RADBOUD UNIVERSITY
Nijmegen School of Management
Master Thesis

Green Bonds: Lower Returns or Higher Responsibility?

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Due to recent management failures with environmental impact, e.g. BP in the Caribbean see, and in light of recent climate changes, investors begin to turn their attention towards environmentally sustainable and socially responsible investments. One special financial instrument in this realm is the 'green bond', which investments are financing climate change solutions. In this paper, I investigate whether green bonds nowadays are interesting not only for ethical investors but also for the ordinary investor. Hence, using time-series and panel data analyses in a multi-index model framework, I compare the performance of green bond indices and their mainstream counterparts. While recent studies find some evidence that green bonds underperform, I find no evidence for a difference to mainstream counterparts in a time period between 2008-2016. Implications and alternative analysis methods are discussed.

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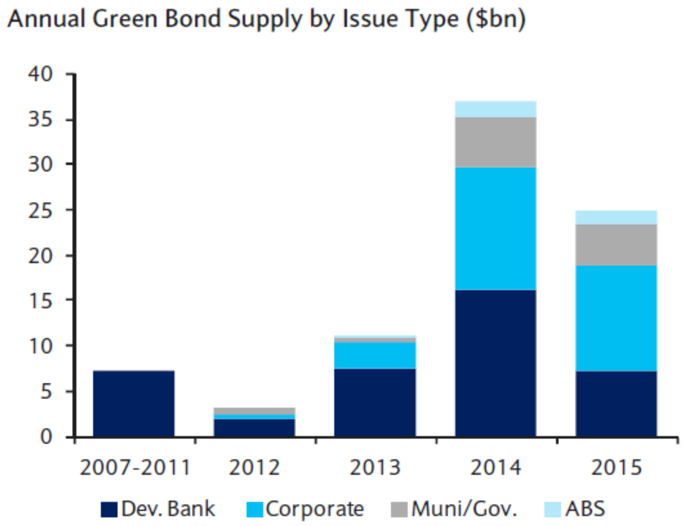
Abbreviations:

SRI	Socially Responsible Investments
CGBI USBIG	Citigroup US Broad Investment-Grade Bond Index
S&P GBI	Standard & Poor's Green Bond Index
S&P GBPI	Standard & Poor's Green Bond Project Index
Solactive GBI	Solactive Green Bond Index
S&P US ABI	Standard & Poor's US Aggregate Bond Index
Corp AAA TRI	BofA Merrill Lynch US Corporate AAA Total Return Index
Corp Master TRI	BofA Merrill Lynch US Corporate Master Total Return Index
PCA	Principal Component Analysis
OLS	Ordinary Least Squares
GLS	Generally Least Squares
RE	Random Effects Model
FE	Fixed Effects Model

1. Introduction

With increasing global warming mostly caused by human economic activities, the issue of environmental sustainability and corporate responsibility gains more and more attention (Stern, 2006). Countries have started implementing strategies to decrease the negative impact they have on the climate change, and strive for more ways to be environmentally friendlier (Mathews, Kidney, 2012; IMF, 2010). Companies reformed their investment plans (The Economist, 2014) and aim much more for environmentally sustainable projects, while increasing their corporate social responsibility level. In the recent years a substantial growth has been witnessed towards SRI (Socially Responsible Investments) and all its variations as a corporate strategy.

One of the most popular, and relative new, green investments nowadays are the green bonds (Mathews, Kidney, 2012), which can be found in the SRI framework. This recent innovation in the credit market aims to support environmentally friendly institutions, projects (Barclays, 2015), and beneficial investments for decreasing the exposure to environmental changes (Climate Brief, 2015). Green can be called projects that aim a mitigation of climate change including low-carbon and clean technology investments, like renewable energy and efficiency, or aim to adapt to climate change, including investing in climate-resilient growth projects (CICERO, 2015). Nevertheless, not only the exact definition of being green is very important in order to classify the investment (The Economist, 2014), but also companies have to incorporate the advantages and disadvantages of going green in their future financial strategies. Although still very small, the green bond market shows a rapid growth in the last years, in which investors see an opportunity for more responsible green funding (Mandel, 2015; Schroders, 2015; Kochetygova & Jauhari, 2014). This can be better seen in Figure 1, which also displays a higher participation in the green bond market of corporate institutions compared to previous years (Barclays, 2015). Due to the fact that this capital innovation is very young (approximately eight years), there is not enough empirical information available yet, that could embrace all sides of the green bond and its effects on investment. This explains the relevance of this paper, and the urgency for deeper analysis reasons the choice of this topic.



Note: Data through September 8, 2015.
Source: Climate Bonds Initiative, Barclays Research

Figure 1 Green Bond Market Growth

Despite of the lower yield, shown by the majority of empirical studies as in Figure 2, green bonds continue raising their attractiveness among investors compared to standard, *vanilla* bonds (Derwall & Koedijk, 2009; Schroders, 2015; Jo, Kim & Park, 2014; Ulrika Ross, 2014;). In the last few years more green bond indices have been developed, which gives researchers the opportunity to investigate the performance of those green investments. Some years have passed, enabling analyses to work with more information, thus, extracting more efficient empirical results. Since indices comparisons have been made excessively for SRI funds some years ago, but none for green bond markets in particular, this paper tries to fill this gap. Furthermore, the methodology chosen in this paper to investigate green bonds cannot be seen in the empirical literature yet. The research question here is how are green bond markets performing compared to the mainstream bond market, especially since their lastly observed rapid growth. The hypothesis here is whether green bonds have superior performance relative to their mainstream counterparts. Indices comparison using a multi-index performance evaluation model would show at the end if a shift could already be observed from the standard bond market towards the new green bond market. Such an event would also mean a shift in investor's preferences according to his/her environmental awareness. In such a way, an overview of the current bond situation can be established and future investment plans can be formed, based on the following analysis on green bonds.

Yields for select green bonds may be lower than their similar counterparts

Description	Green bond?	Coupon	Maturity	Price	Yield to maturity	Yield to worst	Next call date
State of CA GO 13063CNP1	**Yes**	3.00%	10/1/2028	103.69	2.68%	2.57%	10/1/2024
State of CA GO 13063CNR7	**Yes**	5.00%	10/1/2028	124.72	2.81%	2.15%	10/1/2024
State of CA GO 13063CEV8	No	5.00%	9/1/2028	122.41	2.98%	2.13%	9/1/2023
State of CA GO 13063CNQ9	**Yes**	3.75%	10/1/2037	106.35	3.35%	2.99%	10/1/2024
State of CA GO 13063CNS5	**Yes**	5.00%	10/1/2037	120.47	3.66%	2.59%	10/1/2024
State of CA GO 13063B3W0	No	5.00%	4/1/2037	118.35	3.77%	2.50%	4/1/2023
State of CA GO 13063BD90B	No	4.00%	9/1/2037	108.25	3.47%	2.78%	9/1/2022

Source: Schwab Bond Source, as of 2/3/2015.
Note: Prices based on 25 bonds which includes a $25 total commission. Yields may be different due to a number of different factors, such as maturity, coupon, call date and investor demand. **For illustrative purposes only.**

Figure 2 Green bond returns comparison

The remainder of this paper is organized as follows. In the next section, a literature overview available up until now on green bonds and their effect on the bond market will be presented. After choosing an appropriate model to investigate green bonds' performance, the sample data will be described presented with the empirical methodology used to test the built hypothesis. The statistical results will be provided in the section that follows. Lastly, the findings will be summarized and presented along with a small discussion about how such an analysis could otherwise be approached. The section is followed by a conclusion.

2. Literature Overview

To be beneficial, the green bond market has to be able to provide return for all market agents. Compared to standard bonds, green bonds are not different at all, except for the fact that their investments are directed to a certain green environment. There is an existing guideline called the Green Bond Principles giving key aspects of the green framework. However, these rules associated with the process of issuing green bonds is voluntary, which in turn is a reason of concern, since it could lead to falsely labeling ordinary bonds only due to visible shades of green (Barclays, 2015). Only a small number of bonds can be labeled as “green”, in particular SRI and ethical funds, so as expected, the green market is still very small (Schroders, 2015). According to the Financial Times reports on size and novelty of the green bond market, this financial instrument would be less easy to sell in panic. On the contrary, it also means that green bond issuers are more likely to be long-term traders holding them to maturity (Atkins, 2015; Schroders, 2015). Since there is a reverse relationship between interest rates and bond prices, a long-term debt instrument increases the default risk, inflation risk and market volatility, which will be further discussed later. This is the reason why green bonds come along with different types of incentives, in order to attract traders with a better risk/return tradeoff compared to their expectations from unsupported financial instruments. Three main types of incentives are tax privileges, guarantees (or insurance policies), and letters of comfort (Veys, 2010). Moreover, using green bonds instead of standard bonds the issuer can further diversify by accessing SRI in her/his investment decisions, which also include non-economic criteria such as social, environmental and governance, increasing the overall rating of the portfolio (Climate Brief, 2012). Most importantly, the urgent need to finance the change to a low-carbon economy makes green bonds such an attractive and essential investment.

