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Deglobalization and debt pricing: The Case of Brexit's Influence on British Corporate Bond Performance

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Abstract

This paper examines how deglobalization affects private investment for companies in anti-globalization countries by focusing on analyzing the impacts of Brexit on British companies' corporate bond investment, typically bonds issued on the US bond market from 2010 to 2020. I apply difference-in-difference (DID) regression models using panel ordinary least squares (OLS) to determine the differential changes in British and American firms' bond yield spread and issuance amount after the Brexit referendum on June 23, 2016. The model is further optimized by adding controlled variables and a cluster-robust variance-covariance estimator. I find out that after the referendum, bonds offered by British companies are experiencing greater yield spread and less issuance amount. The results indicate that Brexit has caused a relatively negative impact on British firms by reducing investors' confidence to invest in British firms' corporate bond securities.

***Keywords*:** deglobalization, Brexit, corporate bond securities, yield spread, bond issuance amount

Contents:

1. Introduction

After the Great Recession in 2008, deglobalization has reduced cross-border international flows of trade, people, technology, and investment with decreasing trade openness index (see appendix A) (Irwin 2020). Under interrupted trade flows, exporting countries are experiencing unemployment or underemployment, some countries are struggling to repay external debt by global trade, and interrupting flows of capital and people reduce investment for business and infrastructure projects (James 2018). Deglobalization generates overall negative impacts on economies.

As a typical deglobalization event, the impact of Brexit on the UK economy has been widely studied from macro prospects and macro-level data. It is estimated that uncertainty related to Brexit has led to a slowdown of UK's GDP growth from 2.4% in 2015 to 1.5% in 2018 (Amadeo 2020), with the UK government estimating the worst condition of a 9.3% decrease in GDP level over 15 years (Harari 2019). GDP per capita may be reduced by between 0.9% and 3.4% until 2030 due to restriction on immigration from the European Union (EU) (Portes and Forte 2017). The restriction on immigration also led to a fall in the number of EU-born workers by 95% in 2017, increasing employers' recruitment pressure and difficulties (CIPD 2018).

Regarding investment, British firms have played a significant role in increasing foreign direct investment (FDI) net inflows in the EU. Compared to other OECD countries, the EU members can attract more FDI as a percent of GDP, from 1.7 percent without the entrance of the UK to 3.7 percent with the entrance of the UK, and the UK's withdrawal from the EU shows mostly adverse effects on FDI projects in the UK and the EU (Simionescu 2018). Stock markets' index and exchange rate demonstrate negative impacts as a result of uncertainty, and investors' confidence is said to be adversely affected. However, the economic indicators such as GDP and statistics related to FDI, the stock market as a whole and exchange rate are all macro-level. Many variables can affect these aggregate level data, making it hard to find the true impact of Brexit on private investment on firms. Therefore, in this research, I use micro-level or individual bond level data of corporate bond information to clearly show clean causal implications of the adverse impacts of the Brexit on corporate debt.

The main purpose of this paper is to provide evidence for the hypothesis that Brexit reduces investors' confidence on British firms typically in the corporate bond market, bonds are believed to be riskier with bond yield spreads widened due to uncertainty over Brexit, and therefore, companies are reducing their finance by corporate bonds either switching to new means or facing financing difficulties as they do not want to pay for the increasing yields on bonds. This is done by conducting quantitative research based on bond-level and issuer-level bond information to evaluate the influence of Brexit on yield spread and amount of bond issuance.

I focus on corporate bond markets, which have rarely been analyzed to show the impact of Brexit on corporate finance. It is a different type of investment than foreign direct investment as being either a portfolio investment or domestic investment through loans that foreigners do not have direct control on the business, which shows a different aspect of investors' confidence that focuses on the impact of Brexit on business performance and default rate rather than the impact on the business environment for opening a new factory or company in the UK for FDI.

Compared to the stock market, corporate bond markets are less volatile and more related to business performance, considering the possibility of default. Bond yields are more dependent on private sector saving that tends to increase with uncertainty and low economic growth, leading to less attractive bonds and pushing down bond prices, increasing bond yields. Therefore, the corporate bond market should be dependent on economic prospects such as the impacts of Brexit on the economy, which is the relationship that I want to study in this research.

Besides, issuing corporate bond securities is one of the major ways for firms in the UK to finance their company, with a corporate debt-to-GDP ratio of 83.3% (Richter 2019). If Brexit affects the corporate bond market negatively, as an essential way of financing, this result might be representative in indicating the adverse impact of Brexit on private investment as a whole.

Hence, this research results provide a better evaluation of Brexit's impact on investors' confidence for British firms and more references related to this topic form a new and important aspect of private investment, as analyzing the corporate bond securities market. Micro-level data are used instead of macro-level data in previous studies to provide more accurate analysis to shed light on the impacts of Brexit on corporate debt performance with granular data.

In this paper, I apply a difference-in-difference (DID) specification using panel OLS with fixed effects to show the impact of Brexit on British firms' corporate bond investment after the referendum day on June 23, 2016. I first analyze the effect of Brexit on bond yield spread and then the bond issuance amount for bonds issued by British firms using individual bond level and issuer level panel data from the beginning of 2010 to 2020. I find out the differential changes between the treatment group, bonds issued by British firms, and the control group, bonds issued by American firms, after the treatment of Brexit's impacts. Confounding variables are controlled by adding extra independent variables, including a categorical variable, and by using a cluster-robust variance-covariance estimator, heteroscedasticity is corrected.

The research results show that Brexit has increased the yield spreads for British bonds issued after the referendum, which means that investors lose confidence over British corporate bonds. Since companies need to pay for a higher yield, they may reduce their financing in the form of corporate bond securities.

The paper is organized as follows. Section 2 provides background information from previous works and literature related to deglobalization impacts, the timeline of Brexit events, and the effects of Brexit on private investment. Section 3 shows the process of pulling and cleaning data with all the independent and dependent variables explained. Section 4 includes the assumptions, hypothesis and the DID empirical methodology used in the analysis. Section 5 interprets the estimation results and tests the parallel trends assumption. Section 6 draws a general conclusion of the whole paper and provides ideas for possible further researches based on this model.

2. Background

2.1 Deglobalization and its Impacts

With the widespread of the COVID-19 pandemic adding further momentum, deglobalization, referring to the process of declining interdependence and integration between countries, continues to develop and escalate after the global financial crisis in 2008 (Irwin 2020). One of the typical deglobalization events is Trumpism and the trade war between the two largest economies, the US and China, with President Donald Trump shifting away from trade liberalization, advocating "America First" and President Xi Jinping aiming to implement economic policies to promote domestic leading industries instead of international trade. These policies had reduced the exports share of China's GDP from 31 percent in 2008 to 17 percent in 2019. The world is now in the fifth era of "slowbalization" indicating weak trade growth and falling world trade volume, with a declining world trade openness index from the peak at 61.6 in 2008 to 53.5 in 2017 (Irwin 2020).

Policymakers and businessmen are doubting that the world supply chain has been stretched too far, and global interdependence may need to be reduced by protectionism, indicating the death of globalization (Irwin 2020). However, some economists, for example, Michael D. Bordo (2017), argue that this era of globalization will not come to an end regarding its long-run dynamics of international capitalism and its contribution on raising worldwide living standards, but just facing a rest under trade protections, increasing financial regulation and anti-immigrant sentiment.

The impacts of deglobalization are studied through different aspects. With International Futures Model, Evan E. Hillebrand (2010) believe that although deglobalization may help poor countries to expand domestic manufacturing industry, shifting their relative wage structure in a way that improves overall equality, these outcomes are achieved at the expense of reducing average income in almost all countries due to slower productivity growth after reducing international trade.

Political instability and the probability of interstate wars both increase as a result of diminishing economic interdependence (Hillebrand 2010). Overall, estimations and studies related to deglobalization show few positive consequences.

