Buy/Sell).

3. Once we execute the agency filter, we are left with the correct number of transactions. We keep this first database in order to have the best quality data for research on volume and liquidity.

3.2.5. Verifying and applying the TRACE filter

The Trade Reporting Compliance Engine provides a TRACE fact book that gives the official number of transactions on TRACE for specific bonds. In his 2009 paper, Dick-Nielsen tests the performance of his error filter by matching the number of transactions he obtains after applying his filter to the number of transactions for the same bonds from the official TRACE fact book.

Applying a similar approach for Green Corporate Bonds presents a challenge as the TRACE Fact Book only gives information on the 50 most traded investment grade and high-yield bonds as well as the top 25 convertible bonds, none of which are in our sample.

We resolve this issue by extracting all TRACE data for the 50 most traded investment grade bonds of Q1 and Q2 2017. We then develop the filter using this dataset and verify the filter's accuracy using the TRACE Fact Book. For the 40 Investment Grade bonds that have been most issued for the first semester of 2017, our error rate is less than 0.1%. The results of our filter are shown in appendix 1.

Once our filter has been validated, we apply it to our green bond and climate bond datasets. We obtain a dataset of 76,204 observations for green bonds, 533,418 observations for climate bonds. Table 3 describes the resulting post-filter TRACE datasets that are obtained.

3.2.6. Transforming TRACE clean data into daily bond prices

Once we have successfully cleaned and processes TRACE data, we can obtain daily prices for each corporate bond from this data. The literature applies two distinct methods.

Following Jostova et al. (2013), the first method consists in computing daily prices as the trade-size weighted average of intraday prices, as findings in Bessembinder et al. (2009) show that a daily price based on trade-size weighted intraday prices is less noisy than the last price of the day. This method puts more weight on institutional trades as these have lower execution costs and should reflect the underlying price of the bond more accurately. However, choosing this price leads to it reflecting market conditions during the day rather that at the end of the day. This is referred by Bessembinder et la. (2009) as the "trade-weighted price, all trades" approach.

Another method consists in following Harris and Piwowar (2006) and eliminating all trades under $100,000, which tend to be non-institutional trades, and then relying on the last trade price in the remaining sample (the "last price, trade > 100k" approach). A problem with this approach is the loss of daily observations for bonds that only have small trades during the day; further, the trade selected may not reflect end-of-day market conditions. The problem of losing observations is somewhat mitigated if the firm has multiple bonds, and this approach will tend to reflect the price changes on the most liquid bonds of a particular firm.

Our approach for this step will vary depending on the type of analysis we wish to pursue. For corporate event studies, we will tend to drop trades below $100,000. When our focus will be on studying the cross section of bond returns, keeping all trades will be more relevant. This gives us two distinct databases. As the objective set in this paper is to obtain corporate bond returns for our sample of green bond and climate bonds, I apply the "trade-weighted price, all trades" approach commonly used in the literature to compute daily prices for the green bond and climate samples. I obtain 11,798 daily prices for the green bonds sample and 125,374 daily prices for the climate bond sample.

3.2.7. *Transforming TRACE clean data into monthly bond prices*

In order to obtain monthly prices from daily prices, I develop a methodology similar to that of Bai, Bali and Wen (2019)[12]. I first identify the bond price for the last trading day for each bond-month. If the last trading day is one of the last five trading days within month t, then this daily price is used as a monthly price. If that is not the case, I identify the bond price for the first trading day of month t+1. If this trading day is one of the first five trading days of month t+1, it is used as a price for month t. This allows for a more complete dataset of bond monthly prices in order to be able to compute more monthly returns using data from months t and t+1, where returns are either computed using (1) end of month t-1 to end of month t daily prices (2) start of month t to end of month t daily prices (3) start of month t to start of month t+1. Using this methodology, we compute monthly prices for our dataset. We first compute end-of-month prices for each month and complete this database with beginning-of-month t+1 prices where end-of-month prices were not available. We obtain 896 monthly prices for our green bond sample and 10,190 monthly prices for our climate bond sample.

