SCHOOL OF ECONOMICS AND MANAGEMENT

The Impact of Brexit on Levels of Corporate Credit Risk

Evidence from UK and EU Non-financial Companies

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Abstract

The impact of the UK's decision to leave the EU has received a lot of attention in scientific research in recent years. The effect of Brexit on many different variables and factors related to financial markets and general economy has been studied extensively. Corporate credit risk is, however, an area which did not receive as much attention. This study therefore focuses on the quantification of the impact of Brexit-related events on the levels of corporate credit risk in the UK and the EU, respectively. Using the structural Merton model, monthly real-world default probabilities are estimated and used in a regression analysis, together with other PD determinants in order to assess the effects of Brexit. The results of our empirical analysis indicate that, following the announcement of the referendum, default probabilities increased both for the UK and the EU companies. In contradiction to the previous studies, however, the effect of referendum result announcement was associated with a decrease in default probabilities for the European companies and insignificant results for the UK companies. All aforementioned effects can be regarded as marginal.

Keywords: Brexit, credit risk, probability of default, Merton model, panel data analysis

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List of Abbreviations

PD	Probability of Default
CDS	Credit Default Swap
FOREX	Foreign Exchange
IRB	Internal Ratings-Based Approach
LGD	Loss Given Default
EAD	Exposure at Default
M	Effective Maturity
GBM	Geometric Brownian Motion
ROA	Return on Assets
ROE	Return on Equity
ROIC	Return on Invested Capital
BIS	Bank for International Settlements
UK	United Kingdom
EU	European Union

1. Introduction

1.1. Background and problem discussion

The UK's decision to leave the European Union, also known as Brexit, has been frequently described in the media as the biggest decision of the UK government since World War II (MacAskill, 2019). Even though Brexit is mostly a political phenomenon, its economic significance cannot be stressed enough because of its potential (and already manifested) influence on financial markets.

Since the emergence of the idea for the UK to leave the EU, the possible implications of this decision have been studied quite extensively – as described in more detail later in this paper. The main motivation for such a surge of interest among academics is that the majority of business, policy and financing decisions have been considerably affected by the prospect of Brexit happening in 2019 (the most recent confirmed date being October 31st). Market participants perceive a lot of uncertainty surrounding Brexit as it is still not clear which scenario (deal or no-deal) is the UK government going to opt for and how trade is going to work when the UK eventually leaves the EU (Cumming and Zahra, 2016). This perceived uncertainty has already manifested itself in terms of adverse impact on the UK's GDP growth, exchange rates or volatility in financial markets.

Many UK-based as well as international companies are now contemplating or have even begun to prepare relocations of their operations or headquarters to other countries. Banks, investment funds and other financial institutions have started bulk-moving assets to other EU countries. Manufacturers are stocking up on components or considering holding larger amounts of inventory, while others are postponing the development of new products and major financing decisions, laying off UK employees and moving jobs to the EU or even issuing warnings of factory closures in case of a no-deal Brexit. Examples of these "precautionary steps" can be found in Appendix 1.

1.2. Purpose

Even though the body of literature focusing on short-term effects of Brexit on financial markets is quite extensive to date, most of the attention has been directed towards the effects on interest rates, exchange rates and stock market returns. The impact of Brexit on credit risk levels, on the other hand, has not been in the spotlight as much, despite being an equally important factor in investors' and banks' financial decision-making.

This paper therefore aims to extend the existing literature on credit risk levels in the UK and the EU following Brexit. The main objective of this study is to determine and quantify the magnitude of the impact of UK's decision to leave the EU on the levels of credit risk (and hence the credit quality) in the UK and the EU financial markets.

To measure the level of credit risk of non-financial UK and EU companies, we use probability of default (PD), most commonly defined as the likelihood that an obligor will not be able to make debt repayments on time (Grene, 2019), as opposed to corporate credit spreads used in previous studies. Monthly PD is estimated using Merton's Distance-to-Default framework, based on historical daily data spanning the period from January 2012 to December 2018. Calculated probabilities of default for individual companies are then further used as dependent variables in panel regressions with various determinants of credit risk (based on previous studies) and Brexit-related dummy variables on the right-hand-side of the regression equation.

Specifically, we focus on addressing the following research questions:

Has there been a more pronounced increase in default probability of UK companies compared to EU companies following the announcement of the Brexit referendum/referendum results?

Is the increase in default probability associated with the announcement of Brexit referendum/referendum results?

This study aims to differentiate itself from previous studies on this topic through the application of a different credit risk measure, as well as the utilization of the most recent dataset.

1.3. Limitations

Our study analyzes the development of default probability following the events of Brexit with respect to UK and EU companies. The sample of companies, whose data are then used to estimate PD, is limited to large-cap non-financial companies listed on the FTSE 100 and Euro Stoxx 50 indices.

Since we do not include any mid- or small-cap companies, the resulting sample may seem to be unrepresentative of the actual conditions and structure of the respective financial markets. The effect of firm size has indeed been shown to affect default risk. Vassalou and Xing (2004) however, show that this effect only exists within the high default-risk quintile.

Furthermore, our study focuses on the effects of Brexit in more general fashion and rather than comparing the effects on small and large companies within their respective markets, it seeks to compare the magnitude of these effects on UK and EU companies.

As mentioned above, we also exclude financial companies from our sample. This modification follows the research of Nagel and Purnanandam (2018) who found the standard Merton model (used in our study) to be ill-suited to estimate the probability of default for financial companies. The researchers point out that for financial companies, the assumption of constant asset volatility, as employed in structural models, is violated, leading to severe understatement of default risk in periods with high asset values. The adaptation of our model for estimation of PD for financial companies, as suggested by the aforementioned study, is out of the scope of this thesis and therefore, these companies have been removed from the sample.

1.4. Thesis outline

A predefined structure is followed throughout this research paper.

In chapter 2, we begin with the review of existing literature and empirical research connected to the effects of Brexit on various elements of financial markets.

Chapter 3 outlines the process of development of our research hypotheses based on the presented previous findings.

In chapter 4, we introduce the theoretical background which is essential for the reader to understand how the research questions will be addressed and which concepts and models will be used.

Chapter 5 aims to describe the adopted research methodology and its attributes, provide further arguments related to the process of estimation of default probabilities and explain important considerations regarding regression analysis.

Chapter 6 gives details about the data collection process and presents a critical appraisal of the information sources used in this process.

Chapter 7 then focuses on presenting and discussing the main empirical findings of our study as well as relating them to the existing literature.

And finally, in chapter 8, we conclude with the main points from the preceding discussion and examine the implications of our results for investment, funding and regulation in the UK. The very last part then aims to present recommendations for future research, based both on the limitations of the present study and the presented findings.

2. Review of existing literature

As pointed out in the previous section, Brexit has received quite a lot of attention in the recent years, even more so now that the UK government is approaching the final stages of negotiations.

Majority of studies conducted to date has focused on the reaction of stock markets either to the referendum announcement or to the final result of the Brexit vote. Their results, however, seem to offer a similar verdict, whereby Brexit effects are described as rather negative.

The probability of Brexit alone (before the vote even took place) was shown to impact stock markets internationally, with the UK-market bearing the most negative effects (Belke et al., 2018). These pre-referendum findings were then confirmed by other authors investigating the effect of the referendum's results. For example, Raddant (2016) analyzed the effects of the Brexit vote result on stock prices both in the UK and other European countries. He found that despite major spikes in stock price volatility in most EU markets[1], the stock prices returned to their pre-referendum levels in less than 3 weeks. This was, however, not true for the UK stock market, where full recovery was not reached within the studied period – this was especially distinguishable in the financial sector.

Similar results were presented in an event study carried out by and Ramiah et al. (2017) where strong adverse effects on stock prices in all UK sectors were observed following the Brexit vote announcement, with financial and travel&leisure sectors taking the worst hit. Moreover, according to Schiereck et al. (2016), the short-term reaction to the "leave vote" announcement in the UK stock market was even more distinct than the reaction to 2008 Lehman Brothers' bankruptcy.

Another extensively-studied Brexit effect is that on exchange rates. Plakandaras et al. (2016) attribute the depreciation of the British Pound against the US Dollar to the uncertainty caused by the Brexit-vote. Korus and Celebi (2018) come to a similar conclusion when focusing on the Pound-Euro exchange rates in the aftermath of the referendum. The implied volatility of the British pound versus the US Dollar, Japanese Yen or the Euro were also shown to be affected by the referendum. Furthermore, as Caporale et al. (2018) aptly note in their research paper describing this effect, the implications of Brexit might be more serious and longer lasting for the FOREX than for the UK stock market.

[1] Effect of Brexit on stock price volatility in the UK studied e.g. by Caporale et al. (2018)

Many studies also indicate a significant increase in sovereign CDS spreads (Belke et al., 2018; Schiereck et al., 2016; Kierzenkowski et al., 2016) which, as noted by one of the authors, reflect investors' concerns, rather than an actual risk of sovereign debt default.