Even though the first and by far the biggest issuers of green bonds are central banks and significant institutions (World Bank, EIB, EBRD, KfW Bank), these responsible instruments gain attractiveness also among another major market player- pension funds (Richardson, 2007). Although their investment level towards green bonds remains low due to lack of environmental policy support, or lack of appropriate investment vehicles and market liquidity, among many others, there are established frameworks how pension funds could enter the green bond market on a larger scale (Della Croce, Kaminker & Stewert, 2011).

The demand for green bonds grows, although there are mixed opinions on how green bonds perform compared to the standard ones. Some economists argue that the pricing and yields (despite the lower liquidity in the green bond market) of both types are the same, whereas others claim that green bonds deliver a lower yield (Schroders, 2015). This, in turn could be reasoned by the perceived additional costs spend on identifying the green bond, whereas standard bonds do not have this disadvantage. Nevertheless, empirical research shows that issuers are willing to pay that price for being socially more responsible. For example, Mohr, Webb & Harris (2001) reject the common assumption that consumer behavior is based only on the consumer's own benefit and self-interest. They show that for a large group of market agents it is of great importance to be responsible and environmentally friendly, and thus go beyond their purely corporate goals (Mohr, Webb & Harris 2001). This cost argument can be settled with the new established indices, representing only bonds labeled as green (some of which will be used for the analysis in this paper), with the help of which these additional identification costs are no longer necessary.

When it comes to benefits, Wu & Shen (2013) show a positive relationship between corporate social responsibility and financial performance, in terms of return on assets, return on equity and non/net interest income, while the main drivers for such an SRI are strategic choices, altruism, and green washing (Wu & Shen, 2013). On the contrary, they find a negative relation with non-performing loans, which means that issuers turn to SRI purely out of strategic motives. Evidence even show the average SRI bond fund has a similar performance as standard funds, whereas the average SRI balanced fund outperforms it by more than one percent yearly (Derwall & Koedijk, 2009). A slightly different results can also be found in the literature, showing with a specifically modified model also a neutral impact (McWilliams & Siegel, 2000). Overall, research show that SRI is gaining on importance in the international financial industry (Scholtens, 2009). Although a significant number of empirical analyses has been made associated with SRI performance, none can be found for the performance of green bonds.

When looking deeper into green bonds, historical returns show similar results with conventional bonds (Barclays, 2015). With an own modeled empirical analysis, the results of their paper does not show a significance difference in the performance of both debt securities. On the contrary, IIGCE (2011) show that European investors could not issue green bonds due to low early yields, which is the reason for the institution, not to take part in the green bond market yet. SRIs are often related to long-term investments, which in turn can lower firm's environmental costs, which would boost operating performance (Jo, Kim & Park. 2014). Furthermore, green bonds attract investors with additional positive signaling effects resulting from participating, and the presence of second opinion institutes decreases the transaction costs even further (Tiselius & Kronqvist, 2015). So, even very similar, green bonds tend to be more desirable than conventional bonds.

The aim of this paper is to present a sufficient empirical analysis on the performance of green bonds towards mainstream bonds, filling the literature gap existing on that topic. It aims to show that traders are becoming more responsible in their investments with the idea of decreasing the negative impact on the environment and long-term sustainability. All in all, issuers should look at this green investment as a new opportunity not only for gaining profits, but also to be socially responsible.

3. Data and Methodology

3.1. Multi-index model

This paper evaluates the performance of green bonds relative to the returns of their mainstream counterparts. As the literature review shows, many researchers make use of factors to explain bond returns in order to estimate the performance of investments and indices.

Elton et al (1995) include in their multifactor model a premium associated with unexpected inflation changes and economic growth. Further in 2001, Elton et al suggest that systemic risk factors related to expected return on equity are very important to explain bond returns. However, green bond indices have a special exemption clause for equity-like and inflation-linked bonds, which makes these two possible variables unsuitable for this analysis. Liquidity risk has been extensively analyzed and agreed upon to be an important factor for explaining bond returns (Lin, Wang & Wu, 2011; Pastor and Stambaugh, 2003). Bauer et al (2005) use a Carhart (1997) multifactor model to investigate ethical mutual fund performance, while focusing on size, book-to-market, and momentum effects. The Carhart (1997) model is consistent with the CAPM and momentum effects from Jegadeesh and Titman (1993), however, the results do not support the expectations of higher returns. Another approach by Belghitar et al (2014) compares four socially responsible FTSE4Good indices with other mainstream indices and with indices composed of standard firms matched to those in the FTSE4Good indices. Investing in terms of mean and variance, the results of the paper still do not suggest higher returns of SRIs. Another approach by Tiselius and Kronqvist (2015) compares the performance of green bonds with the mainstream using Sharpe ratios and t-values. The paper shows no statistical support for performance differences between the green and the other two included bond indices.

Elton et al (1993, 1995, 2001) develop relative pricing (APT) models to better explain bond returns. On the one hand, they use a multifactor model, including market returns, default risk, term risk, unexpected changes in inflation and unexpected changes in a measure of economic performance, as explaining factors, and another model including also taxes. On the other hand, they measure the performance of bonds using multi-index model (which will be also applied in this paper) and compare it with the results of a single-index model. Among many others, Sauer (1997) and Statman et al (2000, 2005) make use of multi-index models when it comes to comparing SRI. All in all, their papers show that a multi-index model is perfectly capable of capturing bond returns to analyze the performance of bonds listed in particular indices. The bond indices serve as performance attribution variables in the four-factor model, chosen here to test the performance of the two types of investment (Derwall & Koedijk, 2009; Ross, 1976; Elton et. al, 1995; Fama & French, 1993; Merton, 1973).

Multi-factor benchmark model:

$$R_{it} - R_{ft} = \alpha_i + \sum \beta_{ij}F_{jt} + \sum \gamma_{ik}G_{kt} + \varepsilon_{it,}$$

where R_{it} represents a bond portfolio of both conventional and green bonds, and Rf is the risk-free return. Jensen's alpha is consistent with the ICAPM (Merton, 1973) and the APT (Ross, 1976) and represents here not only the added value, but also the corporate responsibility element of the analysis, the "greenness" of the green bonds. In such a way, we can additionally see the social impact on the portfolio return. F_{jt} is the excess return on determinant j at t, while G_{kt} is the value of the risk premium associated with fundamental economic variable k at t.

In this particular analysis I will make use of a four-factor model, including four different explanatory variables, which could be sufficient to explain bond returns. Since there is no rule which indices are the best to use in a multi-index performance evaluation model (Elton et al. 1995), in order to create one, I make use of a set of benchmark indices by Citigroup (Derwall & Koedijk, 2009). The first one called CGBI US Broad Investment-Grade Bond Index (USBIG) is value-weighted index with various long-term bonds, which excess return represents a measurement how the economic conditions are expected to develop. According to Derwall & Koedijk (2009), the chosen index to account for the impact of high-yield instruments is Meryll Lynch High Yield Index, which would mirror the default risk in investments. The USBIG GNMA Mortgage Index has been included, which excess return would capture the options element in bond returns while using such an index to measure the return on mortgages relative to the mainstream. Lastly, the CGBI 20-year+ Treasury Index and the 1-3-year Treasury Index are taken into account to capture effects of maturity differences on bond returns.

The model looks as follows:

$$R_{pt} - R_{ft} = \alpha_i + \beta_{0i}(USBIG_{mt} - R_{ft}) + \beta_{1i}\ Default_t + \beta_{2i}\ Option_t + \beta_{3i}\ Term_t + \varepsilon_{it}$$

where the first variable captures broad market sensitivity, which is calculated as the return on the CGBI US Broad Investment-Grade Bond Index in excess of risk free rate proxy. The second variable, *Default*, represents the return spread between the Meryll Lynch High Yield Index and the USBIG Treasury Index, capturing the default risk compensation in portfolio returns. The third variable, *Option*, shows the difference in return between the USBIG GNMA Mortgage Index and the USBIG Treasury Index, capturing option features in specific bonds. Lastly, the fourth variable, *Term*, represents the return difference between CGBI 20-year+ Treasury Index of long-term bonds and of short-term ones extracted from the 1-3 year Treasury Index (Fama & French 1993). It captures differences in maturity range and risk premia among securities. When it comes to the constant term, I associate superior performance with positive Jensen measures. The null hypothesis is that green bonds do not outperform vanilla bonds. All collected data has been retrieved from Datastream, converted into daily values, and analyzed with the statistical software STATA. Partial deletion of values has also been conducted for specific dates, like weekends and national holidays, when no trading takes place, so all variables have the same time horizon. Although very rarely, a value imputation has been implemented for missing values.

There are different ways how to approach this multi-index model, however, only two of them will be further analyzed in this paper. The first one is a time-series analysis consistent with Fisher, Jensen and Scholes (1972), which will give insights about effects on green bond returns compared to conventional ones over a specific period of time, in this case from November, 2008 until April, 2016. The second approach is a panel data analysis, which is taken into account to inspect the existence and magnitude of causality of the chosen factors upon the indices at the given time between 2008 and 2016. Two more ways will be presented as an extension later in the paper as alternative methods that could be implied here, PCA and Fama-MacBeth approach, which can be found in the discussion section.