3.2.8. *Extracting Bloomberg and Datastream Data*

Once we have computed monthly prices using trade-based data from TRACE, we extract monthly prices from Bloomberg and Datastream. For our green bond sample, we extract 1318 bond-month observations from Bloomberg and 1595 bond-month observations from Datastream. For our climate bond sample, we extract 7826 bond-month observations from Bloomberg and 15906 from bond-month observations from Datastream. In Table 2, we show commonalities and differences amongst the different datasets in terms of bond-month observations.

For our green bond sample, the correlation between TRACE and Datastream data is of 0.93, showing that the relationship between these two data sources is strong but not perfect, and that the quote-based and matrix-based approach that is applied by Datastream is not entirely precise. This correlation stands at 0.96 for the climate bond sample, which further adds to the strength of this relationship though it does not quite reach a perfect correlation.

Correlation with data originating from Bloomberg is lower, as it corresponds to 0.28 between TRACE and Bloomberg data for green bonds and 0.41 between Datastream and Bloomberg. These values are higher for the larger climate bond sample but are still lower for Bloomberg data which only has a correlation of 0.75 with TRACE data and 0.72 with Datastream data. This analysis of correlation between bond-month observations originating form our different datasets allows for a better understanding of the literature, which considers Datastream as a better source of information for corporate bond prices.

Going further into this analysis, we also understand that Datastream has much more data on bond-month prices available on both green bonds and climate bonds than the other two databases. For green

[12] In Bai, Bali and Wen (2019), the authors identify two scenarios to compute end-of-month returns for corporate bonds using daily data. To compute a return for month t, they either use data from the end of month t – 1 and the end of month t, or data from the beginning of month t and the end of month t. If a return can be computed through both methods, they apply the first method (end of month t-1 to end of month t).

bonds, the TRACE dataset only has 50 bond-month observations that are not available in Datastream and Bloomberg only has 43, while Datastream has 749 observations that are not available in TRACE and 320 that are not available in Bloomberg. For climate bonds, TRACE provides 203 bond-month observations that are not available in Datastream when Datastream has 5919 observations not available on TRACE and Bloomberg provides 65 observations not available on Datastream when Datastream has 8145. Even though TRACE provides the best quality data on corporate bond pricing, Datastream seems to have a very consequent lead regarding the quantity of available data on monthly corporate bond prices and maintains a strong correlation with TRACE trade-based data.

3.2.9. Merging databases

As we continue to follow the literature, we merge databases We keep all information regarding bond characteristics from FISD, and, when there are prices from the same bond and month available from multiple sources, we take the first available price in the following sequence, willingly setting precedence to trade-based data: TRACE, Datastream, Bloomberg. Our final dataset for monthly prices green bonds is composed of the 896 bond-month observations from the TRACE dataset, of 749 bond-month observations from the Datastream dataset and 20 observations from the Bloomberg dataset. Our final dataset for climate bonds is composed of 10,190 bond-month observations from the TRACE dataset, of 5,919 bond-month observations from the Datastream dataset and 65 bond-month observations from Bloomberg. We notice that even though Datastream has the most data in terms of corporate bond monthly prices, most of these observations are also available on TRACE, which makes the TRACE dataset our primary source of data, for both green bonds and climate bonds.

3.2.10. Computing monthly returns using month-end prices

We refer to the formula developed in Jostova et al. (2011) to compute monthly returns:

$$r_{i,t} = \frac{(P_{i,t} + AI_{i,t} + Coupon_{i,t}) - (P_{i,t-1} + AI_{i,t-1})}{P_{i,t-1} + AI_{i,t-1}}, \quad (1)$$

where ri,t is bond i’s month-t return, Pi,t is its price at month-end t, AIi,t is its accrued interest at month-end t, and Couponi,t is any coupon paid between month-ends t-1 and t.