As we can see, all previous studies mentioned here suggest that the impact of Brexit on the financial markets and the UK economy as a whole has been rather negative. And as we have finally touched upon the topic of credit risk, albeit only related to sovereign debt, we may already have an idea, how corporate debt and the associated credit risk might have reacted to Brexit.

All the elements of financial markets presented in this section up until now have received a fair amount of coverage over the years. Corporate credit risk, however, remains overlooked with only one research study engaging with this topic. In their research paper, Kadiric and Korus (2019) examine the impact of Brexit on corporate credit spreads in the UK and the EU. They focus on various Brexit-related events, as well as the magnitude of Brexit effects on specific sectors (both financial and non-financial). Their results also follow the pattern observed in all previous studies - negative impact on corporate credit spreads with stronger influence in the UK than in the EU. Furthermore, the increase in corporate credit spreads is shown to be associated only with the announcement of the referendum results, whereas the effects of other Brexit events come out insignificant.

3. Development of research hypotheses

Our investigation focuses on the same pattern regarding corporate credit risk as the aforementioned paper by Kadiric and Korus (2019). We, however, propose the use of a different credit risk measure - probability of default (PD). The reasoning behind this decision and the formulation of research hypotheses based on this modification are presented in the following subsections.

3.1. Credit risk measure modification

The main motivation for this modification comes from the reasoning behind the "credit spread puzzle" phenomenon. As Collin-Dufresne et al. (2001) established, this phenomenon arises from the fact that corporate bond spreads have a tendency of being many times larger than what the expected loss from default alone would imply. Even though credit spreads should represent the compensation for credit risk, the exact relationship between such risk and credit spreads has been rather difficult to explain (Amato and Remolona, 2003).

To help shed some light on this problem, we consider the fact that corporate credit spreads are the basis for calculation of implied default probabilities (also called "risk neutral" default probabilities) which exist under the assumption that all investors are risk-neutral. These PDs are very different from those estimated using historical data (also called "physical" or "real world" default probabilities). Hull (2012) lists several reasons for this difference – e.g. compensation for relative illiquidity of corporate bonds, compensation for bearing additional systematic risk due to defaults being correlated, influence of derivative markets or even subjective adjustments to default probabilities by bond traders.

Consequently, we use the so-called "real-world" default probabilities in our study because we are interested in the PD values which would, in case of banking institutions, eventually be involved in regulatory capital calculations (Basel II), that is, a measure which is less prone to investors' and traders' sentiment and expresses the genuine risk of default.

3.2. Research hypotheses

Since the investigation of the general pattern followed by other elements of financial markets has yielded similar results – that is, the effects of Brexit are largely negative and stronger for the UK financial markets as compared to the European financial markets – we formulate our research hypotheses in the following way:

H1: The probability of default (PD) for non-financial UK companies has increased following the announcement of Brexit referendum.

H2: The PD of non-financial UK companies has increased following the announcement of the results of Brexit referendum.

H3: There is a stronger negative effect on PD of non-financial UK companies than for non-financial companies from the EU following the announcement of Brexit referendum.

H4: There is a stronger negative effect on PD of non-financial UK companies than for non-financial companies from the EU following the announcement of the results of Brexit referendum.

These hypotheses are formulated in pairs with respect to the sample-split according to two distinct events in the Brexit timeline – the announcement of the Brexit referendum, i.e. European Union Referendum Bill featured in the Queen's official speech on May 27th, 2015 and the announcement of the results of the referendum on June 24th, 2016.

4. Theory and concepts

Having introduced previous research in our area of investigation, it is also necessary to introduce the main theoretical frameworks and concepts which are essential to understanding the research problem at hand.

4.1. Credit risk and the probability of default

Credit risk is a major source of risk faced by banking institutions, together with operational and market risk, as recognized in the Basel Accords. Hull (2012, p.37) defines credit risk as "the risk that counterparties in loan transactions and derivatives transactions will default". It contributes as a major component to the calculations of regulatory capital and therefore, its analysis and precise assessment is of paramount importance under the Basel II regulation.

There are several components involved in credit risk analysis, that constitute the Internal Ratings-Based approach (IRB), i.e. the fundamental part of the Basel Accords – Probability of Default (PD), Loss Given Default (LGD), Exposure at Default (EAD) and Effective Maturity (M) (BCBS, 2004). Despite the fact that all these concepts are of great importance in credit risk evaluation process, probability of default is the most essential one – both in the Basel II framework with regards to banks and in the present study in relation to non-financial firms.

Probability of default is not just paramount to the banking sector, it is also widely used by investors in the assessment of credit quality and evaluation of investment decisions (Croen, 2018). This fact leads us to believe that choosing this measure for our study can provide valuable information regarding investment decisions in the Brexit era.

4.2. Default risk modelling

There are two leading approaches to the estimation of default risk – structural and reduced-form models. Structural models link default to the firm's asset value - that is why they are also referred to as "asset-based models" (Schmid, 2004). These models provide the economic intuition regarding the driving mechanism of credit default – i.e. a situation, where the firm's asset value drops below a pre-specified point, such as the face value of debt at maturity. In our analysis, we employ the basic structural model developed by Merton (1974) – the detailed description of which is given in the following section. Other authors, who developed their models most often as an extension or modification to the original Merton model, are for example Black and Cox (1976) or Vasicek (1987).

Reduced-form models which represent an alternative method used for credit risk modelling, are only interested in modelling the time of default which is driven by the default intensity process (Bielecki and Rutkowski, 2002). Examples of reduced-form models include Jarrow-Turnbull model (1995) as well as models developed by Duffie and Singleton (1999) or Hull and White (2000). These models are seen as more flexible than those from the structural group and usually outperform the basic Merton model when dealing with large amounts of corporate debt. However, they are not really grounded in theory with respect to what drives default and as Arora et al. (2005) note, they cannot consistently outperform more sophisticated structural models.

4.3. Merton model

As indicated above, the estimation of default probabilities in this research paper will be carried out using the basic Merton model. This model applies the option-pricing theory (as presented by Black and Scholes in 1973) to the pricing of corporate liabilities. Specifically, the model operates under the assumption that the value of a company's equity E_T essentially represents a call option written on the value of the company's assets A_T with the exercise price equal to the face value of debt at maturity F (Hull, 2012). The shareholders' payoff at time T can be expressed as:

$$E_T = max[A_T - F, 0] \tag{1}$$

According to this logic, the company defaults when A_T drops below F at time T (as default can only occur when the debt matures), i.e. the face value of debt cannot be repaid as the asset value is simply not large enough.

This model also operates under the assumption that the value of the company's assets follows the GBM process (Merton, 1974). Subsequently, we can express the company's total asset value with the stochastic differential equation below (The Fields Institute, 2019):

$$dA_t = \mu_A A_t dt + \sigma_A A_t dW_t \quad \text{where } \ 0 \leq t \leq T \tag{2}$$

Here, dA_t represents the change in the value of company's assets, μ_A is the mean return on the company's assets (drift rate in the GBM) and σ_A is the asset volatility.

Under such conditions, the asset values are assumed to follow a lognormal distribution as per the assumptions in the Black-Scholes model, which are also valid for debt (Hull, 2012):

$$\ln(A_T) \sim N\left[\ln(A_0) + \left(\mu - \frac{\sigma_A^2}{2}\right) \times T, \sigma_A \times \sqrt{T}\right] \tag{3}$$

First part in the brackets represents the mean of the normal distribution and the second part represents the standard deviation.

And finally, bearing in mind that the probability of default is the likelihood that the debt payment cannot be made at maturity:

$$PD = \mathbb{P}\ (lnA_T < lnF), \tag{4}$$

we express PD as:

$$PD = N\left(-\frac{ln(\frac{A_0}{F}) + \left(\mu - \frac{\sigma_A^2}{2}\right) \times T}{\sigma_A \times \sqrt{T}}\right) = N(-DD) \tag{5}$$

as per Bielecki and Rutkowski (2002) and Hull (2012). It is helpful to note here that DD is the distance-to-default measure, defined as “the number of standard deviations that the value of a company’s assets must move for a default to be triggered” (Hull, 2012, p.600).