Brexit and its referendum are widely regarded as a prominent deglobalization event followed by Donald Trump elected. In recent years, Trumpism and Brexit are regarded as two major symbols of deglobalization (Bergeijk 2019). This paper focuses on the impact of Brexit

2.2 Brexit Timeline and Impacts on Private Investment for British Firms

As an abbreviation for "British exit," Brexit is the withdrawal of the UK from the EU. Beginning from June 23, 2016, the Brexit referendum, as one of the most significant political earthquakes over decades, resulted in British voting to leave the EU by 52 to 48 per cent, forcing Mr. David Cameron to resign as the prime minister, with Mrs. Theresa May taking over his post. Reasons for this voting result include the issue of sovereignty to end the EU influence on the UK (Jennings and Lodge 2018), the agreement to catch "the best chance for the UK to regain control over immigration and its own borders." (Ashcroft 2016), the act of populism to protest against the elites as citizens have the power to make decisions (Jennings and Lodge 2018), the influence of euroscepticism on people's views from political parties and elites (Curtice 2017) and the imbalance position of media supporting Brexit rather than remaining, such as BBC (Harding 2016).

On March 29, 2017, then-Prime-Minister May submitted Article 50 withdrawal to the EU. On December 15 2017, Brexit moved to phase two as "sufficient progress" had been made in the Brexit negotiations. In January and March 2019, Meaningful vote No.1 and No.2, the House of Commons eventually rejected the government's Brexit deal and a "flexible extension" is agreed. On July 24, 2019, Boris Johnson took over May’s position as the UK's Prime Minister. In October, European Council agreed with the last extension until January 31, 2020. As pushing forward a new deal, and by winning the general election in December 2019, Johnson cleared all its parliamentary hurdles for the Brexit withdrawal. On January 31, 2020, the UK left the EU, and it enters the "transition period", beginning negotiations with the EU over a future trading relationship, ending on December 31 2020.

This research chooses the referendum day as the start of Brexit impact on corporate bond investment, as investors and firms began reacting to the uncertainty and possible Brexit consequences on British firms when seeing the ultimate referendum results.

The impact of Brexit on investment for British companies has been studied. Previous studies have shown FDI declined, even though some may argue that it is easy to over-emphasize the impact of Brexit on FDI as inter-related determinants such as sunk costs and agglomeration effects are likely to deter existing FDI from outward relocation (Whyman and Petrescu 2017). The British pound dropped from \$1.48 to \$1.36 on the day after the referendum (Amadeo 2020). The announcement of the referendum's result also results in an adverse effect on the stock market with a sharp decline of 7% of FTSE 350 value in the first two days after the event (Davies and Studnicka 2017). It is widely believed that uncertainty and instability related to further UK-EU relationship would dent corporate confidence and affect companies' investment decisions, negatively influencing investors' confidence and triggering a period of increased financial market volatility (Goodwin 2016).

2.3 Research Methodology and General Process

The whole procedure starts from data collection then to data cleaning, using data from three different sources, from 2010 to 2020. Difference-in-difference (DID) models with panel OLS regression identifies the causality between Brexit and bond yield spread as well as bond issuance amount for bonds issued by British firms on the US bond market. The method finds out differential changes of Brexit on bonds issued by British firms, the treatment group, and by American firms, the control group, after the referendum day on June 23, 2016.

To improve the model, I apply fixed-effects models to avoid unobserved time-invariant heterogeneities across the entities or issuers. I control confounding variables by adding extra independent variables to avoid omitted variable bias, and I use a categorical variable to control the influence of bond rating on the two dependent variables. To correct heteroscedasticity due to different variance for bond issuers, I use a cluster-robust variance-covariance estimator. After running the entire regression, I analyze and discuss the estimation results to find the implication of causal relationship between the dependent and explanatory variables, as well as the differential changes between bonds from the two countries. The following flowchart sums up the general process, presented in Figure 1 below.

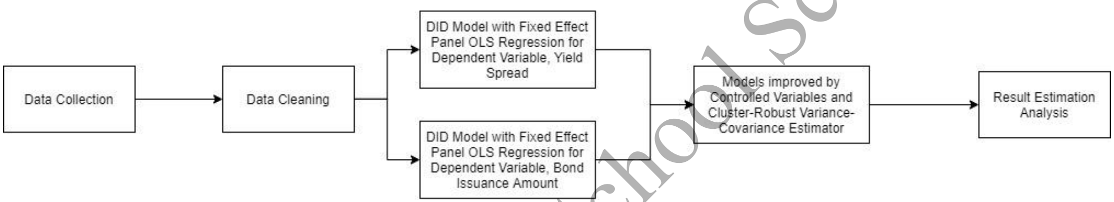

Figure 1. The General Process Flowchart

3. Data

3.1 Data Collection and Data Cleaning

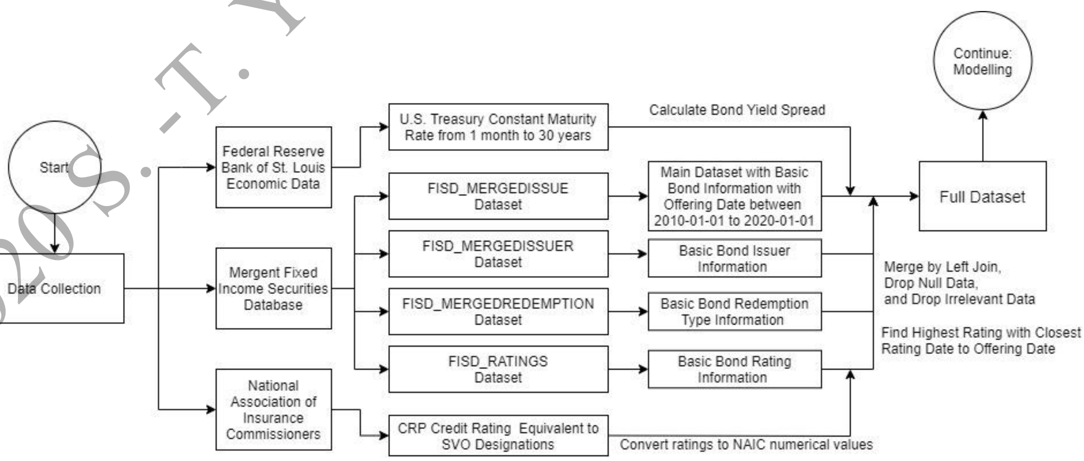

Figure 2. The Data Collection and Cleaning Process Flowchart

The flowchart above shows the general data extraction and cleaning process. Data were from three different sources in ten years from January 1, 2010, to January 1, 2020. The main dataset comes from Mergent Fixed Income Securities Database (FISD) in which data is extracted from four sub-datasets in FISD, including bonds' issue ID, issuer ID, issuer CUSIP, offering date that is between the ten years, maturity date, offering yield and offering amount from FISD_MERGEDISSUE Dataset; country of domicile of the bond issuer from FISD_MERGEDISSUER Dataset with only American and British companies; bond redemption types from FISD_MERGEDREDEMPTION Dataset only selecting bonds that are not callable, putable, and convertible; and bonds' rating type (the rating agency that provides the rating), rating date, and rating from FISD_RATINGS Dataset. There might be several ratings and rating dates for the same bond.