3.2. Time-series analysis

Due to the fact that only one comparison of the factor- indices with one green bond index will perhaps not be sufficient enough to make certain conclusions about green bond index performance, I take three green bond indices into account in this analysis. The first one, S&P Green Bond Index (GBI), exists since November 2008 and embraces the global green bond market. The second one, S&P Green Bond Project Index (GBPI), exists since 2007 and complements the S&P GBI while tracking not only green bonds but also green projects. Although very similar, the S&P GBPI has shown slightly higher historical returns throughout the years compared to the S&P GBI. The third one, the Solactive Green Bond Index (GBI), is a ruled-based, market value weighted index tracking green bonds and exists since 2014. The reason for converting the collected data into daily values is the length of the sample. Since the indices are still very young compared to their counterparts, a monthly estimation would substantially decrease the sample volume and perhaps fracture the statistical analysis. The returns of all green bond indices have been extracted from their respective online sources, since Datastream does not provide any information about these bonds in particular. All green bond indices are denominated in USD and represent the core of the three dependent variables in this multi-index model.

The three time-series regressions are described as follows:

1. $\text{S\&P GBI}_t - R_{ft} = \alpha_i + \beta_{0i}(\text{USBIG}_{mt} - R_{ft}) + \beta_{1i}\,\text{Default}_t + \beta_{2i}\,\text{Option}_t + \beta_{3i}\,\text{Term}_t + \varepsilon_{it}$
2. $\text{S\&P GBPI}_t - R_{ft} = \alpha_i + \beta_{0i}(\text{USBIG}_{mt} - R_{ft}) + \beta_{1i}\,\text{Default}_t + \beta_{2i}\,\text{Option}_t + \beta_{3i}\,\text{Term}_t + \varepsilon_{it}$
3. $\text{Solactive GBI}_t - R_{ft} = \alpha_i + \beta_{0i}(\text{USBIG}_{mt} - R_{ft}) + \beta_{1i}\,\text{Default}_t + \beta_{2i}\,\text{Option}_t + \beta_{3i}\,\text{Term}_t + \varepsilon_{it}$

When it comes to time-series analysis, there are several things that need to be tested to make sure that the end results are not biased, such as serial correlation (autocorrelation), stationarity of the variables and cointegration of the error terms. Serial correlation affects the regression estimates and leads to unreliable hypothesis testing (Studenmund, 2014). Test for stationarity is also important, since non-stationary data cannot be modeled and could lead to spurious results. Similarly, cointegration of the variables causes biased regression outcomes, since variables appear to be somehow dependent. The first section of the part with results will present the outcomes of these tests, while the regression tables can be found in the Appendix.

3.3. Panel data analysis

Another alternative to make use of a multifactor model and analyze the performance of indices next to a time-series analysis, is a panel data analysis, also known as cross-sectional time-series analysis. The data has observations on the same returns in several different time periods and multiple entities (indices), each being measured repeatedly at several points in time (Park, 2011). This type of analysis gives researchers the opportunity to also look for causal effect and pattern of the variables and not only controlling for time-invariant ones, which cannot be done with a simple time-series analysis. The advantage of panel data is that it increases the degrees of freedom and the efficiency of the coefficients estimates, so the outcomes would be more reliable.

Here, I make use of a narrow in width, long panel, strongly balanced data. Differently compared to the previous model, the dependent variable here represents both green and conventional bond excess returns together, including the following five indices' excess returns (entities): 1) S&P GBI; 2) S&P GBPI; 3) S&P US ABI; 4) Corp AAA TRI, and 5) Corp Master TRI. The formal two are green bond indices, which can be also found in the previous analysis. The latter three are mainstream benchmark total return indices, which daily values are extracted from the official page of the Federal Reserve. The S&P US ABI and the Corp Master TRI are suitable benchmark indices for comparison, capitalization- and value-weighted indices, representing the US bond market. The choice to include the Corp AAA TRI lies in the idiosyncratic value of green bonds. Since they are (mostly) given the highest rating, it would be interesting to see a comparison with a bond index containing also high rated debt instruments. The explanatory variables remain the same as in the initial multifactor model, which apply to daily excess returns since November 2008. For this reason and in order to balance the data, the Solactive GBI has not been included in this analysis due to its short lifetime. This gives the opportunity to extend the panel data analysis and run it also with monthly values, which method would remove to some extend the noise captured usually in daily values. Both outcomes will be presented in the section with results.

The regression model looks as follows:

$$(R_{pt} - R_{ft})_{green\ \&\ normal} = D_{it} + \alpha_i + \beta_{0i}(USBIG_{mt} - R_{ft}) + \beta_{1i}\ Default_t + \beta_{2i}\ Option_t + \beta_{3i}\ Term_t + \varepsilon_{it}$$

Similar approach can be found also in Lin, Wang & Wu (2011), consistent with Fama & French (1993) and their multifactor model. They also make use of the explanatory variables *Default* and *Term*, as in this paper, but also add *Liquidity*, which concept will be later further discussed.

The most essential part here and the difference from the previous time-series model is the included dummy independent variable, which identifies the included index in the model as a green bond index or not. It would help to inspect the differences in the intercept term and/or variable coefficients, and it is a time-invariant variable, indicating the use of a random effects model (RE). With the help of RE not only time-invariant variables can be estimated but also "standard errors of estimates tend to be smaller" (Williams, 2015). Similarly as before, a positive value of Jensen's alpha is associated with overperformance, representing here the average difference in excess returns from investing in green bonds against vanilla bonds. The null hypothesis constitutes that the green investments do not outperform the mainstream.

The next section shows the results of both multifactor analyses, and thus divided in two. The first part represents the outcomes of the three time-series regressions. The second provides the results of both panel data analyses, one with daily and one with monthly values.

4. Results

This part of the thesis with its results will be split in two, corresponding to the two models implemented in the paper. The first part consists of the results associated with the multi-index model analyzing time-series, while the second part describes the results of the second dummy-model analyzing panel data.

4.1. Time-series results

Table 1 shows the results of all three time-series regressions tested against three green bond indices as dependent variables, namely the S&P GBI, S&P GBPI and Solactive GBI.

Several tests have been ran for serial correlation, where different observations of the error term are correlated with each other (Stundenmund, 2014). This causes biased results and it mostly occurs in time-series data sets. After testing with a correlogram, a Cochrane-Orcutt regression, Durbin Watson's Test and its alternative, Breush-Godfrey Test, and even testing for white noise, it can be concluded that no autocorrelation exists (Appendix). The Durbin-Watson d-test examines the residuals for first order autocorrelation, however, it is sometimes inconclusive. Another way is the Cochrane-Orcutt method, which is a two-step "iterative technique" (Cochrane and Orcutt, 1949). The Breush-Godfrey test, also known as the Lagrange Multiplier Serial Correlation test, is a perfect substitute of the d-test, and can also be applied to test for heteroscedasticity and white noise. Working with time-series implies testing not only for correlation, but also for stationarity and cointegration of the variables/ and error terms. Dickey Fuller test has been conducted to test for stationarity, with trends and drifts. Nonstationarity causes issues, because its series has one or more basic properties (mean, variance) changing over time (Stundenmund, 2014). All results are significant, showing no unit root. It has been also found no unit root in the error terms.

Although overperformance is in place in the first two regressions, R^2 shows that the model does not explain the returns of the indices, since its predictive power is very low, only around 10% for the first and 1% for the second. Even if the adjusted R^2 is a better statistical measure because it takes the size of the sample into account, it does not vary substantially. The significance of the four explanatory variables in the model when analyzing their t-statistics varies across regressions.

Table 1: Results Time Series Analysis

The sample period is from 2008 through 2016. The multi-index model is $R_{pt} - R_{ft} = \alpha_i + \beta_{0i}(USBIG_{mt} - R_{ft}) + \beta_{1i}\, Default_t + \beta_{2i}\, Option_t + \beta_{3i}\, Term_t + \varepsilon_{it}$, where Rp represents the return of three green bond indices, the S&P GBI, S&P GBPI and Solactive GBI, shown in the three regressions, respectively.

Significance levels: *** indicates 1%, **indicates 5%, *indicates 10%

Variable	Regression 1	Regression 2	Regression 3
USBIGRf	0.977***	0.00576	0.155
	(0.0891)	(0.0355)	(0.155)
Default	-0.213**	-0.0846*	-0.694***
	(0.0932)	(0.0448)	(0.155)
Option	0.192**	-0.0194	0.583***
	(0.0871)	(0.0393)	(0.153)
Term	-0.378***	-0.0200	0.00904
	(0.0274)	(0.0125)	(0.0499)
Constant	0.000245	0.000230	-0.000257
	(0.000686)	(0.000404)	(0.000245)
Observations	1,907	2,400	545
R-squared	0.097	0.016	0.150

While all of them are significant in the first regression, where the dependent variable is the S&P GBI, they are not in the second, where the dependent variable is the S&P GBPI. Lastly, the regression with a dependent variable Solactive GBI shows t-scores of only two independent variables, *Default* and *Option*, to be significant, while every other value, including those of the control variables, are all insignificant.

4.2. Panel data results

All regression tables of the panel data analysis can be found in Appendix D. The description starts with the outcomes of the estimates with daily values and continues with those with monthly excess returns. Table 2 shows the results of the model with both daily and monthly values.