The procedure for calculating PD is therefore straightforward. First, the market value of assets (A_0), as well as the asset volatility (σ_A) have to be estimated because they are not directly observable. To do this, we need to make use of the Black-Scholes (1973) framework once again. The expression for the value of equity (E_0 – a known value, market capitalization) in this framework can be written as follows:

$$E_0 = A_0 \times N(d_1) - F \times exp^{-r \times T} \times N(d_2) \tag{6}$$

$$d_2 = d_1 - \sigma_A \times \sqrt{T} \qquad \text{where} \qquad d_1 = \frac{ln\left(\frac{A_0}{F}\right) + (\mu + \frac{\sigma_A^2}{2}) \times T}{\sigma_A \times \sqrt{T}} \tag{7}$$

This, however, still leaves us with one equation and two unknowns, A_0 and σ_A. We therefore bring into play another formula known as Ito's lemma:

$$\sigma_E E_0 = \left(\frac{\partial E}{\partial A}\right) \times \sigma_A \times A_0 \tag{8}$$

where, according to Hull (2012), $\frac{\partial E}{\partial A}$ can be expressed as $N(d_1)$ from the Black-Scholes formula shown above. This substitution leaves us with a second equation:

$$\sigma_E E_0 = N(d_1) \times \sigma_A \times A_0 \tag{9}$$

Provided that σ_E can be estimated from the sample, either by calculating the sample volatility or by using GARCH models (the former method being used in this paper), we can proceed with the calculation of distance-to-default and finally transforming it into PD.

5. Research methodology

The empirical part of this study consists of two substantial sections – probability of default modelling and regression analysis. In the first empirical section, as a general frame of reference for the employed research method, we use elements of event study as laid out by MacKinlay (1997). We centre our analysis around the events of interest, i.e. announcement of Brexit referendum and the announcement of referendum result, and set the period preceding these events as the benchmark for "normal performance" with regards to the level of credit risk. We then analyse the development of credit risk levels connected to Brexit, i.e. after the aforementioned events. This later allows us to make appropriate inferences. The regression analysis then aims to find out whether the effects of Brexit can explain the variation in PD calculated in the first section.

5.1. PD estimation

Implementation of the Merton model in our study requires making some assumptions and simplifications. Even though the main structural modifications and possible problems were explained in the theory section, there are still some minor adjustments that need to be made for the model to work in practice, with data that are available to us.

Following the reasoning in section 4.3., which explores the practicalities of PD estimation using the basic Merton model, we focus on the estimation of unobservable variables (A_0 and σ_A) by applying the Merton-Black-Scholes framework to observable variables.

These are extracted from the companies' financial statements (book values of debt, structure of debt, number of shares outstanding) as well as from market-related resources (share prices, risk-free rate proxies, debt risk premia).

Some of the obtained data need to be further modified in order to suit our needs with regards to precision and correctness of our model. The first necessary modification relates to data frequency. Our objective is to estimate monthly PD based on daily data. While equity prices and risk-free rate proxies can be obtained with daily frequency, this does not apply to book values obtained from financial statements which are published annually. This problem can be resolved by applying linear interpolation to yearly data to increase their frequency to daily[2]. Furthermore, we apply the reasoning of Crosbie and Bohn (2003) who found that the assumption regarding default triggered by asset value dropping below the point marked by face value of total debt is too simplistic. The authors suggest that the point where a company defaults can generally be found somewhere between total debt and the company's respective portion of short-term debt. This is based on the properties of long-term debt, which allows some companies to survive even beyond the point of default. In our model, we therefore use half of the company's long-term debt and the total amount of short-term debt. The product of this adjustment is called "composite debt" in our model's dataset.

Another important modification is linked to the concept of risk premia. As mentioned in the introductory section, our aim is to estimate the real-world probabilities of default. Most research papers and theses do not include any asset risk premium in their PD calculations and their resulting PD is therefore considered "risk-neutral". Such simplification, however, leads to overestimation of the default probability (Hull, 2012).

Our proposed solution, albeit somewhat stylized, is to use the median credit spreads[3] of respective Moody's rating classes of our companies' corporate debt and add them to the risk-free rates to introduce a risk-premium component in the PD-calculations[4]. Companies for which credit ratings could not be obtained were assigned an industry-average credit spread based on the ratings of their peers in the sample.

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[2] For some of the companies in the sample, whose fiscal year ends at a different date than December 31, interpolation had to be carried out separately and the resulting values copied to the dataset for our PD-model.

[3] Obtained from Moody's Investor Service Market Implied Ratings

[4] Credit ratings issued by rating agencies other than Moody's were transformed to Moody's ratings using a conversion table published by the Bank for International Settlements (BIS) - available at: https://www.bis.org/bcbs/qis/qisrating.htm

Final assumption is made with regard to the maturity of debt, which is indicative of the time horizon of the investment and has been set to equal one year for the purposes of our study.

Once these modifications are made, the unobservable variables can be obtained by using optimization tools in MS Excel (Solver). This is carried out using the approach described by Löffler and Posch (2007), where the objective of the Solver is set to minimize the deviation of market-obtained equity-related data (E_T, σ_E) from those obtained from the Merton model by changing the initial values[5] of asset-related data (A_T, σ_A). The resulting estimated asset values and volatilities are then used, together with variables obtained from the market, to calculate the distance to default and subsequently the probability of default, applying the already discussed relationship:

$$PD = N\left(-\frac{ln(\frac{A_0}{F}) + \left(\mu - \frac{\sigma_A^2}{2}\right) \times T}{\sigma_A \times \sqrt{T}}\right) = N(-DD) \qquad (10)$$

5.2. Regression analysis

Having obtained the probabilities of default for our respective companies, we use panel regression to study the relationship between PD and our main variables of interest. The regression specifications are given in the results section.

Because our dataset has both cross-sectional and time-series properties (i.e. variation over cross-sectional units and over time), panel data analysis is considered to be the most appropriate econometric approach (Wooldridge, 2002). Moreover, according to Baltagi (2005), panel regressions offer many advantages. Selecting this approach (as opposed to estimating individual regressions) is not only less time-consuming, but it also enables us to observe more variation in the data, gives us more degrees of freedom (improved explanatory power) and helps us to get rid of some collinearity problems.

Assuming that heterogeneity is present in the dataset, we need to make some decisions regarding the choice of error component models (i.e. fixed or random effects model) and the choice of dimension in which the respective models should be applied (Brooks, 2014).

[5] Initial values for A_T and σ_A were set as: $A_T = E_T + F_T$ (i.e. value of assets equals the value of equity and debt) and the asset volatility represented by $\sigma_A = \frac{\sigma_E \times E_T}{A_T}$

Furthermore, we run multiple diagnostic tests on our specifications to ensure all potential problems with e.g. heteroscedasticity, non-normality, multicollinearity, residual autocorrelations in cross-sectional units, etc. have been taken into account.

5.2.1. Explanatory variables

As previous studies indicated, the negative influence of Brexit on macroeconomic and financial market variables has been fairly strong. Furthermore, many studies have shown that such variables also influence default probabilities – see for example Dionne et al. (2008), Koopman et al. (2009) or Bonfim (2009). This leads us to believe that Brexit influences default probabilities indirectly, through the changes in macroeconomic and financial market variables. However, macroeconomic variables are not the only determinants of default. Based on previous literature addressing this topic, we have identified a number of firm-specific variables that we aim to later include in our regressions, alongside the most frequently used macroeconomic variables (such as GDP growth, market index returns and risk-free interest rates)[6].

The first, and fairly obvious PD-determinant is the company's profitability. This variable shows the efficiency with which the company uses its funds and is particularly useful for comparing company performance. According to Altman (1986) a profitability indicator, such as Return on Assets (ROA) is a useful PD-determinant because the survival or existence of a company essentially depends on it. Similar results were presented in the study of Grammenos et al. (2008), who found a negative relationship between PD and the Return on Equity (ROE). In our regressions, we will however use a different profitability measure, based on the argumentation of Koller et al. (2015) who consider ROA and ROE to be inadequate measures, which hinder comparability and do not capture the company's operating performance sufficiently. Based on the recommendation of the authors, we use Return on Invested Capital (ROIC) to ensure consistency of our regression results.

Another heavily researched default determinant is the company's size. The research studies of Altman (1968), Dewaelheyns and Van Hulle (2005), as well as Johnson and Melicher (1994) suggest that the size of a company exhibits a negative relationship towards default probability. However, as mentioned in one of the previous sections of this paper, the firm's size effect seems to manifest itself only in the high-default-risk quintile (Vassalou and Xing, 2004) – hence, even though we include this variable in our regressions, we expect it to have insignificant effects.

[6] The choice of macroeconomic variables is based on the studies of Bonfim (2009), González-Aguado and Moral-Benito (2012) as well as the work of Altman and Hotchkiss (2006).

Several studies have also identified the level of financial leverage as one of the determinants of PD (Ohlson, 1980; Kavussanos and Tsouknidis, 2016; Altman, 1968). Highly leveraged firms are inherently riskier and therefore we expect the relationship between this variable and default probability to be positive. In our model, the financial leverage of a company is represented by debt-to-equity ratio.

The last company-specific PD determinant used in our regressions is the company's liquidity. In the study of Petit (2011), this is measured by the current ratio, showing whether a company has enough current assets so as to meet its short-term liabilities. As evidenced by Grammenos et al. (2008), not enough liquidity can lead to default in stress situations. In our case, an adjustment to this liquidity measure is necessary because of the stockpiling tendencies of some companies in preparation for a no-deal Brexit. This short-term increase in inventory represents a bias component in the current ratio calculation and therefore, our liquidity-variable should not include the inventory line-item in order to filter out this artificial liquidity boost. Hence, our regressions feature the more conservative liquidity ratio – quick (sometimes referred to as acid test) ratio.