Computing accrued interest requires the bond’s coupon size, coupon frequency, and day count convention. If the coupon frequency is missing, we assume it is semiannual. If the day count convention is missing, we assume it is 30/360.

Once again, information relative to the bond’s coupon size, frequency and day count convention can be obtained from FISD. We can use this to transform our datasets of monthly prices obtained from TRACE, Datastream and Bloomberg data into monthly returns. Our final dataset for green bond returns contains 1,636 observations and our final dataset for climate bond returns contains 16,062 observations.

Table 2

Data Treatment Process

	Green Bonds	Climate Bonds
FISD	253	332
Enhanced TRACE data (raw)	107,848	755,847
Filter 1 - Corrections and Cancellations	103,469	706,013
Filter 2 - Interdeal Transactions	76,204	533,418
Daily TRACE Prices	11,798	125,374
Monthly Datastream Prices	749	5,919
Monthly TRACE Prices	20	65
Total Monthly Prices	769	5,984
Total Monthly Returns	1,636	16,062

4. Resulting Datasets and Possible Applications

Advancing through the different phases of the data processing methodology results in obtaining a variety of different datasets and data types that can be used for different purposes. We explore these different datasets and the resulting insights they can provide in the following section. As an example, in their work on capital commitment and illiquidity in the corporate bond markets, Bessembinder et al. (2018) keep inter-dealer transactions

4.1.1. The TRACE Dataset without Reporting Errors

This dataset gives us a preview of every transaction made on TRACE, including inter-dealer transactions and agency transactions. This type of dataset is used in the literature by academics that wish to study dealer behavior and trading costs in the corporate bond market, as well as total trading volume. As an example, in their work on capital commitment and illiquidity on the corporate bond markets, Bessembinder et al.(2018) keep inter-dealer transactions in their sample in order to determine the size of total yearly trading volume for the US corporate bond market.

I apply the same approach for our sample of green bonds and climate bonds to have a better understanding of the trading volume on these markets since 2014.

4.1.2. The TRACE Dataset without Reporting Errors and without Agency Transactions

This dataset gives us more precise data on the amount of transactions performed on the secondary market. Interdealer transactions are a form of double counting and can have both an impact on certain liquidity measures that are developed using intraday data as well as on the computation of daily prices. In Bai, Bali and Wan (2011), the authors develop a liquidity measure that can be applied to trade-by-trade data and develop a methodology that relies on difference in prices between two trades to develop their measure. In this context, we can understand how having a trade be counted multiple times can distort the calculation of this measure, especially if we consider the fact that inter-dealer transactions represent around 30% of raw enhanced TRACE data.

In addition, when considered the different size-weighted approaches used by Bessembinder et al. (2009) to compute daily prices using intraday transaction data on TRACE, we can also understand how counting some intraday trade multiple times could have an important impact on daily prices. However, we compute daily prices for green bonds and climate bonds with and without treating interdealer transactions and find correlations that are superior to 0.99, indicating that the treatment of interdealer data has little impact on corporate bond daily pricing.

Table 3

Trading Volume

	Green Bonds			Climate Bonds		
Year	Trading Volume (Millions)	Corporate Bond Outstanding Amount (Millions	Trading Volume Relative to Amount Outstanding	Trading Volume (Millions)	Corporate Bond Outstanding Amount (Millions)	Trading Volume Relative to Amount Outstanding
2014	1,172	750	1.56	44,463	14,756	3.01
2015	3,709	5,050	0.73	47,998	13,924	3.45
2016	10,057	7,075	1.42	44,484	14,732	3.02
2017	14,737	10,400	1.42	49,625	16,359	3.03
2018	13,556	3,875	3.50	76,254	21,340	3.57

4.1.3. The TRACE Dataset without Reporting Errors and without Agency Transactions

This dataset gives us more precise data on the amount of transactions performed on the secondary market. Interdealer transactions are a form of double counting and can have both an impact on certain liquidity measures that are developed using intraday data as well as on the computation of daily prices. In Bai, Bali and Wan (2011), the authors develop a liquidity measure that can be applied to trade-by-trade data and develop a methodology that relies on difference in prices between two trades to develop their measure. In this context, we can understand how having a trade be counted multiple times can distort the calculation of this measure, especially if we consider the fact that inter-dealer transactions represent around 30% of raw enhanced TRACE data.