Table 1 below shows the first ten rows of data after merging from Mergent FISD.

issue_id	issuer_id	issuer_cusip	offering_date	maturity	country_domicile	offering_yield	offering_amt	rating_type	rating_date	rating	puta-ble	conver-tible	calla-ble
705127	1494	3134GB	2017/8/8	2019/2/14	USA		501500	FR	2017/8/8	AAA	N	N	N
706952	6122	3132X0	2015/6/25	2018/7/30	USA	1.2	10000	FR	2015/6/25	NR	N	N	N
706952	6122	3132X0	2015/6/25	2018/7/30	USA	1.2	10000	MR	2015/6/25	NR	N	N	N
706952	6122	3132X0	2015/6/25	2018/7/30	USA	1.2	10000	SPR	2015/6/25	NR	N	N	N
705127	1494	3134GB	2017/8/8	2019/2/14	USA		501500	FR	2018/2/16	NR	N	N	N
705127	1494	3134GB	2017/8/8	2019/2/14	USA		501500	MR	2017/8/8	Aaa	N	N	N
705127	1494	3134GB	2017/8/8	2019/2/14	USA		501500	MR	2018/2/14	NR	N	N	N
705127	1494	3134GB	2017/8/8	2019/2/14	USA		501500	SPR	2017/8/8	AA+	N	N	N
705127	1494	3134GB	2017/8/8	2019/2/14	USA		501500	SPR	2018/4/16	NR	N	N	N
521406	1497	31398A	2010/4/23	2012/5/7	USA	1.25	2000000	FR	2010/5/13	AAA	N	N	N

Table 1. Sample Data from Mergent FISD

The second database is the National Association of Insurance Commissioners (NAIC). I get the NAIC Securities Valuation Office (SVO) numerical designations for each rating, and I rank the ratings by this numerical value. For rows of bond information for the same bond, I then select the row with rating date closest to the offering date, and if still having multiple rows I choose the one with the highest rating, leaving only one row for one bond.

The third database is the Federal Reserve Bank of St. Louis Economic Data (FRED). I get the daily US Treasury Constant Maturity Rate from 1 month to 30 years, from January 1, 2010, to January 2, 2020. By using this, I calculate and merge the yield spread or credit spread of bonds using US government bonds with equivalent or similar maturity as a risk-free benchmark to be subtracted, indicating the risk level of the bonds.

Finally, two columns of dummy variables of Brexit flag and countryGBR are added to the dataset. I delete irrelevant columns to the model to get the full dataset. Table 2 below shows the first ten rows of the full dataset.

issue_id	Issuer _cusip	offering _date	offering _amt	NAIC	brxt_flag	country _GBR	ttm	yld_sprd
629917	913017	2015/4/29	1099838	2	0	0	3.014435615	0.72723
521406	31398A	2010/4/23	2000000	1	0	0	2.03974072	0.15
511882	06739G	2010/1/5	3000000	1	0	1	10.00705011	1.46096
512854	31331J	2010/1/21	125000	1	0	0	1.431925365	0.24
514699	50075N	2010/2/4	1000000	2	0	0	3.255371431	1.37417
514703	50075N	2010/2/4	1750000	2	0	0	6.012443787	1.13005
514705	50075N	2010/2/4	3750000	2	0	0	10.01526383	1.86315
514711	50075N	2010/2/4	3000000	2	0	0	30.01293661	2.04402
518319	78010X	2010/3/9	2000000	1	0	1	5.018583544	2.58792
519147	718172	2010/3/23	1000000	1	0	0	10.00978802	0.97199

Table 2. Sample Data from Full Dataset

3.2 Independent and Dependent Variables

In the models, I analyze two dependent variables, which is the bond yield spread and (log) bond issuance amount, or offering amount.

For independent variables, apart from the dummy variables, I control confounding variables that influence dependent variables other than Brexit, including time to maturity that has a positive correlation with bond yield and negative correlation with offering amount. This is because long-term bonds are considered to be riskier, reducing investors' confidence and demand, pushing up bond yields, and therefore, reducing offering amount as a higher yield is required to be paid.

Another independently controlled variable is rating, as investors tend to refer to ratings given by rating agencies based on company performance and credit, a poorer rating tends to have a higher yield as being considered riskier, and therefore, having lower offering amount. I present NAIC ratings in the model as a categorical variable. The table below shows the summary statistics for all continuous variables.

	Variable	Name in Model	Mean	Std.Dev	Obs
Dependent	Yield spread	yld_sprd	0.98	1.51	467
Variables	Offering amount	log_amt	12.62	2.22	467
Independent Variable	Time to maturity	ttm	7.33	7.10	467

Table 3. Summary Statistics for Variables

4. Empirical Model and Methodology

4.1 Assumptions and Hypothesis

To run the model and analyze the results, these following assumptions are made to make the regression logical and reliable:

i) Considering the models, for panel OLS regression, the regression equation should be linear, with random sampling of observations, and without multicollinearity and heteroscedasticity. The error terms should have no relationship with independent variables indicating no omitted variable bias so that the equation is under the zero conditional mean assumption $E(u|X)=0$ with u standing for error terms and X for independent variables.

ii) For DID estimators, to make causal implications, the parallel trends assumption is required to find out the effect of treatment on the treatment group. This means that in the absence of treatment, both the treatment and control groups should experience the same change in outcome.

iii) I assume that the data collected from the database is representative of the entire corporate bond market. In this way, measurement errors may be avoided, and standardized information is analyzed.

The main hypothesis for this research is that Brexit leads to reduced investors' confidence to British firms that drives up yield spread, and results in a decline in bond issuance amount for British firms. Increasing yield spread may indicate reduced investors' confidence as investors regard bonds riskier and reduce demand for bonds, which leads to a decline in bond price and resulting in higher bond yield. Higher yield and less investors' confidence reduce bond issuance amount for companies due to more yield payment and less demand.

4.2 Difference-in-Difference Analysis

A simple DID estimator tests the hypothesis and to examine the causal relationship between Brexit and bond yield spread as well as bond issuance amount, by identifying differential changes in bonds issued by British and American firms after the referendum day. The regression model is shown below:

$$\boldsymbol{Y_{it} = \beta_0 + \beta_1 brexFlag_t \times countryGBR_i + \theta_n + \rho_t + \varepsilon_{it}} \tag{1}$$

In this model, $\boldsymbol{Y_{it}}$ refers to dependent variables including bond yield spread and issuance amount or offering amount of bond $\boldsymbol{i}$ in year $\boldsymbol{t}$. $\boldsymbol{\beta_0}$ is the intercept of the linear equation. $\boldsymbol{brexFlag_t}$ is a dummy variable that has a value of 1 when the bond offering date is after Brexit referendum day and 0 of not, which means that this variable determines whether the year $\boldsymbol{t}$ is post-referendum that is exposed to the treatment of Brexit impacts. $\boldsymbol{countryGBR_i}$ is another dummy variable that has a value of 1 if the bond is issued by a British firm and 0 if not, which indicates that this variable determines whether the bond $\boldsymbol{i}$ is issued by British companies, belonging to the treatment group. The coefficient $\boldsymbol{\beta_1}$ is the parameter of interest before the interaction term $\boldsymbol{brexFlag_t \times countryGBR_i}$ that indicates the causal relationship between the impact of Brexit and the dependent variables, and captures the unilateral impact of Brexit on bonds issued by British firms and the differential outcomes of the effect of Brexit and its uncertainty as a treatment on the two groups. $\boldsymbol{\theta_n}$ is the entity fixed effect for an issuer as an entity, $\boldsymbol{n}$ is the six-digit issuer CUSIP. This effect can be interpreted as industry fixed effect that controls the heterogeneous unobserved impact of the issuer's industry on the issuer as issuers or firms rarely changes their business products or services or switch to another industry. $\boldsymbol{\rho_t}$ is the year fixed effect that captures common unobserved time-invariant year effects to both bonds issued by British and American firms, such as changes in investors' demand and interest rate environment. By using fixed effects that absorb the controls for $\boldsymbol{brexFlag_t}$ and $\boldsymbol{countryGBR_i}$, time-invariant heterogeneities across the entities and bonds are eliminated from the regression which makes it more flexible than directly controlling effects of different countries on dependent variables as it also controls the effect on the coefficient by different industries and different years across all years in the ten-year period. $\boldsymbol{\varepsilon_{it}}$ is the error term.