Table 2: Results Panel Data Analysis

The sample period is from 2008 through 2016. The multi-index model with a dummy variable is $(R_{pt} - R_{ft})_{green \,\&\, normal} = D_{it} + \alpha_i + \beta_{0i}(USBIG_{mt} - R_{ft}) + \beta_{1i}\, Default_t + \beta_{2i}\, Option_t + \beta_{3i}\, Term_t + \varepsilon_{it}$, where the dependent variable includes the excess returns of five bond indices: two green and three mainstream bonds. The regression shows the outcomes of both daily and monthly values.

Significance levels: *** indicates 1%, **indicates 5%, *indicates 10%

Variables	Model Daily	Model Monthly
Dummy	1.98e-05	-1.52e-06
	(0.000114)	(0.000253)
USBIG-Rf	0.481***	0.384*
	(0.154)	(0.197)
Default	-0.156***	-0.438
	(0.0237)	(0.554)
Option	0.0849**	0.0836
	(0.0354)	(0.313)
Term	-0.00138	-0.224
	(0.101)	(0.197)
Constant	7.08e-05	5.17e-05
	(4.76e-05)	(7.45e-05)
Observations	9,525	450
Number of index	5	5

When working with panel data, a choice needs to be made concerning the use of a Random or Fixed effects model. Since I do not assume fixed effects but rather investigate individual effects of time-invariant variables in the model, the RE model is the accurate one to be taken into account. Furthermore, the RE is preferable before the pooled OLS due to the fact that the latter estimator would not deliver efficient results from this particular panel data analysis. Its usual standard errors would not be correct and all the tests based on them would be biased (Schmidheiny, 2015). This can be seen with the help of the Breusch and Pagan Lagrangian multiplier test for random effects, showing an insignificant score. This implies rejecting the null-hypothesis and continue the analysis with the RE. To achieve correct standard errors I make use of the so-called cluster-robust covariance estimator, treating each individual as a cluster.

The results from the random-effect GLS regression show a significant chi^2 score, indicating that the model is acceptable. However, its predictive power is very small, around 17%. Looking at the two-tail p-values of the variables, I can conclude that all independent variables, accept for *Term*, are significant at the 95% confidence interval with economically plausible signs, however the dummy and constant term are not. These results cannot give us any further information about how the factors are affecting the performance of indices, since the outcomes are untrustworthy. In order to look for discrepancies in the sample, a Wooldridge test has been run to search for presence of serial correlation in panel data. This is an important test due to the fact that the presence of serial correlation in panel data models biases the standard errors and, thus, makes the results less reliable (Drukker, 2013). The significant score of Wooldridge test implies not rejecting the null hypothesis, which shows no autocorrelation in the model. Another potential issue in panel data needs to be tested in the analysis, namely heteroscedasticity, which causes the variance formulas and standard errors to be biased, leading again to untrustworthy results. This is the reason for running two robustness checks, with and without clusters. It is worth mentioning that both are showing a missing Wald-score. This could be reasoned with the fact that the sample data's time period is too short, only around 8 years. Here can again be seen that the values of the constant and dummy variables are highly insignificant.

As mentioned before, although the idea behind the daily returns was to increase the sample volume, it has the disadvantage of the presence of (market) noise in the daily values. This is the reason why further investigation follows, but now the excess returns are converted into monthly values using a geometric average calculation.

The regression tables of the panel data analysis with monthly excess returns can be found in Appendix D following the first regression analysis with the daily values. Implementing the same steps as before, the Breusch-Pagan Lagrangian Multiplier test supports the choice of using RE in the current analysis. Looking at the regression table, the scores show that the model is highly significant and acceptable, with almost 46% predictive power. This is substantially higher than the one estimated with daily returns, indicating that monthly values should be preferable in this case. Nevertheless, most of the p-values of the variables are highly insignificant, including the dummy and the constant term. Only the independent variables *USBIG-Rf, Default* and *Term* seem to be acceptable, however, these outcomes are not sufficient enough to make any conclusions about green bond performance. Lastly, two robustness checks have been conducted to control for heteroscedasticity, displaying all variables as insignificant, besides *USBIG-Rf* and *Default*. The missing probability score in the tests shows a misspecification in the model, which could be again related to the small sample volume.

5. Discussion

5.1. Results

The outcomes of the time-series regression analysis show no evidence on how green bond indices are performing towards the mainstream. Although other studies have used the same method, and/or similar explanatory variables, have shown significance of the results and high R^2 (Derwall & Koedijk, 2009; Elton et. al, 1993, 1995), these studies have focused on mutual funds performance and/or SRI funds. However, there is not much empirical evidence about green bonds, in particular, so a comparison with other authors is not available.

The results of the second regression are to be expected after running the first one, since the two dependent variables taken into account, the excess returns of the S&P GBI and the S&P GBPI, are very similar. Both indices capture the whole green bond market, whilst the S&P GBPI includes as well bonds for green projects, which are not theoretically green bonds. This time the t-statistics of all independent variables are insignificant, including the control variables. This implies that this particular selection of variables is not satisfying for explaining green bond returns.

Similarly, the insignificant values of the factors in the third regression are not surprising, since the dependent variable inspects returns on long-term bonds, while the Solactive GBI includes bonds starting in 2014. The lifetime of the index is problematic in general, because short samples are not sufficient enough when it comes to analyzing returns on investments making empirical research very difficult. Furthermore, the Solactive GBI embraces only these green bonds, which proceeds are spent for climate mitigation or adaptation efforts. Although the bond portfolio of the index is quite voluminous, it does not include all bonds that could be found on the green bond market.

Looking now at the panel data analysis, the results show a significant increase in the predictive power of the model when monthly returns are taken under consideration, instead of daily. This implies that market noise indeed biases the empirical outcomes and monthly estimations should be rather analyzed for future research. However, the insignificance of the dummy, constant term and explanatory variables does not allow making any conclusions about green bond returns and index performance. The paper by Lin, Wang & Wu (2011), using a similar empirical approach, does not show outperformance, although their methods are shown to be significant. However, their paper concentrates on global bond mutual funds using monthly estimates. Here, the length of the sample, in particular the short lifetime of the indices, makes it still very difficult to extract more information on green performance. More time is needed in order to use this kind of analysis, when researchers will be able to situate more available statistical data and will have more detailed information on green bond performance.

It will be interesting to see in future analyses, if these green investments outperform their counterparts when the green bond market increases, becomes more liquid and transparent. In such a framework, both markets would be more compatible and perhaps perfect substitutes for investment decisions.

According to recent climate change events, SRI gain on popularity. The lack of a faster solution for these environmental issues in the future could lead to a necessity for market agents to invest in SRI, green bonds among others. This would not only increase the volume of that particular bond market even more, but it would substantially boost market volatility and credit risk. The reason behind it is that green bonds tend to be long-term investments held until maturity, as mentioned before (Atkins, 2015). The higher the duration of the security, the greater is also the inflation risk for issuers.

Nevertheless, there are other alternative ways to test green bond returns and observe their performance. The next section will present two more methods, which are broadly used in the empirical literature, the PCA and Fama-MacBeth Approach.

5.2. Principal Component Analysis

Since there is no rule for choosing specific factors in a multifactor model to explain bond returns, there is also another alternative to exploit the performance of green bonds, namely when the factors are not observable. Such method has been used extensively in the academic literature, called Principal Component Analysis, which is a useful statistical tool when also other latent factors could impact the return of bonds. In order to determine the factors, researchers make use of a variance-covariance matrix (Fabozzi et al, 2012). When the model takes the form of

$$\acute{Y}_t=\beta f_t+\dot{\varepsilon}_t\,,$$

where f_t represents the latent factors in the model, two steps are conducted: “First, we subtract the factor f_t from its mean so that the alphas are the expected returns of the assets. Second, we subtract the asset returns from their means (de-meaning)”[1]. The equation becomes then $\acute{Y}_t=\check{R}_t-\alpha$. According to the estimated factors, the factor loadings can be computed with the help of a standard OLS regression of the bond returns on the factors. When it comes to determining the factors, there are different ways provided in the literature depending on the sample volume. In this case, it would be sufficient to estimate the eigenvalues and eigenvectors and taking into account the largest three, since three factors is the standard amount to explain bond returns. These are called level, steepness, and curvature factors.

Aussenegg et al, 2015, for example, present a two-factor Fama and French model using 23 corporate bond indices and focusing on the level and slope components of term and default factors and liquidity risk. To better understand these variables and “to apply a parsimonious and orthogonal representation of the risk factors”, the authors make use of PCA. Perignon et al (2007) also show how PCA captures both local and common influences on bond returns. The two big advantages of latent factor models are firstly their ability to decrease the dimensionality of models so an estimation can be made, and secondly, they point out the possible causes that drive data (Fabozzi et al, 2012).

Litterman and Scheinkman (1991) are one of the first authors applying PCA and realizing these three factors. The empirical results of their three factor model on Treasury bonds indicate that the factors explain most of the returns on these investments. They conclude with the statement that this analysis is capable of analyzing any asset or liability stream for which a covariance-variance matrix with bond returns is available.

All in all, PCA is a useful statistical tool to search for other factors influencing bond returns, when the chosen factors in the model do not explain them efficiently enough.