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4.1.4. *The TRACE Daily Prices Dataset*

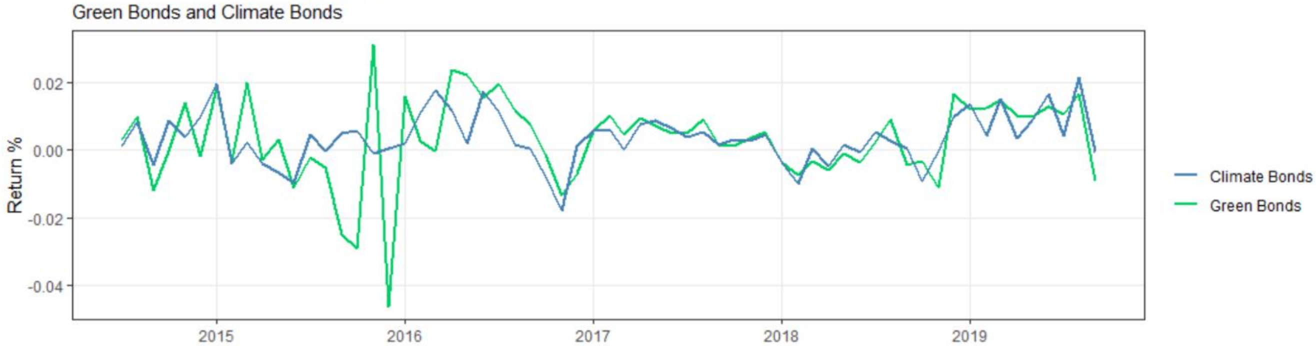
TRACE daily prices can prove useful for various research designs. As aforementioned, using the trade-weighted price for all trades is best for research focusing on the cross-section of corporate bond returns and using the trade-weighted price for all trades superior to $100 000 is best for research focusing on corporate event studies. Daily prices can also be used to compute daily returns that are used for computing liquidity measures such as the Amihud liquidity measure (Amihud, 2002) or the Pastor-Stambaugh liquidity measure (Pastor and Stambaugh, 2003), common liquidity measure to evaluate liquidity on corporate bond markets.

4.1.5. *The Monthly Price and Monthly Return Dataset*

Depending of the different methodologies that we choose to apply to our daily price dataset, we obtain a dataset of monthly prices which we convert to monthly returns for our green bond and climate bond datasets. The monthly return dataset is the most useful dataset to obtain, as it can not only be used to construct a variety of factors that are based on return trends, such as momentum and reversals, or volatility factors, such as market beta, return volatility or idiosyncratic volatility, but also most importantly to study the cross-section or times series of corporate bond returns.

Figure 1 shows the behavior of corporate bond returns for our sample of green bonds and climate bonds. This visualization helps us understand how the green bond market and the climate bond market have an overall similar behavior but shows a vast difference in terms of volatility in the last months before 2016. Though this graphical visualization is simply illustrative in the context of this paper, it provides interesting insight on the behavior of these two markets and is an interesting starting point for more specific research on this subject.

Figure 1 - Monthly Corporate Bond Returns
Green Bonds and Climate Bonds



5. Conclusion

As the market for climate-oriented products continues to develop, large amounts of rich data on the green corporate bond market and the climate corporate bond market is emerging. The methodology developed in this paper can be used as a guideline to develop intelligent algorithms that can clean and process the different data types as they are provided and apply various data processing approaches depending on the type, scope and aim of research. The resulting datasets could provide academics with interesting opportunities to better understand green corporate bonds and climate bonds and their impact on corporations, other financial products and markets as well as their various stakeholders.