This is the basic DID model generated to show the effect of Brexit on British firms' bond yield spread and issuance amount. To increase accuracy, I make improvements by controlling other confounding variables that can influence the dependent variables, and are independent to other explanatory variables. I should also fix the problem of increasing heteroscedasticity volatility (Huang et al. 2019), leading to the regression model below:

$$\boldsymbol{Y_{it} = \beta_0 + \beta_1 brexFlag_t \times countryGBR_i + \theta_n + \rho_t + X_i\gamma' + \varepsilon_i t} \quad (2)$$

In this model, $\boldsymbol{X_i}$ as a vector of independent controlled variables are added to reduce omitted variable bias and improve the accuracy of the results, including ratings and time to maturity which both have a positive relationship with yield spread, and a negative relationship with offering amount. For ratings, a categorical variable is applied. Even though NAIC value is numerical, it is not continuous, and I use a categorical variable as the quantitative differences between the categories are uneven, including a range of several different credit ratings for one NAIC value (see Appendix C for full conversion between credit ratings and NAIC ratings), even though the differences between the values are the same. I use dummy coding with NAIC value of 1 as the control group with the largest number of observations and lowest yield compared to other categories, and therefore, the coefficient of other NAIC categories should show a positive relationship with yield spread and negative with offering amount as comparing to NAIC value of 1. By using a categorical variable for NAIC ratings, I control the impact of rating on the dependent variables.

For heteroscedasticity, basically due to different variance for different bond issuers, I use a cluster-robust variance-covariance estimator so that standard errors at entity level or industry level are clustered.

6. Estimation Results

5.1 Bond Yield Spread

The table below shows the main results of DID models for the dependent variable of bond yield spread. The second column refers to the regression without controlled variables and cluster-robust variance-covariance estimator, whereas the third column shows the regression that includes these two improvements. Both models include entity and year fixed effects, and the results related to the parameter of interest are robust as the difference between coefficient estimations for the parameter of interest in the two models is much smaller than the corresponding standard errors, indicating that the controlled variables are not the main reason for changes in yield spread, or are having a relatively small impact than Brexit on the treatment group. For both models, the coefficients in interest show positive values, indicating positive relationships between the effects of Brexit and yield spread of bonds issued by British issuers.

	(Without controlled variables)	(With controlled variables)
Dependent Variable:	**Bond Yield Spread**	**Bond Yield Spread**
After Brexit referendum Bonds issued by British issuers	1.0273***	1.0474***
	(0.3638)	(0.3927)
NAIC (2)		0.1301
		(0.2977)
NAIC (3)		0.7132
		(0.7739)
Time to Maturity		0.0268***
		(0.0057)
Entity Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
R-squared	0.0266	0.1167

No. of Observations	467	467

Notes: The first row of coefficient is the coefficient of the parameter of interest for the interaction term of Brexit flag (either before or after Brexit referendum) and country GBR (issuer either from the UK or the US) dummy variables. Clustered standard errors at entity level are shown below coefficients in parentheses. *,**and *** represents p-value statistical significance at 0.1, 0.05 and 0.01 level respectively, with a p-value lower than 0.05 considered as statistical significant value.

Table 4. DID Regression Results for Bond Yield Spread

Presenting the value, the equation of the first DID model is shown below:

$$\widehat{\boldsymbol{yld\_sprd}}_{\boldsymbol{it}} = \mathbf{0.9605} + \mathbf{1.0273} \times \boldsymbol{brexFlag_t} \times \boldsymbol{countryGBR_i} + \boldsymbol{\theta_n} + \boldsymbol{\rho_t} + \boldsymbol{\varepsilon_i t} \quad (3)$$

When adding controlled variables and the cluster-robust variance-covariance estimator, the coefficients change, and the equation is shown below:

$$\widehat{\boldsymbol{yld\_sprd}}_{\boldsymbol{it}} = \mathbf{0.7293} + \mathbf{1.0474} \times \boldsymbol{brexFlag_t} \times \boldsymbol{countryGBR_i} + \mathbf{0.0268} \times \boldsymbol{ttm_i} + \boldsymbol{\theta_n} + \boldsymbol{\rho_t} + \boldsymbol{\varepsilon_i t} \quad (4)$$

Both equations show positive coefficients before the interaction term, with the previous one indicating a percentage increase of 1.03% or an increase of 102.73 basis point in yield spread regarding the impacts of Brexit. With improvements, the coefficient in interest shows a 1.05% or 104.74 basis point increase in yield spread on bonds with British issuers after Brexit. The regression result is more rigorous in a better model considering clustered standard errors and controlled variables. For both models, the coefficient in interest is statistically significant at 0.01 significance level with low p-values. These results prove with empirical evidence that the impact of Brexit increases yield spread on bonds issued by British firms.

5.2 Bond Issuance Amount

For another dependent variable, the bond issuance amount, the table below shows the results of the two different models the same as the regression for bond yield spread. The third column presents the data from the improved model with both models applying fixed effects. The results are robust regarding the smaller difference in the values of the coefficient in interest than the corresponding value of standard error, showing Brexit having more influence on bond issuance amount than other controlled variables. Negative values of the coefficients in interest represent negative relationships between the impact of Brexit and issuance amount of bonds issued by British issuers in both models.

	(Without controlled variables)	(With controlled variables)
Dependent Variable:	**Bond Issuance Amount**	**Bond Issuance Amount**
After Brexit referendum Bonds issued by British issuers	-2.0893***	-2.0783***
	(0.5388)	(0.7223)
NAIC (2)		0.3801
		(0.3384)
NAIC (3)		-0.1130
		(0.9427)
Time to Maturity		-0.0217***
		(0.0078)
Entity Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
R-squared	0.0490	0.0762
No. of Observations	467	467

Notes: The first row of coefficient is the coefficient of the parameter of interest for the interaction term of Brexit flag (either before or after Brexit referendum) and country GBR (issuer either from the UK or the US) dummy variables. Clustered standard errors at entity level are shown below coefficients in parentheses. *,**and *** represents p-value statistical significance at 0.1, 0.05 and 0.01 level respectively, with a p-value lower than 0.05 considered as statistical significant value.

Table 5. DID Regression Results for Bond Issuance Amount

With numerical coefficients, the equation for the first DID model is shown below:

$$\widehat{\boldsymbol{log\_amt}}_{\boldsymbol{it}} = \mathbf{12.665} - \mathbf{2.0893} \times \boldsymbol{brexFlag_t} \times \boldsymbol{countryGBR_i} + \boldsymbol{\theta_n} + \boldsymbol{\rho_t} + \boldsymbol{\varepsilon_i t} \quad (5)$$

With improvements by adding controlled variables and clustered standard errors, the new equation is shown below:

$$\widehat{\boldsymbol{log\_amt}}_{\boldsymbol{it}} = \mathbf{12.770} - \mathbf{2.0783} \times \boldsymbol{brexFlag_t} \times \boldsymbol{countryGBR_i} - \mathbf{0.0217} \times \boldsymbol{ttm_i} + \boldsymbol{\theta_n} + \boldsymbol{\rho_t} + \boldsymbol{\varepsilon_i t} \quad (6)$$

For bond issuance amount, both equations present negative coefficients before the interaction term, with an (exp(-2.0893)-1)*100%=-87.6% relative decrease in (log) bond issuance amount regarding the impacts of Brexit. This is a large decrease by percentage. With controlled variables, the coefficient in interest shows a similar -87.5% relative decrease in (log) bond issuance amount. Both models show a statistically significant value of coefficient in interest at 0.01 significance level. The results suggest that the hypothesis is true as the impact of Brexit reduces the amount of bonds issued by British firms.

5.3 Parallel Trends Assumption Test

Parallel trends assumption is essential for this regression model to be reliable that requires the treatment group and control group to experience the same, constant change over time in the absence of the treatment. To test this assumption, I conduct a regression model based on the improved regression with controlled variables and clustered standard errors as being more accurate. I add several dummy variables from year2010 to year2015 for the bonds related to the year of the offering date, for example, if a firm offered a bond on August 28, 2010, the dummy variable of year2010 has a value of 1, but for year2011 to year2015 the value is zero. The regression with these dummy variables are shown below:

$$Y_{it} = \beta_0 + \beta_1 brexFlag_t \times countryGBR_i + \sum_{t=2010}^{2015} \beta_t year_t \times countryGBR_i + \theta_n + \rho_t + X_i\gamma' + \varepsilon_i t \quad (7)$$

The coefficients $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_t}$ are the parameters of interest before the interaction terms $\boldsymbol{brexFlag_t \times countryGBR_i}$ and $\sum_{t=2010}^{2015} \boldsymbol{\beta_t year_t \times countryGBR_i}$ that contain interaction terms in the six years before Brexit, to find the differential changes between the treatment group of British firms' bonds and the control group of American firms' bonds during specific year treatments. These differential changes should be zero to show parallel trends as the parallel trends of yield spread and (log) bond issuance amount for bonds issued by British firms and American firms should not be affected by the years before Brexit. The value of $\boldsymbol{\beta_{2010} year_{2010} \times countryGBR_i}$ is set as the benchmark so the coefficients $\boldsymbol{\beta_t}$ show the difference between the differential changes with the impact of the year 2010 on dependent variables and differential changes with the impact of other year treatments on the variables. The difference should be zero for years before Brexit as the differential changes are zero.