5.3. Fama-MacBeth Approach

The Fama-MacBeth cross-sectional analysis is another practical way to test a multifactor model in order to explain bond returns. Aiming its search at the premia's factor exposure, the Fama-

1 . Fabozzi et al, 2012

MacBeth approach is expressed by a two step regression. First, in order to estimate each return exposure, a time-series regression is being ran for every premium against all factors (four factors-independent variables- in this particular case). Second, to declare time series of all premia coefficients γ and for all four factors, a cross-sectional regression is being ran against all factor exposures β. The idea behind the Fama-MacBeth approach is to estimate the average value of these coefficients γ for all four factors after the second step.

The equation looks as follows:

$$E(R_i) = \gamma_0 + \gamma_1\beta_{i;F1} + \gamma_2\beta_{i;F2} + \dots + \gamma_m\beta_{i;Fm} + \acute{\varepsilon}_i \ ;$$

where $E(R_i)$ is the average return over time for every bond return. According to the method, the coefficients γ remain unchanged in both regressions, whilst the standard errors and t-statistics are expected to change (Fama and Macbeth, 1973).

Lin, Wang & Wu, 2011 are some of the many authors applying the Fama-MacBeth cross-sectional approach to test individual bonds. With the help of the two-step regression and tests to fix the errors in variables, they compute coefficients representing the effect of the factors on expected bond returns, focusing on liquidity. Their results show a strong relation between expected corporate bond returns and liquidity risk, suggesting that it is an important factor in explaining bond returns. As an extension of the model in this paper, not only the Fama-MacBeth methodology could be taken into consideration, but also the factor *liquidity* could also be added to the model equation.

When it comes to stock returns, Chen, Roll & Ross (1986) and Fama & French (1993) also apply the Fama-MacBeth approach in their analyses. Similarly as here, they investigate returns including the factors *Default* and *Term*. However, their regressions do not deliver the same results. While these two factors show a large explanatory power in Chen et.al (1986)'s paper, the results in Fama & French (1993)'s paper are rather weak.

Derwall & Koedijk (2009) examine equity mutual fund and SRI fixed-income fund performance, reaching out for the Fama-MacBeth methodology. This robustness check, relating fund alphas to fund-specific attributes in a panel analysis, is a practical way to stabilize the results from the initial factor analysis. The authors use expense ratio, turnover, logarithm of total net assets for fund size, and maximum load fees as explanatory variables. In the similar way as here, Derwall & Koedijk (2009) use a dummy variable identifying a socially responsible fund (here green bonds) to explain the cross-sectional variation in fund alphas ($\alpha_{it} = a_{ot} + \gamma_{1it}\ LogTNA_{it-1} + \gamma_{2it}\ EXPENSES_{it} + \gamma_{3it}\ TURNOVER_{it} + \gamma_{4it}\ SRI + \varepsilon_{it}$).

All in all, the Fama-MacBeth approach seems to be a recommendable robustness check that should be included as an alternative for proving the correctness of the previously established results.

6. Conclusion

This paper concentrates on a relative new capital investment, namely the green bond. This financial product aims to support environmentally friendly and climate stimulating projects. Along recent climate change events, green investments gain more and more popularity among market participants with the idea of being socially more responsible. Although it was more difficult and expensive some years ago to track these green bonds, nowadays exist several green bond indices representing the global green market. This, in turn, gives researchers the opportunity to explore these green investments in more depth and efficiency.

Here, I focus on the performance of green bond indices compared to the mainstream bonds using a multi-index model (Derwall & Koedijk, 2009; Ross, 1976; Elton et. al, 1995; Fama & French, 1993; Merton, 1973). I compare the excess returns of several indices with the help of four different explanatory factors, consistent with Fama & French (1993). However, since green bonds entered very recently the financial market, there is no literature to be found on performance of green bonds yet. This paper aims to fill this gap. Although still very small and illiquid, the green bond market grows rapidly, especially in the recent few years. This is the reason to ask the question if green bonds would or already are over-performing their mainstream counterparts.

In order to test the multifactor model and estimate the performance of green bond indices, I make use of several analyses. Firstly, I present a time-series analysis with three regressions, corresponding to three different green bond indices and their excess returns. Secondly, I implement a panel data analysis including a dummy variable for green bond indices in the model in two ways- once with daily excess returns, and once with monthly values.

The results of this paper show that the applied model is significant, however, for all regressions in both analyses, time-series and panel data, the estimated values are insignificant. Although the coefficients of the constant terms in most regressions show a slightly overperformance of the green investments compared to the vanilla bonds, their scores are everywhere highly insignificant. The results of the panel data analysis with monthly values are slightly better than those with daily excess returns, however, the scores of the variables of inspection are all insignificant. This makes it not possible to extract any essential information about the performance of green bonds.

There are different reasons for the noncompliance of the analyses, such as the lifetime of the sample data, the daily format of the observations, which returns are noise-consisting, or even the inability of the model to capture green bond returns, since the market is still too small/illiquid. With time, this analysis will be able to deliver more conclusive estimations, nevertheless, other models should also be taken under consideration. I present two more methods that can be further implemented to extend this analysis: the Principal Component Analysis and the Fama-MacBeth cross-sectional approach.

To conclude, the multifactor model used in this analysis helps to inspect bond index returns, however, with time-series and panel data analyses it does not provide any evidence about green bond performance. Nevertheless, it is necessary for all investors to turn their attention to these green financial products, if they would like to be environmentally sustainable and socially responsible. The greener profit-seekers become on a personal level, the higher payoff will they receive on a global one.

7. References

Atkins, R. 2015. Are green bonds a fair weather phenomenon? Financial Times

Aussenegg, W., Goetz, L., Jelic, R. 2015. Common Factors in the Performance of European Corporate Bonds- Evidence before and after the Financial Crisis. European Financial Management, Vol.21, No.2, 265-308

Barclays 2015. The Cost of being Green. US Credit Focus.

Bauer, R., Koedijk, K., Otten, R. 2005. International evidence on ethical mutual fund performance and investment style. Journal of Banking &Finance 29. 1751-1767

Belghitar, Y., Clark, E. & Deshmukh, N. 2014. Does it pay to be ethical? Evidence from the FTSE4Good. Journal of Banking and Finance 47. 54-62

Carhart, M. Mark. 1997. On persistence in Mutual Fund Performance. Journal of Finance, Vol. 52, Issue 1, 57-82

CICERO 2015. “Second Opinion” on World Bank's Green Bond Framework

Climate Brief No14. 2012. Financing the transition to a green economy: their word is their (green) bond?

Cochrane, D., Orcutt, G.H., 1949. Application of Least Squares Regression to Relationships Containing Autocorrelated Error Terms. Journal of the American Statistical Association, pp. 32-61.

Della Croce, R., Kaminker, C., Stewert, F. 2011. The Role of Pension Funds in Financing Green Growth Initiatives. OECD Publishing, Paris.

Derwall, J., Koedijk, K. 2009. Socially Responsible Fixed-Income Funds. Journal of Business Finance & Accounting, 36(1) & (2), 210-229.

Drukker, D. M. 2003. Testing for serial correlation in linear panel-data models. Stata Journal 3: 168-177

EDHEC-Risk Institute Publication. 2010. Adoption of Green Investing by Institutional Investors- A European Survey

Elton, E.J., M.J. Gruber and C.R. Blake 1993. The performance of Bond Mutual Funds. The Journal of Business, Vol.66, Issue 3. 371-403

Elton, E.J., M.J. Gruber and C.R. Blake 1995. ‘Fundamental Economic Variables, Expected Returns, and Bond Fund Performance,’ *Journal of Finance*, Vol. 50, pp. 1229–56.

Elton, E.J., M.J. Gruber, Agrawal, D. and Mann, C. 2001. Explaining the rate spread on corporate bonds. Journal of Finance 56. 247-277

Fabozzi, F., Edwin, H. Neave and Zhou, G. 2012. Financial Economics. John Wiley & Sons, Inc., Chapter 15, pp.326

Fama, E.F. and K.R. French, 1993. 'Common Risk Factors in the Returns on Stocks and Bonds,' *Journal of Financial Economics*, Vol. 33, pp. 3–56.

Fama, E.F. and Macbeth, J.D. 1973 Risk, Return, and Equilibrium: Empirical tests. *The Journal of Political Economy*, Vol. 81, No. 3. pp. 607-636.

Fischer, Jensen and Scholes, 1971. The CAPM- Some empirical tests. *Studies in the Theory of Capital Markets*, Praeger. New York

Fleming M.J. 2003. "Measuring treasury market liquidity", *Federal Reserve Bank of New York Economic Policy Review*, Vol. 9, p.83-108.

Gabriel, C., Lau, C. 2014. On the distribution of European government bond returns: Empirical evidence from the EMU. Financial Markets and portfolio Management 28:181-203

Jensen, M. (1968), 'The Performance of Mutual Funds in the Period 1945–1964,' *Journal of Finance*, Vol. 23, pp. 389–416.

Jackson, F., Heubaum, H. 2013. Deploying private capital through the Green Climate Fund- the effective mitigation of investor risk. Draft paper. Centre for International Studies and Diplomacy, SOAS, University of London.

Jones C.M., Kaul G. and Lipson M.L. (1994). "Transactions, volume and volatility", *Review of Financial Studies*, Vol. 7, p. 631-651.