And finally, we include "Brexit dummy variables" which help us distinguish between pre-referendum and post-referendum periods (as defined by two different sample-splits discussed earlier). For a table outlining expected signs of individual explanatory variables and the reasoning behind those expectations, please refer to Appendix 2.

6. Data collection and critique of data sources

For the purposes of this research study a reasonable amount of data was collected to allow for a robust and possibly representative sample. The final sample consisted of 40 UK companies and 40 EU companies. However, due to large amounts of missing data, three companies from each group had to be removed, leaving the final sample size at a total of 74 companies.[7] The necessary company data used in PD estimations included daily stock prices, number of shares outstanding, total liabilities, short-term liabilities, credit rating classifications and their corresponding median credit spreads, as well as overnight LIBOR and EURIBOR rates as proxies for the risk-free rate. For the regression analysis, we also collected macroeconomic data, as well as information on financial ratios and other company-specific measures, as detailed in previous sections.

[7] List of companies selected for our final sample can be found in Appendix 3.

In choosing the sampling period, we aimed to set the starting-date at least 2 years before the announcement of the Brexit referendum, as well as to avoid the effects of the 2008 financial crisis. At the other end of the timeline, we were aiming for the most recent observations. However, this was somewhat restricted by the usual year-end date of companies' financial statements. The resulting sampling period therefore starts on January 1, 2012 and ends on December 31, 2018. Furthermore, due to the forward-looking nature of the PD measure, where previous month's data are used to estimate the "current" PD, the values entering regressions started with February 2012 (as January data were used to estimate the PD for February).

All companies, to which the data relate, were randomly selected[8] from stock market indices, specifically FTSE 100 and Euro Stoxx 50. This selection of companies was further restricted to include only non-financial companies. The limitations associated with this sampling method have already been discussed in previous sections.

As a main source of market- and company-related data, the following databases were used: Bloomberg, Morningstar and Yahoo Finance. These databases are commonly referred to as secondary data sources and their usage needs to be subject to increased caution and critical appraisal by the researcher (Bryman and Bell, 2013). This cautionary approach is advised mainly because the aforementioned financial data providers commonly standardize raw company data in order to achieve uniformity in how such data are presented on their platforms. This can result in the data being misleading or wrongly interpreted by the user as a result of differing definitions or measurements. We therefore took great care to inspect the reliability of presented information where possible – e.g. by checking that balance sheet data presented by Bloomberg corresponded with financial statements or by searching for the data providers' definitions of financial ratios used in our research paper.

With regard to sources of qualitative data, i.e. existing literature, the same level of caution was applied as with quantitative data. This means that only research articles from peer-reviewed journals, working papers by established authors and widely used university textbooks were used as a basis for our reasoning and modelling in the theoretical sections of this paper.

[8] The random selection of companies was done using an Excel function, which selects random cells from a list (i.e. a list of index constituents) and displays them in another cell.

7. Empirical findings

This chapter aims to present and discuss the results of PD estimations, as well as the results of panel regression analysis in relation to previously stated research hypotheses and existing literature. Additionally, we provide a discussion of diagnostic testing of the regression models driven by the econometric characteristics of the dataset at hand.

7.1. PD estimation results

The resulting PD values produced by our estimations display a number of common characteristics in both (UK and European) subsamples. Majority of companies in our sample exhibit considerably low default probabilities, rarely exceeding 2% for most of the studied period. This can be attributed to the fact that these companies carry low amounts of debt, when compared to the value of their assets. The evidence of this can be found by looking at the averages of debt-to-equity ratio for both subsamples, which remains below 0.5.

Even though the presented values are rather favourable, we need to bear in mind that this research paper is dealing with companies that have the largest market capitalization in their respective financial markets and some of them also belong to the list of companies with largest revenues worldwide (e.g. Glencore, Daimler, BP…). The financial soundness of the companies in our sample is therefore somewhat implied by their index membership and other favourable characteristics.

Furthermore, because the present sample consists solely of non-financial companies which were previously shown to be less strongly affected by Brexit events (Ramiah et al., 2017), the absence of very high default probabilities in our sample appears to be an acceptable result.

A particular feature of interest in the estimation results is the development of the average PD in UK and EU markets over the studied period. By plotting the PD-development for both subsamples together, we can start focusing on the hypotheses stated in this study:

H1: The probability of default (PD) for non-financial UK companies has increased following the announcement of Brexit referendum.

H2: The PD of non-financial UK companies has increased following the announcement of the results of Brexit referendum.

H3: There is a stronger negative effect on PD of non-financial UK companies than for non-financial companies from the EU following the announcement of Brexit referendum.

H4: There is a stronger negative effect on PD of non-financial UK companies than for non-financial companies from the EU following the announcement of the results of Brexit referendum.

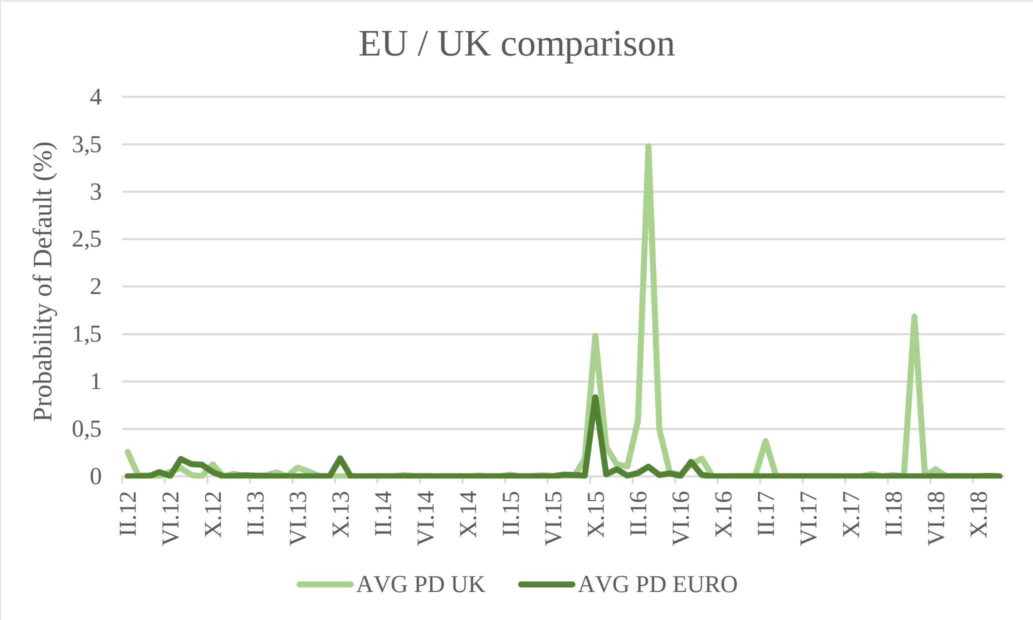

Figure 1 - Average probability of default (%) - comparison between UK and EU companies

As shown in the graph above, the average PD estimated for the UK companies spiked considerably in the aftermath of the referendum announcement (May 2015) and for the second time after the announcement of the referendum results (June 2016). Another noticeable spike occurred at the beginning of 2018, as the main negotiations between the UK and the EU began. As hypothesized, the development in the EU appears to be somewhat smoother, with only one distinct increase in PD after the announcement of the Brexit referendum in May 2015 and a rather weak reaction to the announcement of the referendum result.

Even though these results give us an idea about whether our hypotheses are supported by the data or not, we cannot make direct conclusions just yet because no formal hypothesis testing has been carried out. The purpose of this chart is simply to capture the trends and developments in the estimated PD values and set the scene for the regression analysis.

7.2. Regression analysis

As discussed in the methodology section, we use panel regressions in our analysis. After the removal of companies with missing data from the dataset, we continue working with a balanced panel containing 3071 observations in each subsample (6142 observations in total). Data management and analysis was carried out using MS Excel and EViews econometric software package.

Even though the probability of default (PD) was chosen as a primary subject of analysis in our regressions, we also include outputs of regressions with the distance-to-default (DD) as a dependent variable. This mainly serves as a "robustness test", where we expect to obtain similar results in both sets of regressions (at least in terms of direction of the effects). This expectation is based on the fact that DD is a non-linear transformation of PD and therefore the observed effects should be similar (with a reversed sign)[9]. We also expect additional benefits in the DD-model because non-linear transformations are commonly used to improve the fit of regression models.