The results are shown in the following Table 6:

	(With controlled variables)	(With controlled variables)
Dependent Variables:	**Bond Yield Spread**	**Bond Issuance Amount**
Post-Brexit impact on British firms' bonds compared to year2010 impact	1.2160***	-2.1436***
	(0.5456)	(0.7698)
Year 2011 impact on British firms' bonds compared to year2010 impact	0.1576	-0.6054
	(0.4212)	(0.4355)
Year 2012 impact on British firms' bonds compared to year2010 impact	-0.3457	-0.2413
	(1.0092)	(0.4430)
Year 2013 impact on British firms' bonds compared to year2010 impact	0.5065	0.3638
	(0.5561)	(0.4513)
Year 2014 impact on British firms' bonds compared to year2010 impact	0.2177	0.1437
	(0.5749)	(0.5005)
Year 2015 impact on British firms' bonds compared to year2010 impact	0.0456	0.0205
	(0.6483)	(0.4385)
NAIC (2)	0.1025	0.3654
	(0.2952)	(0.3368)
NAIC (3)	0.7288	-0.2042
	(0.7608)	(0.9176)
Time to Maturity	0.0266***	-0.0221***
	(0.0056)	(0.0076)
Entity Fixed Effect	Yes	Yes

Year Fixed Effect	Yes	Yes
R-squared	0.1247	0.0829
No. of Observations	467	467

Notes: The first six rows of coefficients are the coefficients of the parameters of interest for the interaction terms. Clustered standard errors at entity level are shown below coefficients in parentheses. *,**and *** represents p-value statistical significance at 0.1, 0.05 and 0.01 level respectively, with a p-value lower than 0.05 considered as statistical significant value.

Table 6. Parallel Trends Assumption Test Results for Dependent Variables

The coefficients of post-Brexit impact on British firms' bonds yield spread is still positive, and for bond issuance amount, it is negative compared to the impact of the year 2010. The results again prove the hypothesis to be true, and the coefficients are both statistically significant. For year impacts before Brexit, despite having different coefficients, the values are all not statistically significant, which means that the values are likely to zero by accepting the null hypothesis. Therefore, this indicates that there are no differential changes in the trends of yield spread and bond issuance amount between the treatment and control groups before Brexit, and the parallel trends assumption is not violated.

7. Conclusion

This paper examines the impact of Brexit on investors' confidence to British firms by analyzing the influence of Brexit on yield spread and bond issuance amount for bonds with British issuers after the referendum in the corporate bond market. Brexit is selected as a typical deglobalization event, and therefore, the results may be seen as a reference for measuring the impact of growing deglobalization trend on investors' confidence. By using individual bond level and issuer level micro data, I apply difference-in-difference (DID) identification with panel OLS linear regression to find the differential changes experienced by bonds issued by firms in the control group, the US, and the treatment group, the UK, after the treatment of Brexit's impacts starting from June 23, 2016. I improve the model by including controlled variables that affect the two dependent variables of yield spread and bond issuance amount, with a categorical variable of rating, and I use a cluster-robust variance-covariance estimator for correcting heteroscedasticity related to different issuers.

The results find that Brexit has a relatively strong positive causal relationship with bond yield spread for bonds issued by British firms, which means that its impacts do reduce investors' confidence and demand for bonds, increasing bond yield and yield spread for bonds with British issuers by causing declining bond prices and investors viewing corporate bond securities as a riskier investment. The relationship between issuance amount for bonds of British issuers and impacts of Brexit is strongly negative due to decreasing investors' confidence that leads to higher bond yields or yield spreads which force British firms to switch to other financing channels and reducing finance by issuing bonds to avoid paying higher yields and deal with reducing investment demand.

Multicollinearity may be a potential problem as ratings themselves may show linear relationships with Brexit impacts, which means that there is a causal relationship between explanatory variables. Brexit impacts may affect business performance and financial statement, which result in poorer ratings, therefore, controlling ratings may reduce some effects of Brexit on dependent variables, leading to a downward bias of results. For example, Fitch Ratings was planning to downgrade Jaguar Land Rover, considering risks from Brexit (Yahoo 2019). However, these news are rare, some are only warnings but not real actions, and most of the times the rating agencies downgrade outlooks instead of actual ratings. Therefore, this would not be a severe problem or cause obvious underestimated results. If multicollinearity does exist, it may be fixed by removing highly correlated independent variables, by linearly combining the correlated variables, or by performing principal components analysis or partial least squares regression.

More analysis could be done based on this model. It could be used in other bond market databases to include more observations while evaluating the impacts of Brexit on corporate bond investment. The model could be applied with other deglobalization events to show their effects on bonds issued by firms of a particular country exposed to the deglobalization conditions. Further researches could be finding the difference of the impacts of Brexit internally between British industries. A promising research question is whether Brexit has more influence on bond yields or financing for companies in manufacturing industries than the non-manufacturing industries. There are controversial debates on whether the manufacturing sector is affected the most by Brexit (Irwin Mitchell 2019), or the service sector is receiving a larger impact than other sectors (Jonquières 2019). Moreover, the effectiveness of different policies on reducing the shocks of Brexit to investors' confidence may be a beneficial topic to discover.

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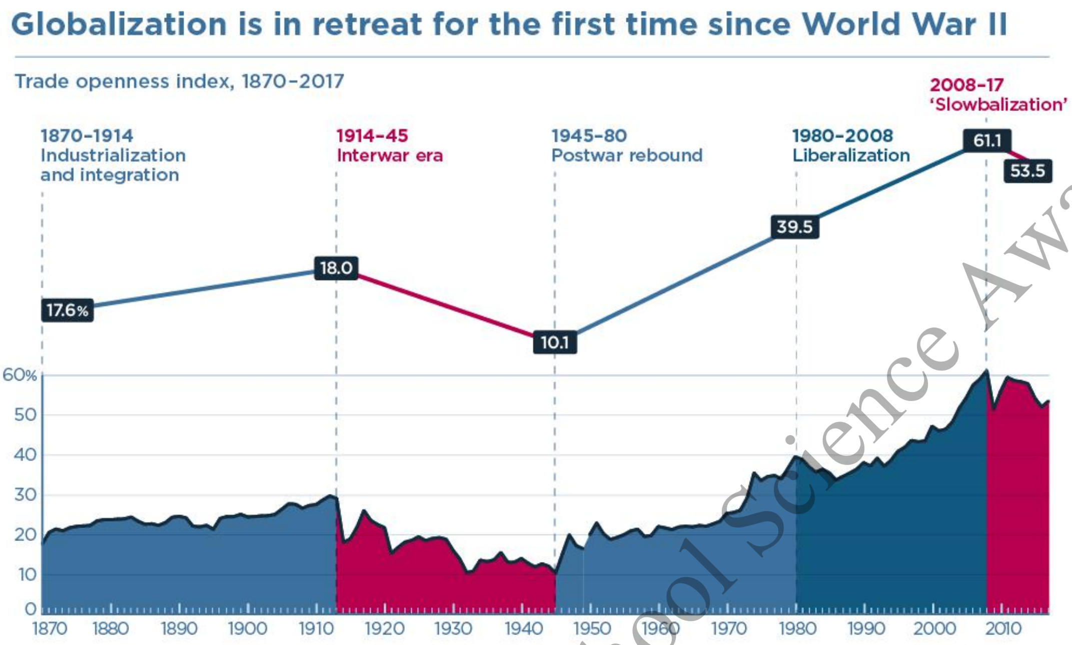
9. Acknowledgement