Herzog, B. & Mueller, J. 2014. A Theory on European Bond Market Turmoil Deutsche Asset & Wealth Management. Deutsche Bank

Hoje Jo, Hakkon Kim, Kwangwoo Park. 2014. Corporate Environmental Responsibility and Firm Performance in the Financial Services Sector. Journal Bus Ethics 131:257-284. Springer Science+ Business Media Dordrecht.

Houweling, P., Mentink, A., Vorst, T. 2003. Comparing Possible Proxies of Corporate Bond Liquidity

IIGCC, 2011. Positioning paper on green bonds Statement by the Institutional Investors Group on Climate Change

IMF; Bredenkamp, H. & Pattillo, C. 2010. Financing the Response to Climate Change. Staff

Position Note; SPN10/06

Kochetygova, J., Jauhari, A. 2014. Climate Change, Green Bonds and Index Investing: The New Frontier. *Mcgraw Hill Finance*.

Lin, Wang & Wu, 2011. Liquidity risk and expected corporate bond returns. Journal of Financial Economics, Vol.99, 628-650

Litterman, R. and Scheinkman, J., 1991. Common Factors Affecting Bond Retunrs Journal of Fixed Income 1, 54-61

Mandel, K. 2015. The rise and rise of green bonds. ENDS Report 479, pp 44-48

Mathews, J., Kidney, S. 2012. Financing climate-friendly energy development through bonds. Development Southern Africa Vol.29, No.2. Routledge

McWilliams, A. & Siegel, D., 2000. Corporate social responsibility and financial performance-correlation or misspecification. Strategic Management Journal 21: 603–609

Merton, R.C. (1973), 'An Intertemporal Capital Asset Pricing Model', *Econometrica*, Vol. 41, pp. 867–87.

Mishkin, F., S. 1986. Economics of Money, Banking, and Financial Markets. Pearson

Mohr, L., A., Webb, D., J. & Harris, K., E. 2001. Do consumers Ecpect Companies to be Socially Responsible? The Impact of Corporate Social Responsibility on Buying Behavior. The Journal of Consumer Affairs; Vol. 35, No 1;

Park, H.M., 2011. Practical Guides to Panel Data Modeling: A Step by Step Analysis Using Stata. Public Management & Policy Analysis Program. International University of Japan

Pastor and Stambaugh, 2003. Liquidity Risk and Expected Stock Returns. Journal of Political Economy, Vol. 111, No. 3. 642-685

Pe´rignon, C., Smith, D., Villa, C., 2007. Why common factors in international bond returns are not so common. Journal of International Money and Finance 26. 284-304

Richardson, Benjamin J., 2007. Do the Fiduciary Duties of Pension Funds Hinder Socially Responsible Investment. Banking and Finance Law Review

Ross, S.A. (1976), 'The Arbitrage Theory of Capital Asset Pricing', *Journal of Economic Theory*, Vol. 13, No. 3, pp. 341–60.

Sauer, David, 1997. The Impact of Social-Responsibility Screens on Investment Performance: Evidence from the Domini 400 Social Index and Domini Equity Mutual Fund. Review of Financial Economics, Vol. 6, No 2. 137-149

Schmidheiny, K., 2015. Short Guides to Microeconometrics. Universitaet Basel

Schroders 2015. Green Bonds – A Primer. Talking Point

Scholtens, B., 2009. Corporate social responsibility in the international banking industry. Journal of Business Ethics 86:159–175. Springer

Shi, C. & Zhang, S. 2010. Measuring Bond Market Liquidity: An Empirical study of the Chinese inter-bank bond market. Lunds University

Statman, Meir, 2000. Socially Responsible Mutual Funds. Financial Analysts Journal, 30-39

Statman, Meir and Glenn Klimek, 2005. Socially Responsible Indexes-Composition performance and tracking errors. Santa Clara University

Stern, N, 2006. Stern Review on the Economics of Climate Change. HM Treasury, London.

The Economist, 2014. Green Grow The Markets, O.

Stundenmund, A.H., 2014. Using Econometrics A Practical Guide. 6Th Edition. Pearson New International Edition.

Tiselius, J. and Kronqvist, M. 2015. Drivers of Growth in the Corporate Green Bond Market. Copenhagen Business School. Master Thesis

Ulrika Ross. (2014). *Green Bond Drivers.* HSBC.

Veys, A. (2010) The Sterling Bond Markets and Low Carbon or Green Bonds. (E3G, UK).

Williams, R., 2015. Panel Data: Very Brief Overview. University of Notre Dame

Wu, Meng-Wen & Shen, Chung-Hua, 2013 Corporate social responsibility in the banking industry- Motives and financial performance. Journal of Banking & Finance 37

Zhang, S. 2010. Measuring Bond Market Liquidity: An empirical study of the Chinese inter-bank bond market. Master thesis. Lunds University.

8. Appendix

Appendix A

Time series analysis

Regression 1

Source	SS	df	MS
Model	.007452598	12	.00062105
Residual	.069332505	1894	.000036606
Total	.076785103	1906	.000040286

Number of obs	=	1907
F(12, 1894)	=	16.97
Prob > F	=	0.0000
R-squared	=	0.0971
Adj R-squared	=	0.0913
Root MSE	=	.00605

Dependent1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
USBIGRf	.9770986	.0891079	10.97	0.000	.8023386	1.151859
Default	-.2130372	.0931632	-2.29	0.022	-.3957505	-.0303238
Option	.1915776	.0871183	2.20	0.028	.0207198	.3624355
Term	-.3784464	.0273532	-13.84	0.000	-.432092	-.3248008
y2008	.0015424	.0014412	1.07	0.285	-.0012842	.004369
y2009	-.0010009	.0007835	-1.28	0.202	-.0025375	.0005357
y2010	-.000099	.0007817	-0.13	0.899	-.0016322	.0014341
y2011	-.0001113	.0007824	-0.14	0.887	-.0016457	.0014231
y2012	-.0001802	.0007823	-0.23	0.818	-.0017145	.0013541
y2013	-.0004539	.0007826	-0.58	0.562	-.0019887	.0010808
y2014	-.0002783	.0007827	-0.36	0.722	-.0018134	.0012569
y2015	-.0005651	.0007832	-0.72	0.471	-.0021011	.0009708
y2016	0	(omitted)				
_cons	.0002449	.0006863	0.36	0.721	-.0011011	.0015909

Testing for Autocorrelation:

1) Correlogram

```
                                              -1       0       1 -1       0       1
 LAG       AC        PAC       Q      Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       -0.0098   -0.0124   .18527   0.6669
2       -0.0465   -0.0781   4.3207   0.1153
3       -0.0067    0.0485   4.4068   0.2208
4        0.0098    0.0954   4.5887   0.3322
5       -0.0185         .   5.2406   0.3872
6       -0.0236         .   6.3033   0.3901
7       -0.0570         .   12.528   0.0845
8       -0.0190         .   13.217   0.1046
9        0.0082         .   13.347   0.1475
10       0.0434         .   16.964   0.0752
11       0.0410         .   20.198   0.0427
12       0.0473         .   24.499   0.0174
```

2) Durbin Watson's alternative test

Durbin's alternative test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	1.458	1	0.2272

H0: no serial correlation

3)Breush-Godfrey Test

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	1.468	1	0.2257

H0: no serial correlation

4) Cochrane-Orcutt regression

```
Prais-Winsten AR(1) regression -- iterated estimates

      Source |       SS       df       MS              Number of obs =    1907
-------------+------------------------------           F(  4,  1902) =   49.66
       Model |  .007261132     4  .001815283           Prob > F      =  0.0000
    Residual |  .069520865  1902  .000036551           R-squared     =  0.0946
-------------+------------------------------           Adj R-squared =  0.0927
       Total |  .076781997  1906  .000040284           Root MSE      =  .00605

------------------------------------------------------------------------------
  Dependent1 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     USBIGRf |    .968061   .0869199    11.14   0.000     .7975926    1.138529
     Default |  -.2148409     .09282    -2.31   0.021    -.3968806   -.0328013
      Option |   .1802441    .086868     2.07   0.038     .0098776    .3506107
        Term |  -.3728557   .0268438   -13.89   0.000    -.4255021   -.3202092
       _cons |   -.000096   .0001372    -0.70   0.484     -.000365     .000173
-------------+----------------------------------------------------------------
         rho |   -.030313
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    1.609897
Durbin-Watson statistic (transformed) 1.564667
```

5) White noise:

```
Portmanteau test for white noise
---------------------------------------
 Portmanteau (Q) statistic =    81.4249
 Prob > chi2(40)           =     0.0001
```

```
Portmanteau test for white noise
---------------------------------------
 Portmanteau (Q) statistic =    16.9643
 Prob > chi2(10)           =     0.0752
```