The choice of error component models (i.e. fixed/random effects) is yet another important modification which had to be implemented prior to running the final regressions. As mentioned in the methodology section, it is necessary to decide whether to use fixed or random effects as well as the dimension in which these should be used. Following the standard approach, we started by estimating each model with fixed effects and testing for redundant fixed effects, arriving at the conclusion that heterogeneity was present in the dataset and pooled OLS regression was not an option. We then estimated the model with random effects and performed the Hausman test for correlated random effects (included in EViews by default). The results suggested we use random effects for both dimensions in all our models (the H_0 of the Hausman test was not rejected in any of the dimensions).[10]

Having addressed the econometric technicalities of our models, we now move on to the regression specifications. However, instead of stating all four regression equations, we introduce one general equation and add a description of variables that later differ in the individual equations.

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[9] Please see equation (5) for the representation of the relationship between PD and DD.

[10] Because the EViews output of the Hausman test is too long and repeated multiple times, it will not be included in the Appendices. To those interested in the tests performed, as well as their technical side, we recommend referring to Hausman (1978) or Brooks (2014).

$$PD_{it} = \alpha + \beta_1 ROIC_{it} + \beta_2 MARKET\_CAP_{it} + \beta_3 DEBT\_TO\_EQUITY_{it} + \beta_4 QUICK\_RATIO_{it} + \beta_5 RISK\_FREE\_RATE_{it} + \beta_6 INDEX\_RETURN_{it} + \beta_7 GDP\_GROWTH_{it} + \beta_8 BREXIT\_DUMMY_{it} + \varepsilon_{it}$$

We estimate the above equation for each subsample (UK and EU companies) twice, with minor modifications. Firstly, the RISK_FREE_RATE variable differs for the UK and EU subsample, as well as the INDEX_RETURN (taking FTSE 100 monthly returns for the UK and the EURO STOXX 50 monthly returns for the EU companies) and the GDP_GROWTH variable. The most important variable, BREXIT_DUMMY, differs even within the subsamples, splitting the studied period in two ways. For the sake of clarity, these two dummy variables are not included in one regression at the same time but used in two separate regressions.

We should note here that estimating the regressions for each sample separately does not allow us to establish whether the difference between Brexit effects on the UK and EU companies is statistically significant. We simply observe the effects for both markets separately. To test whether there is a significant difference between the effects of Brexit for the UK and EU companies, we joined the two subsamples and estimated the regression equation shown above, while adding a dummy variable distinguishing between UK and EU companies, as well as an interaction term UK_COMMPANY*BREXIT DUMMY to the original specification. The outputs of these supplementary regressions can be found in Appendix 4.

Moving on to the estimation results, it should be noted that the test variable (which is essential for the tested hypotheses) is basically only one (BREXIT_DUMMY), while the other variables act as controls and will be commented on only briefly.

Starting with hypotheses H1 and H3 which are both related to the effect of the announcement of the Brexit referendum, we obtained the following results from our subsamples:

Probability of default

Variable	Coefficient	P-value
C	0.004649	0.9790
ROIC	-0.006358	0.0228
MARKET_CAP_BN	-0.003921	0.0157
DEBT_TO_EQUITY_RATIO	4.18E-05	0.2796
QUICK_RATIO	-0.015563	0.0626
RISK_FREE_RATE	0.443743	0.0827
FTSE_100_RETURN	-0.778239	0.3926
GDP_GROWTH	-0.004569	0.9386
REF_ANNOUNCEMENT	0.200155	0.0632
Adjusted R^2	0.000914	

Distance to default

Variable	Coefficient	P-value
C	12.07160	0.0000
ROIC	0.090839	0.0000
MARKET_CAP_BN	0.044073	0.0000
DEBT_TO_EQUITY_RATIO	-0.001185	0.0055
QUICK_RATIO	0.565167	0.0000
RISK_FREE_RATE	-4.531792	0.0250
FTSE_100_RETURN	13.62787	0.0611
GDP_GROWTH	0.283249	0.6047
REF_ANNOUNCEMENT	-1.955719	0.0267
Adjusted R^2	0.055192	

Table 1 - UK subsample regression output (variables significant at 5% level highlighted)

Probability of default			Distance to default		
Variable	Coefficient	P-value	Variable	Coefficient	P-value
C	0.119230	0.0095	C	8.891697	0.0000
ROIC	-0.007802	0.0261	ROIC	0.124341	0.0000
MARKET_CAPITAL_BN	-0.000249	0.0048	MARKET_CAPITAL_BN	0.008966	0.1238
DEBT_TO_EQUITY_RATIO	0.000126	0.3134	DEBT_TO_EQUITY_RATIO	-0.006855	0.0037
QUICK_RATIO	-0.019410	0.0057	QUICK_RATIO	0.250200	0.4731
RISK_FREE_RATE	0.186896	0.3187	RISK_FREE_RATE	-4.704812	0.0227
EURO_STOXX_50_RETURNS	-0.053844	0.7848	EURO_STOXX_50_RETURNS	22.23983	0.0000
GDP_GROWTH	-0.007710	0.4799	GDP_GROWTH	0.488442	0.1030
REF_ANNOUNCEMENT	0.100648	0.0492	REF_ANNOUNCEMENT	-1.148716	0.0380
Adjusted R^2	0.004754		Adjusted R^2	0.043256	

Table 2 - EU subsample regression output (variables significant at 5% level highlighted)

The regression coefficients for REF_ANNOUNCEMENT variable in both subsamples are shown to support the aforementioned hypotheses. There is a significant positive effect of the announcement dummy variable on PD in both subsamples, implying that the probability of default has increased following the referendum announcement in comparison with the period prior to the announcement (H1). Moreover, the effect in the UK subsample appears to be stronger than in the European subsample (H3). This difference has been, nonetheless, found insignificant by our supplementary regressions.

It is important to note that the effects described here are marginal because even the sample-average PD (as indicated by the intercept) is essentially close to 0% in both cases. Therefore, the discussed effects of the announcement variable can be described as marginal as well.

All the coefficients of other explanatory variables carry the expected signs and, in the case of DD as a dependent variable, majority of them is significant at the 10%, 5% and some even at 1% level. These results are in line with previous research studies introduced in section 5.2.1. of this paper.

The second set of regressions relates to the effects of the announcement of the referendum results, as represented by the dummy variable REF_RESULTS. These regressions are related to hypotheses H2 and H4 and their outputs are presented on the following page:

Probability of default

Variable	Coefficient	P-value
C	0.726559	0.0411
ROIC	-0.007800	0.0097
MARKET_CAP_BN	-0.003494	0.0156
DEBT_TO_EQUITY_RATIO	4.58E-05	0.2751
QUICK_RATIO	-0.014628	0.0765
RISK_FREE_RATE	-0.100203	0.5811
FTSE_100_RETURN	-1.345464	0.1050
GDP_GROWTH	-0.141464	0.1113
REF_RESULTS	0.162580	0.1999
Adjusted R^2	0.000456	

Distance to default

Variable	Coefficient	P-value
C	9.465577	0.0000
ROIC	0.092700	0.0000
MARKET_CAP_BN	0.042408	0.0000
DEBT_TO_EQUITY_RATIO	-0.001182	0.0056
QUICK_RATIO	0.563553	0.0000
RISK_FREE_RATE	-2.605024	0.2245
FTSE_100_RETURN	16.31212	0.0227
GDP_GROWTH	0.803519	0.1692
REF_RESULTS	-0.200068	0.7337
Adjusted R^2	0.053647	

Table 3 - UK subsample regression output (variables significant at 5% level highlighted)

Probability of default

Variable	Coefficient	P-value
C	0.141565	0.0103
ROIC	-0.007638	0.0261
MARKET_CAPITAL_BN	-0.000246	0.0055
DEBT_TO_EQUITY_RATIO	0.000141	0.2928
QUICK_RATIO	-0.019082	0.0090
RISK_FREE_RATE	-0.110475	0.0057
EURO_STOXX_50_RETURNS	-0.182421	0.5221
GDP_GROWTH	-0.005770	0.6554
REF_RESULTS	-0.069616	0.0917
Adjusted R^2	0.004466	

Distance to default

Variable	Coefficient	P-value
C	8.055922	0.0000
ROIC	0.123016	0.0000
MARKET_CAPITAL_BN	0.008715	0.1310
DEBT_TO_EQUITY_RATIO	-0.006943	0.0027
QUICK_RATIO	0.253147	0.4675
RISK_FREE_RATE	6.820602	0.0005
EURO_STOXX_50_RETURNS	24.15056	0.0000
GDP_GROWTH	0.668064	0.0157
REF_RESULTS	4.288774	0.0000
Adjusted R^2	0.052787	

Table 4 - EU subsample regression output (variables significant at 5% level highlighted)

In this case, somewhat different estimation results have been obtained. The main variable of interest, REF_RESULTS, exhibits a positive but statistically insignificant effect on PD in the UK subsample. In the European subsample, on the other hand, we observe a negative significant effect of the result announcement, implying that the referendum results can be described as "good news" for the European companies. The difference in magnitude of Brexit effects between the UK and EU companies has also been found insignificant by the results of the supplementary regressions. Again, it is necessary to stress that the effects observed here are certainly marginal and should be interpreted as such.