Deglobalization has been increasingly discussed in recent years due to rising number of anti-globalization events such as the Global Recession, the US's exit from TPP and other organizations, the US-China trade war, the increasing unilateral trade sanctions globally and Brexit. The analysis of the corporate bond market has been mostly used in studies related to the Global Recession, for example, evaluating the changes of the over-the-counter market liquidity of corporate debts during the financial crisis in 2008. The US corporate bond market is mainly studied in various papers to provide a micro-level view of finding the influence of global events. Therefore, I decided to write this paper to estimate the impact of Brexit as a typical deglobalization event on private investment using micro-level data of corporate bond markets instead of macro indicators. Brexit is different from the financial crisis as it was the collapse of the market of bond securities that leads to the deglobalization event in 2008, so the adverse effects on bond securities are obvious, but in the case of Brexit, I intend to find out the impact of deglobalization on the corporate debt market, which could be positive and negative and the hypothesis is relatively uncertain before conducting the regression analysis even though people believe that Brexit has negative effects on other macro aspects. It is important to study the true impacts of Brexit for future policy recommendations, and I hope that this paper will be beneficial for further researches related to Brexit and deglobalization.

I would like to thank Mr. Xu Hui, a postdoc in the University of Cambridge, for his helpful support by teaching logics and codes of python, as well as advising on the data collection and cleaning process and the basics of conducting and interpreting the regression models. This research would have been impossible without his help.

10. Appendix

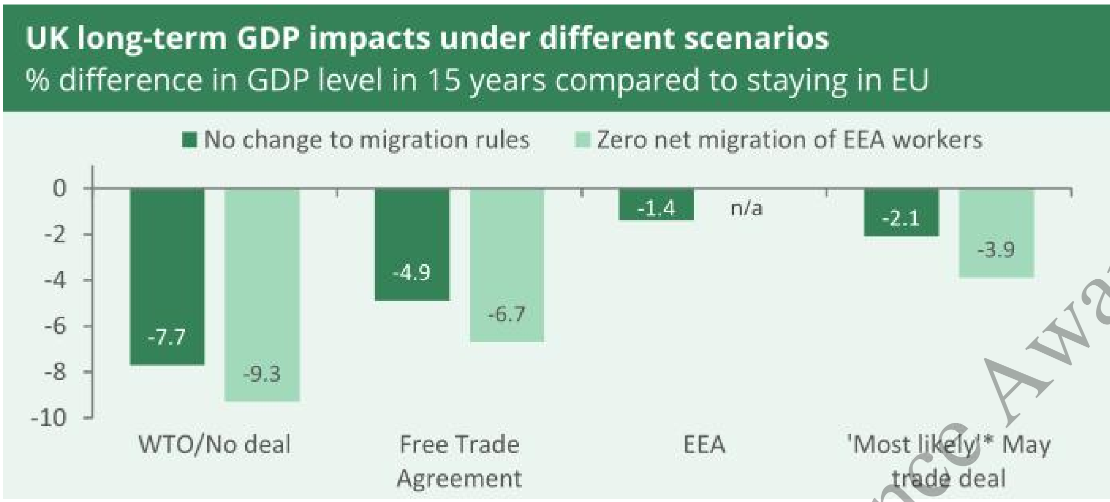
Appendix A



From Our World in Data and Peterson Institute for International Economics (PIIE), Trade Openness Index from 1870-2017 and the Five Globalization and Deglobalization Eras[1]

1 The trade openness index is defined as the sum of world exports and imports divided by world GDP. 1870 to 1949 data are from Klasing and Milionis (2014); 1950 to 2017 data are from Penn World Tables (9.0) (Irwin 2020).

Appendix B



From HM Govt, EU Exit: Long-term economic analysis (HM Government 2018), the UK Long-term GDP Impacts under Different Scenarios

Appendix C

(A) MOODY'S INVESTOR'S SERVICE

Corporate, Government Counterparty and Municipal Ratings	NAIC
Aaa; Aa 1, 2, 3; A 1, 2, 3	1
Baa 1, 2, 3	2
Ba 1, 2, 3	3
B 1, 2, 3	4
Caa, 1, 2, 3	5
Ca, C	6

Commercial Paper and Short Term Counterparty Ratings	NAIC
P 1	1
P 2	2
P 3	3
N P (Not prime)	6

Preferred Stock	NAIC
Aaa; Aa 1, 2, 3; A 1, 2, 3	1
Baa 1, 2, 3	2
Ba 1, 2, 3	3
B 1, 2, 3	4
Caa	5
Ca, C	6

(B) STANDARD AND POOR'S

Corporate Counterparty and Municipal Ratings -- Public Bonds	NAIC
AAA, AA+, AA, AA-, A+, A, A-	1
BBB+, BBB, BBB-	2
BB+, BB, BB-	3
B+, B, B-	4
CCC+, CCC, CCC-	5
CC, C, D	6

Commercial Paper (Standard & Poor's continued)	NAIC
A, A 1	1
A 2	2
A 3	2
B	4
C	5
D	6

Preferred Stock	NAIC
AAA, AA+, AA, AA-, A+, A, A-	1
BBB+, BBB, BBB-	2
BB+, BB, BB-	3
B+, B, B-	4
CCC	5
CC, C, D	6

(C) *FITCH RATINGS*

Fixed Income and Counterparty Ratings	NAIC
AAApre	1*
AAA, AA+, AA, AA-, A+, A, A-	1
BBB+, BBB, BBB-	2
BB+, BB, BB-	3
B+, B, B-	4
CCC,	5
CC, C, DDD, DD, D	6

* This rating is assigned to pre-refunded municipal debt.

Commercial Paper	NAIC
F 1+, F 1	1
F 2	2
F 3	2
B	4
C	5
D	6

Preferred Stock	NAIC
AAA, AA+, AA, AA-, A+, A, A-	1
BBB+, BBB, BBB-	2
BB+, BB, BB-	3
B+, B, B-	4
CCC	5
CC, C	6

From National Association of Insurance Commissioners (NAIC), CRP Credit Rating Equivalent To SVO Designations (NAIC Ratings)

Appendix D

DATE	DGS1MO	DGS3MO	DGS6MO	DGS1	DGS2	DGS3	DGS5	DGS7	DGS10	DGS20	DGS30
1/4/2010	0.05	0.08	0.18	0.45	1.09	1.66	2.65	3.36	3.85	4.6	4.65
1/5/2010	0.03	0.07	0.17	0.41	1.01	1.57	2.56	3.28	3.77	4.54	4.59
1/6/2010	0.03	0.06	0.15	0.4	1.01	1.6	2.6	3.33	3.85	4.63	4.7
1/7/2010	0.02	0.05	0.16	0.4	1.03	1.62	2.62	3.33	3.85	4.62	4.69
1/8/2010	0.02	0.05	0.15	0.37	0.96	1.56	2.57	3.31	3.83	4.61	4.7
1/11/2010	0.01	0.04	0.13	0.35	0.95	1.55	2.58	3.32	3.85	4.64	4.74
1/12/2010	0.02	0.05	0.14	0.34	0.92	1.5	2.49	3.22	3.74	4.52	4.62
1/13/2010	0.02	0.06	0.15	0.37	0.97	1.54	2.55	3.28	3.8	4.6	4.71
1/14/2010	0.02	0.05	0.14	0.34	0.94	1.49	2.51	3.23	3.76	4.52	4.63
1/15/2010	0.03	0.06	0.15	0.33	0.89	1.44	2.44	3.17	3.7	4.48	4.58
1/18/2010											
1/19/2010	0.03	0.06	0.14	0.33	0.93	1.48	2.48	3.2	3.73	4.49	4.6
1/20/2010	0.03	0.05	0.14	0.31	0.92	1.46	2.45	3.16	3.68	4.43	4.54
1/21/2010	0.02	0.06	0.14	0.31	0.87	1.41	2.38	3.09	3.62	4.38	4.5
1/22/2010	0.02	0.06	0.14	0.3	0.84	1.39	2.37	3.09	3.62	4.38	4.5
1/25/2010	0.02	0.06	0.14	0.3	0.86	1.4	2.39	3.12	3.66	4.42	4.55
1/26/2010	0.02	0.07	0.14	0.32	0.87	1.4	2.38	3.11	3.65	4.43	4.56
1/27/2010	0.01	0.08	0.16	0.33	0.9	1.46	2.43	3.14	3.66	4.42	4.55
1/28/2010	0.01	0.08	0.15	0.31	0.87	1.44	2.41	3.15	3.68	4.44	4.57
1/29/2010	0.02	0.08	0.15	0.3	0.82	1.38	2.34	3.08	3.63	4.38	4.51