As the secondary market for green corporate bonds develops and the TRACE dataset grows larger, transaction data provides an opportunity to better analyze green and climate-aligned bond products in ways that were previously impossible. Precise data from TRACE on intra-day transactions can lead to more precise measures of trading volumes and liquidity, but most important provided more precise data on daily bond prices, which can open the way for research work on event studies for green corporate bonds and climate-aligned bonds. Finally, transaction data, once transformed into monthly returns and combined with Datastream and Bloomberg data allows for optimal cross-section computation for green corporate bond prices and returns. As the literature that focuses on the cross-section of corporate bond returns is still to date quite new, such methodology will undoubtedly be needed by academics as research on traditional, green and climate-aligned corporate bonds develops.

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Appendix

Appendix 1
Post 2012 TRACE Filter - S1 2017

Issue Symbol	Cancellations & Corrections	Reversals	Pre-Filter Observations	Agency Transactions	Post-Filter Observations	Official Observations	Error Rate (%)
AAPL4001809	142	0	12280	3121	8875	8875	0.00
AAPL4336441	75	0	8098	2115	5832	5834	0.03
BAC3953004	101	0	8837	2396	6239	6239	0.00
BUD4091519	110	1	10739	1806	8712	8710	-0.02
BUD4327481	148	0	10334	2518	7520	7520	0.00
BUD4327594	90	0	7744	2069	5495	5495	0.00
CBL4434050	163	0	12457	4030	8101	8101	0.00
ESRX4379433	104	0	9101	2169	6724	6726	0.03
F4433681	114	0	9425	2630	6567	6567	0.00
GE4329014	692	1	25401	4772	19239	19245	0.03
GS.AEH	104	3	8712	2460	6041	6038	-0.05
GS.YW	85	0	8232	2238	5824	5824	0.00
GS3956630	111	0	8201	2014	5965	5965	0.00
GS4030214	95	0	8525	2170	6165	6166	0.02
HPQ.AI	131	0	9850	2836	6752	6750	-0.03
HPQ4431601	152	4	8191	2108	5774	5770	-0.07
JPM3999853	71	0	9456	2812	6502	6502	0.00
JPM4132024	338	11	9461	2345	6429	6419	-0.16
JPM4135537	125	0	9931	2518	7162	7163	0.01
JPM4135538	175	0	12096	2957	8789	8785	-0.05
JPM4135539	104	0	8598	2087	6303	6303	0.00
JPM4234071	111	2	10226	2228	7774	7772	-0.03
STX4152326	194	1	9117	2374	6354	6353	-0.02
STX4269186	147	0	9247	2713	6240	6238	-0.03
STX4337814	277	2	18235	5473	12206	12204	-0.02
STX4380193	156	0	10737	3220	7205	7204	-0.01
T3818484	116	0	14653	3806	10614	10615	0.01
T4237446	83	2	8736	2241	6327	6325	-0.03
T4237447	133	1	11004	3048	7689	7688	-0.01
T4237448	160	0	13692	3639	9733	9732	-0.01
T4332470	69	1	8812	2704	5969	5968	-0.02
T4332471	100	0	9676	2521	6955	6955	0.00
T4451560	123	0	9938	2506	7186	6934	-3.63
VZ4050437	199	0	13236	3478	9360	9360	0.00
VZ4176696	95	0	11363	2904	8269	8270	0.01
WFC.LG	58	0	8182	2127	5939	5940	0.02
WFC.NW	157	0	7371	1688	5369	5371	0.04
WFC3827183	75	0	8695	2387	6158	6158	0.00
WFC4130435	72	0	8777	2466	6167	6167	0.00
WFM4411360	194	0	13024	3039	9597	9597	0.00