Testing for Stationarity

1) Dickey Fuller Test

```
Dickey-Fuller test for unit root                   Number of obs   =      1511

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -39.059            -3.430            -2.860            -2.570
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

2) Augmented Dickey Fuller Test, drifts and lags

Augmented Dickey-Fuller test for unit root Number of obs = 362

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Z(t) has t-distribution		
Z(t)	-6.873	-2.337	-1.649	-1.284

p-value for Z(t) = 0.0000

D.Dependent1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Dependent1						
L1.	-.7824065	.1138299	-6.87	0.000	-1.006268	-.558545
LD.	-.1781502	.0909514	-1.96	0.051	-.357018	.0007175
L2D.	-.1093067	.0770517	-1.42	0.157	-.2608389	.0422255
L3D.	-.0953827	.0565128	-1.69	0.092	-.2065225	.0157571
_cons	.0002303	.0003306	0.70	0.486	-.0004199	.0008805

Testing for Cointegration

Dickey Fuller Test Cointegration error terms

Dickey-Fuller test for unit root Number of obs = 1511

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-40.419	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

Appendix B

Time series analysis

Regression 2

Source	SS	df	MS
Model	.000495355	13	.000038104
Residual	.030391651	2386	.000012737
Total	.030887006	2399	.000012875

Number of obs	=	2400
F(13, 2386)	=	2.99
Prob > F	=	0.0002
R-squared	=	0.0160
Adj R-squared	=	0.0107
Root MSE	=	.00357

Dependent2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
USBIGRf	.0057576	.0355291	0.16	0.871	-.0639135	.0754286
Default	-.0846148	.0448023	-1.89	0.059	-.1724702	.0032406
Option	-.0193796	.0393252	-0.49	0.622	-.0964948	.0577356
Term	-.020025	.0125188	-1.60	0.110	-.0445737	.0045238
y2007	.0000437	.0004616	0.09	0.925	-.0008615	.0009489
y2008	-.0007153	.0004619	-1.55	0.122	-.0016211	.0001906
y2009	.0006069	.0004618	1.31	0.189	-.0002986	.0015124
y2010	.0003147	.000461	0.68	0.495	-.0005894	.0012188
y2011	.0001244	.0004612	0.27	0.787	-.0007801	.0010288
y2012	.0000167	.0004614	0.04	0.971	-.0008881	.0009216
y2013	.0000286	.0004614	0.06	0.951	-.0008762	.0009335
y2014	.0001737	.0004614	0.38	0.707	-.0007311	.0010785
y2015	-.0001944	.0004617	-0.42	0.674	-.0010997	.000711
y2016	0	(omitted)				
_cons	.0002295	.0004045	0.57	0.570	-.0005636	.0010227

Testing for Autocorrelation:

1) Correlogram

LAG	AC	PAC	Q	Prob>Q	-1 0 1 [Autocorrelation]	-1 0 1 [Partial Autocor]
1	-0.0245	-0.0299	1.4413	0.2299		
2	-0.0189	-0.0265	2.2968	0.3171		
3	-0.0251	-0.0114	3.8174	0.2819		
4	0.0320	0.0686	6.2884	0.1786		
5	0.0158	.	6.8916	0.2288		
6	0.0129	.	7.2927	0.2946		
7	0.0860	.	25.112	0.0007		
8	0.0657	.	35.521	0.0000		
9	-0.0220	.	36.69	0.0000		
10	-0.0033	.	36.716	0.0001		
11	-0.0019	.	36.725	0.0001		
12	-0.0131	.	37.141	0.0002		

2) Durbin Watson's alternative test

Durbin's alternative test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	1.793	1	0.1805

H0: no serial correlation

3)Breush-Godfrey Test

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	1.803	1	0.1793

H0: no serial correlation

4) Cochrane-Orcutt regression

```
Iteration 0:  rho = 0.0000
Iteration 1:  rho = -0.0169
Iteration 2:  rho = -0.0201
Iteration 3:  rho = -0.0207
Iteration 4:  rho = -0.0208
Iteration 5:  rho = -0.0208
Iteration 6:  rho = -0.0208
Iteration 7:  rho = -0.0208

Prais-Winsten AR(1) regression -- iterated estimates

      Source |       SS       df       MS              Number of obs =    2400
-------------+------------------------------           F(  4,  2395) =    4.27
       Model |  .000218795     4  .000054699           Prob > F      =  0.0019
    Residual |  .030645783  2395  .000012796           R-squared     =  0.0071
-------------+------------------------------           Adj R-squared =  0.0054
       Total |  .030864578  2399  .000012866           Root MSE      =  .00358

------------------------------------------------------------------------------
  Dependent2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     USBIGRf |   .0250339   .0350656     0.71   0.475    -.0437281     .093796
     Default |  -.0856561   .0448471    -1.91   0.056    -.1735992    .0022871
      Option |  -.0147504   .0394398    -0.37   0.708    -.0920902    .0625893
        Term |  -.0239406   .0123923    -1.93   0.053    -.0482414    .0003601
       _cons |     .00027   .0000721     3.75   0.000     .0001286    .0004114
-------------+----------------------------------------------------------------
         rho |  -.0207997
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    1.633515
Durbin-Watson statistic (transformed) 1.607622
```

5) White noise:

```
Portmanteau test for white noise
---------------------------------------
 Portmanteau (Q) statistic =    88.2861
 Prob > chi2(40)           =     0.0000
```

```
Portmanteau test for white noise
---------------------------------------
 Portmanteau (Q) statistic =    36.7157
 Prob > chi2(10)           =     0.0001
```

Testing for Stationarity

1) Dickey-Fuller Test

Dickey-Fuller test for unit root Number of obs = 1903

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-45.913	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

2) Dickey-Fuller Test with trends and lags

Augmented Dickey-Fuller test for unit root Number of obs = 456

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Z(t) has t-distribution		
Z(t)	-11.353	-2.335	-1.648	-1.283

p-value for Z(t) = 0.0000

D.Dependent2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Dependent2						
L1.	-1.12854	.0994073	-11.35	0.000	-1.323899	-.9331807
LD.	-.0298854	.0738947	-0.40	0.686	-.1751061	.1153353
L2D.	-.0394235	.0536203	-0.74	0.463	-.1448002	.0659532
L3D.	-.0685674	.0427358	-1.60	0.109	-.1525534	.0154187
_cons	.0003849	.0001664	2.31	0.021	.0000579	.0007118

Testing for Cointegration

1) Dickey-Fuller Test, residuals

Dickey-Fuller test for unit root Number of obs = 1903

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-45.663	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

Appendix C

Time series Analysis

Regression 3

Source	SS	df	MS
Model	.001190278	6	.00019838
Residual	.006744718	538	.000012537
Total	.007934997	544	.000014586

Number of obs	= 545
F(6, 538)	= 15.82
Prob > F	= 0.0000
R-squared	= 0.1500
Adj R-squared	= 0.1405
Root MSE	= .00354

Dependent3	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
USBIGRf	.1545968	.1553968	0.99	0.320	-.1506622	.4598557
Default	-.6935978	.1549256	-4.48	0.000	-.9979311	-.3892645
Option	.5826209	.1529937	3.81	0.000	.2820827	.8831591
Term	.0090355	.0499463	0.18	0.857	-.0890782	.1071492
y2014	0	(omitted)				
y2015	.000032	.0003301	0.10	0.923	-.0006164	.0006804
y2016	.0007682	.0004748	1.62	0.106	-.0001646	.0017009
_cons	-.000257	.0002449	-1.05	0.295	-.0007381	.0002241

Testing for Autocorrelation

1) Correlogram

LAG	AC	PAC	Q	Prob>Q	-1 0 1 [Autocorrelation]	-1 0 1 [Partial Autocor]
1	-0.1181	-0.1378	7.6467	0.0057		
2	0.0874	0.1254	11.838	0.0027		
3	-0.0252	-0.0023	12.188	0.0068		
4	0.0268	0.0616	12.584	0.0135		
5	-0.0944	.	17.502	0.0036		
6	-0.0030	.	17.507	0.0076		
7	-0.0022	.	17.51	0.0144		
8	-0.0245	.	17.843	0.0224		
9	-0.0116	.	17.918	0.0361		
10	-0.0176	.	18.09	0.0535		
11	-0.0206	.	18.327	0.0743		
12	0.0179	.	18.506	0.1012		

2) Durbin Watson's alternative test

Durbin's alternative test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	11.572	1	0.0007

H0: no serial correlation

3) Breush-Godfrey Test

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	11.497	1	0.0007

H0: no serial correlation

4) Cochrane-Orcutt regression