From Federal Reserve Bank of St. Louis Economic Data (FRED), Sample Data of US Treasury Constant Maturity Rate from 1 month to 30 years

(First 20 rows)

Appendix E

Further explanations for data cleaning process:

The flowchart of figure 2 shows the data cleaning process. As mentioned, I collect data from three sources from January 1, 2010 to January 1, 2020. From Mergent Fixed Income Securities Database (FISD)'s sub-dataset I get my first dataset, including:

i) FISD_MERGEDISSUE Dataset, the main dataset with basic bond issue information including issue ID, issuer ID, issuer CUSIP, offering date, maturity date, offering yield and offering amount which is the bond issuance amount and I further convert this amount into the form of natural logarithm to make the large number smaller and linear. I leave only bonds with offering date between January 1, 2010, to January 1, 2020;

ii) FISD_MERGEDISSUER Dataset with issuer information, which is the country of domicile of the bond issuer for the bonds selected in the previous dataset, merged or left joined to the main dataset from FISD_MERGEDISSUE by common issuer ID, only British and American bonds are selected;

iii) FISD_MERGEDREDEMPTION Dataset with bond redemption types or different methods by which an issuer can redeem an issue before its maturity, in this case, the data shows whether the bond is callable, putable, and convertible, either "yes" or "no". This dataset left joins to the main dataset by common issue ID of bonds, and leaves only bonds that are not having these three bond types as the bonds should not be able to be redeemed before it reaches the stated maturity date, or sold back to the issuer by the holder before the bond's maturity date, or converted into stocks by holders prior to the maturity date. These bonds contaminate the model by having overall lower yield than original bonds and redeeming before maturity will affect the impact of time to maturity on bond yields;

iv) FISD_RATINGS Dataset with rating information, including rating type (the rating agency that provides the rating), rating date, and rating, merged and left joined to the main dataset by common issue ID of bonds. There may be several different ratings for the same bond from different rating agencies and rated on different dates.

Table 1 in the paper shows the outcome for this procedure.

I then merge data from the National Association of Insurance Commissioners (NAIC), the database where I get the NAIC Securities Valuation Office (SVO) numerical designations for each rating, equivalent to credit rating from the three main bond rating agencies, Moody's (MR as an abbreviation for Moody's ratings), Standard & Poor's (SPR) and Fitch (FR). By giving numerical values for different levels of rating, the ratings could be categorized by NAIC value from 1 to 6, for 1 representing the highest bond quality and 6 for the poorest bond quality.

Since there may be several ratings for a single bond, I first drop or delete all the rows with missing data in any column, such as no ratings (NR). I then choose the rating that has the closest rating date to the offering date of the bond, which is the rating that the initial offering yield is based on and changing ratings in the future may be due to changes in the industry affecting firms' performance or unobserved effects on bonds in each year which will be further controlled by fixed effects in the model. If there are ratings with rating dates of the same difference to the offering date, I choose the one with the highest NAIC rating, and if there are highest ratings with the same NAIC value, in this case, I randomly choose one row with the highest rating for the bond. An example of this selecting algorithm is shown below.

issue_id	**offering_date**	**rating_date**	**rating_type**	**rating**	**NAIC**
705127	2017/8/8	2018/2/16	FR	NR	
705127	2017/8/8	2017/8/8	MR	Aaa	1
705127	2017/8/8	2018/2/14	MR	NR	

705127	2017/8/8	2017/8/8	SPR	AA+	1
705127	2017/8/8	2018/4/16	SPR	NR	
709556	2015/8/14	2015/8/14	FR	NR	
709556	2015/8/14	2015/8/3	MR	A3	1
709556	2015/8/14	2017/12/6	MR	A3	1
709556	2015/8/14	2018/10/25	MR	A2	1
709556	2015/8/14	2015/8/3	SPR	A	1
709556	2015/8/14	2015/12/2	SPR	A-	1

Table 7. Input Example for Two Bonds

issue_id	offering_date	rating_date	rating_type	rating	NAIC
705127	2017/8/8	2017/8/8	MR	Aaa	1
709556	2015/8/14	2015/8/3	MR	A3	1

Table 8. Output Example after the Rating Algorithm

The last database is the Federal Reserve Bank of St. Louis Economic Data (FRED), where I get the US Treasury Constant Maturity Rate from 1 month to 30 years, and the rates are daily information and data in the time period from January 1, 2010, to January 2, 2020. There are some missing data due to closing treasury markets on weekends and holidays, and therefore, I use the last rate available for missing dates. I calculate the bonds' time to maturity measured in years by finding the difference between maturity and offering dates of the bonds. By finding the treasury constant maturity rate on the same date as the bonds' offering date with the closest time to maturity related to the bond's time to maturity, I calculate yield spread by subtracting the treasury constant maturity rate from offering yield, using debt issued by the US Treasury as a benchmark because of its risk-free status backed by the full faith and credit of the US government. The results are merged into the dataset.

Finally, I add a column of dummy variable of Brexit flag to the dataset, having a value of 1 if the offering date is after or on the referendum day, and a value of 0 if not. I add another column of country GBR, having a value of 1 if the country of domicile of the issuer is the UK, and a value of 0 if the country is the US. I eventually delete irrelevant columns to the model to get the full dataset, shown in table 2.