As regards the other explanatory variables, much like with the previous set of equations, they push the PD in the expected direction and majority of them is shown to be statistically significant at the 10%, 5%, as well as at 1% level.

Before proceeding to the discussion part, we feel obliged to comment on the very low adjusted R^2 shown in all the regression output tables above. Despite the fact that the aforementioned nonlinear transformation of PD to DD somewhat improved the fit of the model, it still remains far from ideal. It is nevertheless necessary to note that the purpose of our study was not to create a model that would explain all the variation in the dependent variable. As indicated in previous studies (Kadiric and Korus, 2019 or Lozinskaia, 2017) there are many factors and characteristics that may explain the levels of credit risk and because our regressions featured only the most common ones, the resulting adjusted R^2 values are not surprising. Furthermore, this study focuses on measuring the impact of essentially only one specific variable (BREXIT_DUMMY) and therefore, the goodness-of-fit will not be discussed further.

7.2.1. Regression results discussion

Due to the fact that currently, there is only one study which focuses on the effects of Brexit on corporate credit risk levels, it also represents the only point of comparison for our results in terms of the main hypotheses. Despite the general consensus on largely negative effects of Brexit, our results exhibit some deviations from the previous study conducted by Kadiric and Korus (2019), hereinafter referred to as K&K.

In the previous study, only the announcement of referendum results yielded significant coefficients for the Brexit dummy variable (both for the UK and EU companies), while the impact of other Brexit-related events remained weak and insignificant. Our study, on the other hand, showed significant positive effects for the event preceding the results announcement – the announcement of the referendum by the Queen, more than a year before the referendum itself took place.

In the case of the referendum result announcement, our estimations deviated from the original study as well. This was demonstrated mainly in the subsample of EU companies, where K&K found a significant increase in corporate credit spreads (and therefore also levels of credit risk), whereas our study showed that levels of credit risk actually decreased. This “discrepancy” may be due to differences in sample composition (as K&K included financial companies in their sample) but also due to a more recent dataset used in our study which may already account for the effects of company relocations. The authors of the original study admit that the effects of relocations could only be observed at a later point in time, representing an advantage for the European markets.

And finally, a very important difference between the previous and the current study is the described magnitude of Brexit's impact. Whereas K&K observed strong negative impact of Brexit on credit risk, our results point to rather marginal effects. There is certainly a whole collection of explanatory factors for this state of affairs, however, as pointed out in the introductory chapter, the credit risk measure certainly plays an important role. The real-world probability of default used in our study is based on company data and it is therefore relatively immune to the influence of derivatives markets and investors' and traders' sentiment. Corporate credit spreads, on the other hand can be, albeit only slightly, influenced by this sentiment that is being fed daily by the media, politicians and market participants themselves. In other words, the magnitude of Brexit impact is, in our study, described by a more sober, dispassionate measure.

To briefly comment on the effects of the remaining explanatory variables on our default risk measure – again, most of the variables behave in the expected way and replicate the results of previous studies, including the GDP growth which appears to lack statistical significance in all but one of our regressions. This result is not uncommon in the previous literature – see for example González-Aguado and Moral-Benito (2012). It is also worth mentioning that in all regressions, the "strongest effect" (in nominal terms) is exhibited by the variable INDEX_RETURN – which is also in line with the findings reported by Norden and Weber (2009).

7.3. Diagnostic testing

In a regression analysis, there is a variety of potential issues related to the chosen variables which, if left untreated, could cause our estimates to be biased, inefficient or simply wrong. These issues are addressed by performing diagnostic tests and adjusting the regression specifications or modifying the variables accordingly.

Some of the issues that usually appear in basic OLS regression are, in case of panel regressions, resolved straight away – e.g. possible residual autocorrelation in one or both dimensions is handled by using fixed or random effects in the respective dimension(s). Similarly, non-stationarity is usually not an issue in panel regressions, as long as the number of periods in each cross-sectional unit does not heavily exceed the number of cross-sectional units. Additionally, because all our models were already specified including the White diagonal standard errors, the problem of heteroscedasticity has also already been resolved.

The remaining most relevant diagnostic tests to detect other econometric issues therefore are non-normality test and multicollinearity test, the outputs of which can be found in Appendix 5 and 6.[11]

Testing for non-normality is carried out by examining the distribution of residuals (histogram) and the significance of the Jarque-Bera statistic. In all four models, we encounter the issue of non-normal distribution of the residuals. A remedy recommended by Wooldridge (2013) is to transform the dependent variable e.g. by taking logs, estimate the regression again, using the log as a dependent variable and performing the non-normality test again. However, even after having done this, the Jarque-Bera statistic improved only slightly and the null hypothesis of normality was again rejected. The model was therefore re-set to the original specification (without the logged variable), based on the reasoning of Lumley et al. (2002) stating that despite the non-normal distribution of residuals, the regression coefficients can be considered valid if the sample is sufficiently large.

The second (and last) test performed on the current dataset was concerned with multicollinearity. For both subsets of data, a correlation matrix was constructed and correlations between independent variables were searched for.[12] In any of the data-subsets, multicollinearity issue was not detected, and no variables had to be excluded from our models.

8. Conclusions

The purpose of this study was to determine and quantify the extent to which Brexit-related events affected the levels of corporate credit risk in the UK and the EU financial markets. Moreover, because this specific topic has not been researched as extensively as other Brexit-effects on financial markets, this research study also aimed to extend the existing literature and advance the understanding of the presented phenomena.

The credit risk measure selected for the purposes of this study was the probability of default (PD), based on the identified shortcomings of other measures used in previous studies. An extensive data-collection process resulted in a balanced set of daily data for a total of 74 companies over a 7-year period.

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[11] For the sake of brevity and due to similar results for models with PD and DD, only the outputs of diagnostic tests for “DD-models” are reported in the appendices.

[12] Using a well-known and widely used rule of thumb, stating that any correlation exceeding ±0.8 should be addressed.

We used Merton's structural model to obtain the PD estimates and, finally, included them in panel regressions as a dependent variable, together with a set of explanatory variables and Brexit dummy variables.

The main research questions and subsequently derived hypotheses were concerned with the magnitude of change in the default probabilities following the announcement of the Brexit referendum itself, as well as its results, and their comparison between the UK and EU markets.

8.1. Summary of results

The empirical results suggest that the expected effects of Brexit on the levels of credit risk in the UK and the EU generally correspond with those found in previous studies. The announcement of the Brexit referendum has had a significant positive effect on the probability of default in both studied markets.

The announcement of the result of the referendum, however, did not affect default risk in a way that previous studies describe. While the effects in the UK market came out statistically insignificant, yet similar to the previous case (positive effect on PD), the EU markets exhibited a statistically significant decrease in default risk (negative effect on PD). The possible reasons for such contradiction to the existing literature are likely the sample selection, exclusion of financial companies or more recent dataset which accounts for the relocations of UK companies to the EU.

In more general terms, the effects of Brexit on the levels of credit risk, described by many as rather adverse, seem to be quite small in magnitude. Consequently, it may be the case that the real effects are artificially inflated by the market sentiment as well as other external factors.

8.2. Practical implications

The presented results of our research study naturally have implications for companies, policymakers and even for economies. Moreover, these implications can provide guidance on how to prevent or deal with possible adverse outcomes and should form an integral part of the "take-away" message from this research paper.

Apart from the more general implications of Brexit events which have also been mentioned in previous research studies, such as the decrease of the UK's GDP (Baker et al., 2016) or the weakening safe-haven status of the UK (Kadiric and Korus, 2019), we can point out very specific implications related directly to credit risk.

The increase in default probabilities of companies following the studied Brexit events essentially translates to higher credit risk – for companies, this usually means worse financing terms and generally more expensive debt (Antunes et al., 2016). In times of increased uncertainty following Brexit, this might lead to lower investment activity as the companies could refrain from taking on new debt to finance their projects and developments. Some preliminary surveys have already hinted at such development – e.g. a survey conducted by Harvard Business Review (Bloom et al., 2019) indicated that there has been a 6% decrease in investment activity among UK companies between the years 2016 and 2017. These results are likely to be repeated for later years as the uncertainty about future Brexit events is still evident and no final decisions have been made nor any deals were negotiated.

Our research nevertheless brings evidence of Brexit effects being rather short-lived as well as marginal. As the graph in section 7.1. has shown, the sudden increases in PD as a reaction to Brexit events returned to pre-Brexit levels after a certain period of time. This suggests that Brexit should not represent a remarkable "threat" in the long term.

Companies have diverse tools to adjust to the post-Brexit conditions and retain their levels of business – e.g. by pressuring the government into a negotiation of a favourable deal with the EU or by searching for alternative markets as well as by establishing out-of-UK subsidiaries or relocating their entire operations. As shown in Appendix 1, the UK companies have already begun using these "tools" and appear prepared for multiple Brexit scenarios.