```
Iteration 0:  rho = 0.0000
Iteration 1:  rho = -0.1466
Iteration 2:  rho = -0.1500
Iteration 3:  rho = -0.1500
Iteration 4:  rho = -0.1501
Iteration 5:  rho = -0.1501
```

Prais-Winsten AR(1) regression -- iterated estimates

Source	SS	df	MS
Model	.001148878	4	.00028722
Residual	.00662239	540	.000012264
Total	.007771268	544	.000014285

Number of obs =	545
F(4, 540) =	23.42
Prob > F =	0.0000
R-squared =	0.1478
Adj R-squared =	0.1415
Root MSE =	.0035

Dependent3	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
USBIGRf	.2060297	.1482975	1.39	0.165	-.085281	.4973403
Default	-.7119073	.1574676	-4.52	0.000	-1.021231	-.4025832
Option	.5536436	.154039	3.59	0.000	.2510546	.8562326
Term	-.0126828	.0480379	-0.26	0.792	-.1070469	.0816813
_cons	-.0001291	.000135	-0.96	0.339	-.0003942	.0001361
rho	-.1500504					

Durbin-Watson statistic (original) 1.924467
Durbin-Watson statistic (transformed) 1.647578

5) White noise

Portmanteau test for white noise

Portmanteau (Q) statistic	=	39.2511
Prob > chi2(40)	=	0.5038

Portmanteau test for white noise

Portmanteau (Q) statistic	=	18.0896
Prob > chi2(10)	=	0.0535

Testing for Stationarity

1) Dickey-Fuller Test

Dickey-Fuller test for unit root Number of obs = 432

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-24.542	-3.445	-2.873	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

2) Augmented Dickey-Fuller Test

Augmented Dickey-Fuller test for unit root Number of obs = 101

	Test Statistic	Z(t) has t-distribution 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-6.840	-2.366	-1.661	-1.290

p-value for Z(t) = 0.0000

D.Dependent3	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Dependent3						
L1.	-1.146653	.1676438	-6.84	0.000	-1.479424	-.813883
LD.	-.0484476	.1514993	-0.32	0.750	-.3491714	.2522762
L2D.	.0080566	.1309406	0.06	0.951	-.2518584	.2679717
L3D.	-.0615894	.0888118	-0.69	0.490	-.2378794	.1147006
_cons	-.0001758	.0003374	-0.52	0.604	-.0008456	.000494

Testing for Cointegration

Dickey-Fuller Test, residuals

```
Dickey-Fuller test for unit root                     Number of obs   =       432
```

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-25.091	-3.445	-2.873	-2.570

```
MacKinnon approximate p-value for Z(t) = 0.0000
```

Appendix D

Panel data results

First analysis with daily values

Random effects model (RE)

```
Random-effects GLS regression                   Number of obs     =      9,525
Group variable: index                           Number of groups  =          5

R-sq:                                           Obs per group:
     within  = 0.1777                                         min =      1,905
     between = 0.0097                                         avg =    1,905.0
     overall = 0.1776                                         max =      1,905

                                                Wald chi2(5)      =    2057.02
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
```

dependent	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
dummy	.0000198	.0001159	0.17	0.864	-.0002073	.0002469
usbigrf	.4805777	.023562	20.40	0.000	.434397	.5267584
default	-.1556512	.0251412	-6.19	0.000	-.2049271	-.1063753
option	.0849173	.0235776	3.60	0.000	.038706	.1311286
term	-.001383	.0072594	-0.19	0.849	-.015611	.0128451
_cons	.0000708	.0000735	0.96	0.335	-.0000732	.0002148
sigma_u	.00009579					
sigma_e	.00363467					
rho	.00069402	(fraction of variance due to u_i)				

Breusch Pagan Lagrange Test

```
Breusch and Pagan Lagrangian multiplier test for random effects

        dependent[index,t] = Xb + u[index] + e[index,t]

        Estimated results:
                         |       Var     sd = sqrt(Var)
                ---------+-----------------------------
               dependent |   .0000161       .0040078
                       e |   .0000132       .0036347
                       u |   9.17e-09       .0000958

        Test:   Var(u) = 0
                             chibar2(01) =     0.39
                          Prob > chibar2 =   0.2665
```

Wooldridge Test for Serial Correlation

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       4) =      9.289
           Prob > F =      0.0381
```

Robustness check with clusters

```
Random-effects GLS regression                   Number of obs     =      9,525
Group variable: index                           Number of groups  =          5

R-sq:                                           Obs per group:
     within  = 0.1777                                         min =      1,905
     between = 0.0097                                         avg =    1,905.0
     overall = 0.1776                                         max =      1,905

                                                Wald chi2(4)      =          .
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =          .

                                   (Std. Err. adjusted for 5 clusters in index)
------------------------------------------------------------------------------
             |               Robust
   dependent |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       dummy |   .0000198   .0001142     0.17   0.862     -.000204    .0002436
     usbigrf |   .4805777   .1537321     3.13   0.002     .1792684     .781887
     default |  -.1556512   .0236698    -6.58   0.000    -.2020432   -.1092592
      option |   .0849173   .0353969     2.40   0.016     .0155407    .1542938
        term |   -.001383   .1009861    -0.01   0.989     -.199312    .1965461
       _cons |   .0000708   .0000476     1.49   0.137    -.0000226    .0001642
-------------+----------------------------------------------------------------
     sigma_u |  .00009579
     sigma_e |  .00363467
         rho |  .00069402   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Robustness check

```
Random-effects GLS regression                   Number of obs     =      9,525
Group variable: index                           Number of groups  =          5

R-sq:                                           Obs per group:
     within  = 0.1777                                         min =      1,905
     between = 0.0097                                         avg =    1,905.0
     overall = 0.1776                                         max =      1,905

                                                Wald chi2(4)      =          .
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =          .

                                  (Std. Err. adjusted for 5 clusters in index)
```

dependent	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
dummy	.0000198	.0001142	0.17	0.862	-.000204	.0002436
usbigrf	.4805777	.1537321	3.13	0.002	.1792684	.781887
default	-.1556512	.0236698	-6.58	0.000	-.2020432	-.1092592
option	.0849173	.0353969	2.40	0.016	.0155407	.1542938
term	-.001383	.1009861	-0.01	0.989	-.199312	.1965461
_cons	.0000708	.0000476	1.49	0.137	-.0000226	.0001642
sigma_u	.00009579					
sigma_e	.00363467					
rho	.00069402	(fraction of variance due to u_i)				

Panel data analysis

Second regression with monthly values

Random Effects

```
Random-effects GLS regression                   Number of obs     =        450
Group variable: index                           Number of groups  =          5

R-sq:                                           Obs per group:
     within  = 0.1165                                         min =         90
     between = 0.0000                                         avg =       90.0
     overall = 0.1137                                         max =         90

                                                Wald chi2(5)      =      58.15
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
```

dependent	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
dummy	-1.52e-06	.0002724	-0.01	0.996	-.0005355	.0005324
usbigrf	.384383	.1182425	3.25	0.001	.1526319	.616134
default	-.4384929	.2657505	-1.65	0.099	-.9593544	.0823686
option	.083573	.2819019	0.30	0.767	-.4689446	.6360906
term	-.2238319	.03419	-6.55	0.000	-.290843	-.1568207
_cons	.0000517	.0001753	0.29	0.768	-.0002919	.0003952
sigma_u	.00025915					
sigma_e	.00140403					
rho	.03294688	(fraction of variance due to u_i)				

Sargan-Hansen Test

```
Test of overidentifying restrictions: fixed vs random effects
Cross-section time-series model: xtreg re
Sargan-Hansen statistic  58.131  Chi-sq(5)    P-value = 0.0000
```

Breusch-Pagan Test

```
 Dependent[Index,t] = Xb + u[Index] + e[Index,t]

 Estimated results:
                     |       Var     sd = sqrt(Var)
             --------+-----------------------------
           Dependent |   2.25e-06       .0014983
                   e |   1.97e-06       .0014041
                   u |   6.72e-08       .0002592

 Test:   Var(u) = 0
                          chibar2(01) =     5.12
                       Prob > chibar2 =   0.0118
```

Robustness check with clusters

```
Random-effects GLS regression                   Number of obs     =        450
Group variable: index                           Number of groups  =          5

R-sq:                                           Obs per group:
     within  = 0.1165                                         min =         90
     between = 0.0000                                         avg =       90.0
     overall = 0.1137                                         max =         90

                                                Wald chi2(4)      =          .
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =          .

                                   (Std. Err. adjusted for 5 clusters in index)
------------------------------------------------------------------------------
             |               Robust
   dependent |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       dummy |  -1.52e-06   .0002532    -0.01   0.995    -.0004978    .0004947
     usbigrf |    .384383   .1972727     1.95   0.051    -.0022645    .7710304
     default |  -.4384929    .553598    -0.79   0.428    -1.523525    .6465393
      option |    .083573   .3131116     0.27   0.790    -.5301145    .6972606
        term |  -.2238319   .1970325    -1.14   0.256    -.6100085    .1623448
       _cons |   .0000517   .0000745     0.69   0.488    -.0000943    .0001976
-------------+----------------------------------------------------------------
     sigma_u |  .00025915
     sigma_e |  .00140403
         rho |  .03294688   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Robustness check

```
Random-effects GLS regression                   Number of obs     =        450
Group variable: index                           Number of groups  =          5

R-sq:                                           Obs per group:
     within  = 0.1165                                         min =         90
     between = 0.0000                                         avg =       90.0
     overall = 0.1137                                         max =         90

                                                Wald chi2(4)      =          .
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =          .

                                    (Std. Err. adjusted for 5 clusters in index)
------------------------------------------------------------------------------
             |               Robust
   dependent |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       dummy |  -1.52e-06   .0002532    -0.01   0.995    -.0004978    .0004947
     usbigrf |    .384383   .1972727     1.95   0.051    -.0022645    .7710304
     default |  -.4384929    .553598    -0.79   0.428    -1.523525    .6465393
      option |    .083573   .3131116     0.27   0.790    -.5301145    .6972606
        term |  -.2238319   .1970325    -1.14   0.256    -.6100085    .1623448
       _cons |   .0000517   .0000745     0.69   0.488    -.0000943    .0001976
-------------+----------------------------------------------------------------
     sigma_u |  .00025915
     sigma_e |  .00140403
         rho |  .03294688   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```