Appendix F

Python Code:

```
import pandas as pd
import numpy as np
import wrds
from pandas.tseries.offsets import MonthEnd
from dateutil import parser
import time
import seaborn as sns
from numpy.random import randint
import datetime

conn=wrds.Connection()

stmt ="""
select issue_id, issuer_id,issuer_cusip,
offering_date,maturity,COUNTRY_DOMICILE, offering_yield, offering_amt,
rating_type, rating_date, rating,
putable, convertible, callable
from FISD_MERGEDISSUE as a
Left join (
select COUNTRY_DOMICILE,ISSUER_ID as issuerid
from FISD_MERGEDISSUER
where COUNTRY_DOMICILE='USA' or COUNTRY_DOMICILE='GBR' and COUNTRY_DOMICILE!='none'
) as b
on a.issuer_id=b.issuerid
Left join (
select callable,sinking_fund,issue_id as issueid
```

```
from FISD_MERGEDREDEMPTION
) as c
on a.issue_id=c.issueid
Left join (
select rating_type, rating_date, rating, issue_id as issueid
from FISD_RATINGS
)as d
on a.issue_id=d.issueid
where callable='N'and putable='N'and convertible='N'
and offering_date <='2020-1-1'and offering_date >='2010-1-1'

"""
sample=conn.raw_sql(stmt)
samplecols=sample.columns



sample.fillna(value=pd.np.nan, inplace=True)
sample=sample[sample['country_domicile'].notnull()]
sample=sample[sample['offering_yield'].notnull()]
sample['offering_date']=pd.to_datetime(sample['offering_date'])
sample['rating_date']=pd.to_datetime(sample['rating_date'])
sample['maturity']=pd.to_datetime(sample['maturity'])
sample['diff_date']=sample['rating_date']-sample['offering_date']
sample['diff_date_rank']=sample.groupby(['issue_id','offering_date'])['diff_date'].rank
(method='min')
sample=sample[sample.diff_date_rank==1]
rating_order=pd.read_excel('NAIC.xlsx')
sample=pd.merge(sample,rating_order,left_on=['rating','rating_type'],right_on=['Ratin
g','Rating_type'],how='left')
sample['rating_order_rank']=sample.groupby(['issue_id','offering_date'])['NAIC'].rank
```

```
(method='dense')
sample=sample[sample.rating_order_rank==1]
random_choose_idx=sample.groupby(['issue_id','offering_date'])['rating_order_rank'].
head(1).index
sample=sample[sample.index.isin(random_choose_idx)]
sample=sample[samplecols]
sample=pd.merge(sample,rating_order,left_on=['rating','rating_type'],right_on=['Ratin
g','Rating_type'],how='left')

sample ['ttm'] = sample ['maturity']- sample ['offering_date']
sample ['ttm']= sample ['ttm']/np.timedelta64(1,'Y')
data=pd.read_csv("constant_maturity_rate.csv",parse_dates=[0])
data.set_index("DATE",inplace=True)
dt_index=pd.date_range('2010-01-01','2020-01-01',freq='D')
dataNew=data.reindex(dt_index)
dataNew=dataNew.replace(".",np.nan)
dataNew=dataNew.fillna(method='ffill')
dataNew.index.name='DATE'
dataNew=dataNew.astype(float)
dataNew.columns=['1', '3','6','12','24','36','60','84','120','240','360']
sample1=pd.merge(sample,dataNew,left_on='offering_date',  right_on='DATE',  how=
'left')
months = [1,3,6,12,24,36,60,84,120,240,360]
sample1['ttmmonths']=sample1['ttm']*12
sample1['closestUSAmonth']=0
rownum=0
for i in sample1['ttmmonths']:
        sample1['closestUSAmonth'][rownum]=min(months,key=lambda
x:abs(x-i))
        rownum=rownum+1
```

```
sample1['USArate']=0.1
rownum2=0
for j in sample1['closestUSAmonth']:
        sample1['USArate'][rownum2]=sample1[str(j)][rownum2]
        rownum2=rownum2+1
sample1["yld_spread"]=sample1["offering_yield"]-sample1["USArate"]
sample1 = sample1.drop(['1', '3','6','12','24','36','60','84','120','240','360','ttmmonths',
'closestUSAmonth'], axis=1)

sample1.loc[sample['offering_date'] >= '2016-06-23', 'brxt_flag'] = 1
sample1.loc[sample['offering_date'] <'2016-06-23', 'brxt_flag'] = 0
sample1.brxt_flag = sample1.brxt_flag.astype(int)
sample1.loc[sample['country_domicile'] == 'GBR', 'country_GBR'] = 1
sample1.loc[sample['country_domicile'] != 'GBR', 'country_GBR'] = 0
sample1.country_GBR = sample1.country_GBR.astype(int)

import statistics
sample1['log_amt'] = np.log(sample1['offering_amt'])
sample1['yld_spread'].std()
sample1['log_amt'].std()
sample1['ttm'].std()
sample1['yld_spread'].mean()
sample1['log_amt'].mean()
sample1['ttm'].mean()

# Panel Model
from linearmodels.panel import PooledOLS
import statsmodels.api as sm
import statsmodels.formula.api as smf
from linearmodels import PanelOLS
```

```
sample1['year']=sample1['offering_date'].apply(lambda
x:datetime.datetime.strftime(x,'%Y'))
sample1.year = sample1.year.astype(int)
sample1.set_index(['issuer_cusip', 'year'], inplace=True)
yld_sprd=sample1['yld_spread']
log_amt = np.log(sample1.offering_amt)

mod = PanelOLS.from_formula('yld_sprd ~ 1+ country_GBR:brxt_flag +
EntityEffects+TimeEffects', data=sample1 , drop_absorbed=True)
print(mod.fit())

# Panel Model
from linearmodels.panel import PooledOLS
import statsmodels.api as sm
import statsmodels.formula.api as smf
from linearmodels import PanelOLS

sample1['year']=sample1['offering_date'].apply(lambda
x:datetime.datetime.strftime(x,'%Y'))
sample1.year = sample1.year.astype(int)
sample1.set_index(['issuer_cusip', 'year'], inplace=True)
yld_sprd=sample1['yld_spread']
log_amt = np.log(sample1.offering_amt)
sample1['NAIC'] =pd.Categorical(sample1['NAIC'])

mod = PanelOLS.from_formula('yld_sprd ~ 1+NAIC+ country_GBR +ttm +
country_GBR:brxt_flag+EntityEffects+TimeEffects', data=sample1,
drop_absorbed=True)
print(mod.fit(cov_type='clustered'))
```

```
# Panel Model
from linearmodels.panel import PooledOLS
import statsmodels.api as sm
import statsmodels.formula.api as smf
from linearmodels import PanelOLS

sample1['year']=sample1['offering_date'].apply(lambda
x:datetime.datetime.strftime(x,'%Y'))
sample1.year = sample1.year.astype(int)
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sample1['year']=sample1['offering_date'].apply(lambda
x:datetime.datetime.strftime(x,'%Y'))
sample1.year = sample1.year.astype(int)
sample1.set_index(['issuer_cusip', 'year'], inplace=True)
yld_sprd=sample1['yld_spread']
```

```
log_amt = np.log(sample1.offering_amt)
sample1['NAIC'] =pd.Categorical(sample1['NAIC'])

mod = PanelOLS.from_formula('log_amt ~ 1+NAIC+ country_GBR +ttm +
country_GBR:brxt_flag+EntityEffects+TimeEffects', data=sample1 ,
drop_absorbed=True)
print(mod.fit(cov_type='clustered'))

sample1['offering_date']=pd.to_datetime(sample1['offering_date'],
format='%Y-%m-%d')
for i in range(2010, 2016):
    startDate=str(i)+'-01-01';
    endDate=str(i)+'-12-31';
    cond=(sample1.offering_date>=startDate) & (sample1.offering_date<=endDate)
    sample1['year'+str(i)]=np.where(cond, 1, 0)
sample1.reset_index(inplace=True)

from linearmodels.panel import PooledOLS
import statsmodels.api as sm
import statsmodels.formula.api as smf
from linearmodels import PanelOLS

sample1['year']=sample1['offering_date'].apply(lambda
x:datetime.datetime.strftime(x,'%Y'))
sample1.year = sample1.year.astype(int)
sample1.set_index(['issuer_cusip', 'year'], inplace=True)
yld_sprd=sample1['yld_spread']
log_amt = np.log(sample1.offering_amt)
sample1['NAIC'] =pd.Categorical(sample1['NAIC'])
```

```
mod = PanelOLS.from_formula('yld_sprd ~ 1+NAIC+ country_GBR +ttm + country_GBR:brxt_flag+country_GBR:year2011+country_GBR:year2012+country_GBR:year2013+country_GBR:year2014+country_GBR:year2015+EntityEffects+TimeEffects', data=sample1 , drop_absorbed=True)
print(mod.fit(cov_type='clustered'))

from linearmodels.panel import PooledOLS
import statsmodels.api as sm
import statsmodels.formula.api as smf
from linearmodels import PanelOLS

sample1['year']=sample1['offering_date'].apply(lambda x:datetime.datetime.strftime(x,'%Y'))
sample1.year = sample1.year.astype(int)
sample1.set_index(['issuer_cusip', 'year'], inplace=True)
yld_sprd=sample1['yld_spread']
log_amt = np.log(sample1.offering_amt)
sample1['NAIC'] =pd.Categorical(sample1['NAIC'])

mod = PanelOLS.from_formula('log_amt ~ 1+NAIC+ country_GBR +ttm + country_GBR:brxt_flag+country_GBR:year2011+country_GBR:year2012+country_GBR:year2013+country_GBR:year2014+country_GBR:year2015+EntityEffects+TimeEffects', data=sample1 , drop_absorbed=True)
print(mod.fit(cov_type='clustered'))
```