8.3. Suggestions for future research

Due to the aforementioned lack of research concerning credit risk levels in relation to Brexit, this particular field of inquiry still has a lot of potential in terms of further research.

Future studies may focus on corporate credit risk pertaining to small cap firms in the light of Brexit events. As mentioned in the limitations section, large cap firms such as those used in the present study, have more resources and more international reach, thus the observed impact of Brexit may be much more negative.

The focus of future studies could also be shifted to financial companies and the consequences of their relocations from the UK to European countries/markets. Based on the results of previous studies, indicating that UK financial companies experienced the strongest effects of Brexit events, the aforementioned modified Merton model could be used to track the development of default probabilities in the UK financial sector.

Furthermore, since the present study revealed a possible effect of relocations to the EU, it could be interesting to look at whether this notion could be confirmed and what would be the reaction of the European financial markets.

Another suggestion would be to use other measures or indicators of default risk because PD estimation is a very data- and time-intensive process which consequently has a restrictive impact on the sample size. The usage of default risk indicators which can be obtained from various financial data platforms, such as Altman Z-score or Ohlson O-score would greatly reduce the time needed to obtain results.

And finally, because lots of attention is aimed at UK companies, but less so on the EU ones, it might be beneficial to explore how specific sectors in the EU with the highest exposure to the UK (in terms of trade or financial services) reacted and continue to react to the Brexit events.

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10. Appendices

Appendix 1 - Reactions of UK companies to the prospect of Brexit (source: Bloomberg Terminal Market News)

	Company Name	Industry	Preventive Action Taken
Relocations and factory closures	Admiral Group	Insurance	Moving operations to Spain
	Discovery	Media	Setting up new HQ in Europe
	Vauxhall	Automotive	Considering factory closures in Britain
	UBS	Finance	Moving billions worth of assets to Germany
Stockpiling	Airbus	Transport	Stockpiling parts to maintain production rates
	Centrica	Energy	Increasing stocks of EU-sourced equipment
	Coca-Cola	Food and Drink	Stockpiling key ingredients
	Imperial Tobacco	Tobacco	Holding more stocks to mitigate supply disruptions
Plans on hold	Jaguar Land Rover	Automotive	temporarily paused production in Wolverhampton engine factory
	Nissan	Automotive	Plans to make X-Trail SUVs in UK put on hold
	Telefonica	Telecommunications	Holding-off IPO of its UK unit
	Smurfit Kappa	Packaging	Plans to build a 50m-pound factory in the UK abandoned
Staff layoffs and relocations	Citigroup	Finance	Moving 250 jobs out of the UK
	Jaguar Land Rover	Automotive	Cutting 4500 jobs globally
	Morgan Stanley	Finance	Moving 280 jobs to Frankfurt and Paris
Warnings	Airbus	Aerospace	Warning of having to move future investments out of the UK
	Burberry	Retail	Warning of increased costs of materials and logistic delays
	Philips	Health	Warning of UK factory shutdown in case of no-deal Brexit

Appendix 2 - Regression variables and their expected signs

Variable	Expected sign	Proxy for	Justification
ROIC	-	Company profitability	Higher profitability means lower PD (lower default risk)
MARKET_CAP	-	Size of the company	Larger company less likely to default (lower PD)
DEBT_TO_EQUITY	+	Company's leverage	Higher leverage means higher PD (higher default risk)
QUICK_RATIO	-	Company's liquidity	Higher liquidity means lower PD
RISK_FREE_RATE	+	Short-term interest rates	Increasing ST interest rates mean worse compensation for risk in the longer-term and expectations of recession among investors; PD increases (higher default risk)
INDEX_RETURN	-	Overall health of the stock market	Prosperous stock market means lower PD (lower default risk)
GDP_GROWTH	-	Overall health of the economy	Prosperous economy means lower PD (lower default risk)
BREXIT_DUMMY	+	Brexit events	Brexit uncertainty means higher PD (higher default risk)

Appendix 3 - List of companies included in the final sample

Industry sector	UK companies	EU companies
Communication services	Vodafone Group PLC BT Group PLC Pearson PLC ITV PLC	Telefonica SA Vivendi SA Orange SA Deutsche Telekom AG
Consumer discretionary	Whitbread PLC InterContinental Hotels Group PLC Burberry Group PLC Next PLC Ocado Group PLC Kingfisher PLC Marks & Spencer Group PLC	EssilorLuxottica SA LVMH Moet Hennessy Louis Vuitton SE Kering SA Bayerische Motoren Werke AG Volkswagen AG adidas AG Daimler AG
Consumer staples	Diageo PLC Unilever PLC Tesco PLC Reckitt Benckiser Group PLC J Sainsbury PLC	Danone SA Koninklijke Ahold Delhaize NV Unilever NV Anheuser-Busch InBev SA/NV
Energy	BP PLC	TOTAL SA Eni SpA
Health care	AstraZeneca PLC GlaxoSmithKline PLC Smith & Nephew PLC Hikma Pharmaceuticals PLC	Koninklijke Philips NV Sanofi Bayer AG Fresenius SE & Co KGaA
Industrials	BAE Systems PLC Rolls-Royce Holdings PLC Melrose Industries PLC Intertek Group PLC Spirax-Sarco Engineering PLC easyJet PLC	Vinci SA Safran SA Schneider Electric SE Airbus SE Siemens AG Deutsche Post AG
Information Technology	Micro Focus International PLC Sage Group PLC/The	ASML Holding NV Amadeus IT Group SA Nokia OYJ SAP SE
Materials	Glencore PLC Johnson Matthey PLC Smurfit Kappa Group PLC DS Smith PLC Antofagasta PLC	Air Liquide SA CRH PLC BASF SE
Utilities	National Grid PLC SSE PLC Severn Trent PLC	Iberdrola SA Engie SA Enel SpA

Appendix 4 - Supplementary regressions

Referendum announcement effects

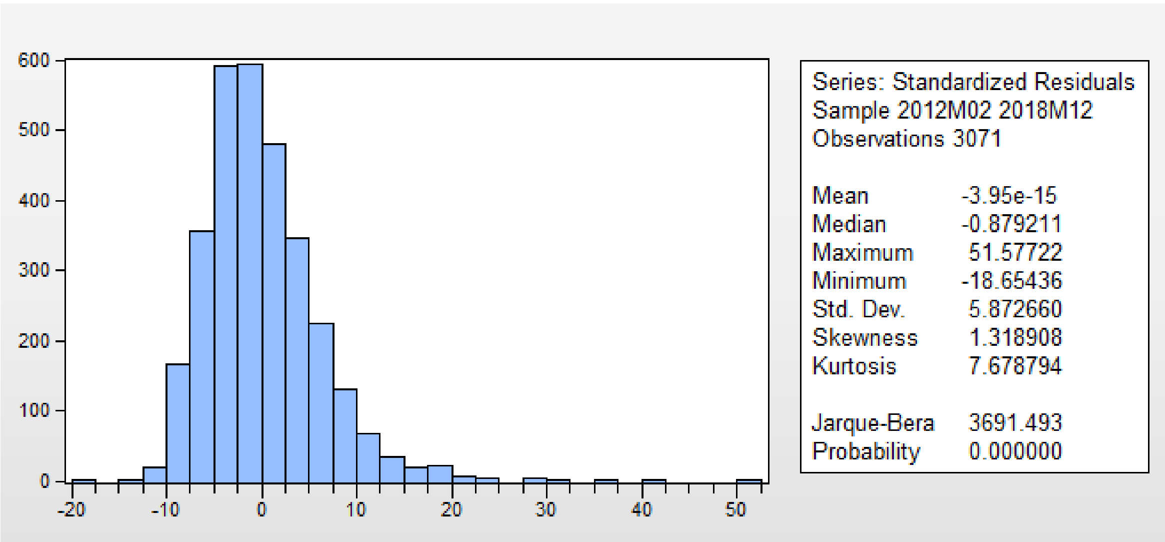
Variable	Coefficient	Prob.
C	0.158830	0.0013
ROIC	-0.006197	0.0060
MARKET_CAP_BN	-0.001532	0.0056
DEBT_TO_EQUITY_RATIO	4.81E-05	0.2264
QUICK_RATIO	-0.011753	0.1191
RISK_FREE_RATE	0.430585	0.0620
INDEX_RETURN	-0.045894	0.8122
GDP_GROWTH	-0.002797	0.8750
UK_COMPANY	0.188725	0.1830
REF_ANNOUNCEMENT	0.057147	0.5456
UK_COMPANY*REF_ANNOUNCEMENT	0.138655	0.3122

Referendum results effects

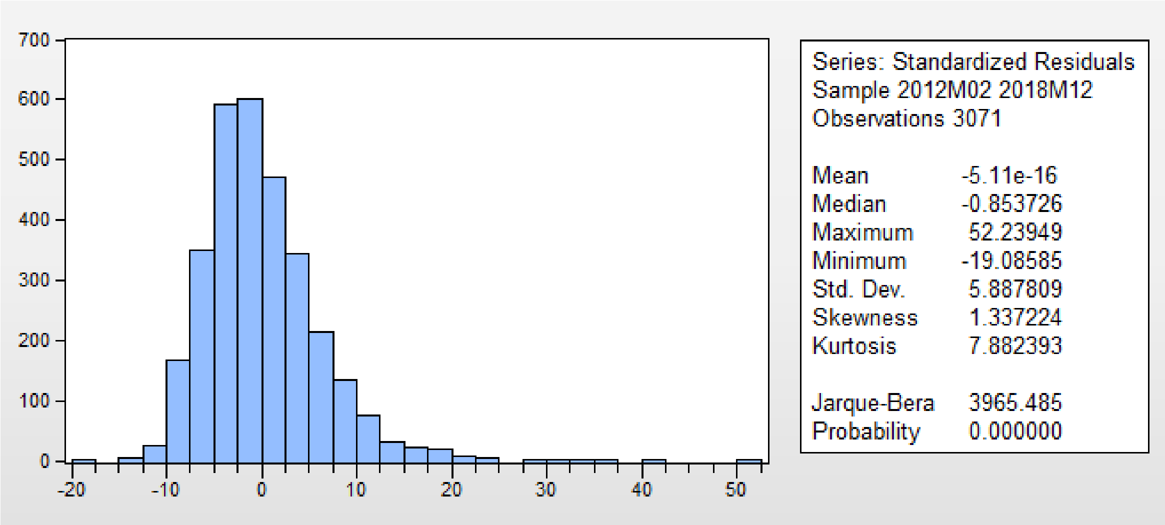
Variable	Coefficient	Prob.
C	0.213119	0.0007
ROIC	-0.007433	0.0022
MARKET_CAP_BN	-0.001293	0.0044
DEBT_TO_EQUITY_RATIO	4.42E-05	0.2685
QUICK_RATIO	-0.010359	0.1709
RISK_FREE_RATE	0.032669	0.8338
INDEX_RETURN	-0.224087	0.0249
GDP_GROWTH	-0.040673	0.0830
UK_COMPANY	0.174923	0.1841
REF_RESULTS	0.054749	0.2939
UK_COMPANY*REF_RESULTS	0.058676	0.6138

Explanation: Our main variables of interest in these regression outputs are the interaction terms (highlighted) at the bottom of the table. Their purpose is to show whether there is a statistically significant difference between the effects of Brexit on the UK and the EU companies. Despite showing a positive effect of Brexit events on PD of the UK companies, they remain insignificant. As for the control variables, their coefficient signs are again as expected, with varying degrees of significance.

Appendix 5 - Results of non-normality and multicollinearity testing (UK subsample)



Part 1 – Regression with REF_ANNOUNCEMENT dummy variable

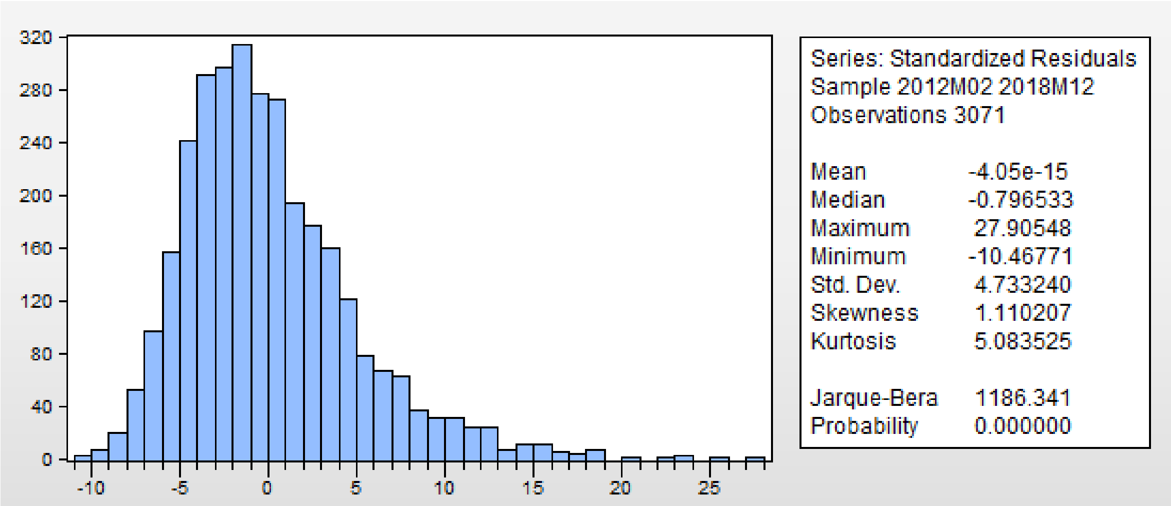


Part 2 – Regression with REF_RESULTS dummy variable

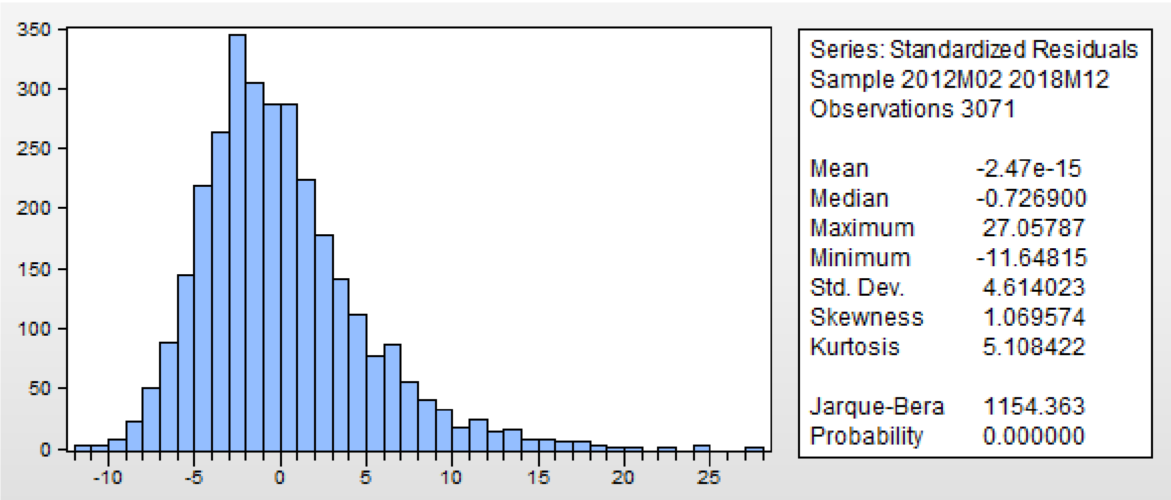
Covariance Analysis: Ordinary
Date: 05/23/19 Time: 13:46
Sample: 2012M02 2018M12
Included observations: 3071

Correlation Probability	DEBT_TO_EQUITY_RATIO	FTSE_100_RETURN	GDP_GROWTH	MARKET_CAPITAL_BN	QUICK_RATIO	RISK_FREE_RATE	ROIC
DEBT_TO_EQUITY_RATIO	1.000000 -----						
FTSE_100_RETURN	0.009374 0.6036	1.000000 -----					
GDP_GROWTH	0.029123 0.1066	-0.039831 0.0273	1.000000 -----				
MARKET_CAPITAL_BN	0.055856 0.0020	-0.000232 0.9897	-0.003514 0.8457	1.000000 -----			
QUICK_RATIO	-0.099398 0.0000	-0.014164 0.4327	-0.007850 0.6637	-0.135161 0.0000	1.000000 -----		
RISK_FREE_RATE	0.011875 0.5106	-0.146698 0.0000	0.002737 0.8795	-0.021837 0.2264	0.025133 0.1638	1.000000 -----	
ROIC	0.308708 0.0000	0.006258 0.7288	0.062018 0.0006	-0.085149 0.0000	0.009672 0.5921	0.046054 0.0107	1.000000 -----

Appendix 6 - Results of non-normality and multicollinearity testing (EU subsample)



Part 1 – Regression with REF_ANNOUNCEMENT dummy variable



Part 2 – Regression with REF_RESULTS dummy variable

Covariance Analysis: Ordinary
Date: 05/23/19 Time: 15:51
Sample: 2012M02 2018M12
Included observations: 3071

Correlation Probability	DEBT_TO_EQUITY_RATIO	EURO_STOXX_50_RETURNS	GDP_GROWTH	MARKET_CAPITAL_BN	QUICK_RATIO	RISK_FREE_RATE	ROIC
DEBT_TO_EQUITY_RATIO	1.000000 -----						
EURO_STOXX_50_RETURNS	0.005903 0.7437	1.000000 -----					
GDP_GROWTH	0.034697 0.0545	-0.109735 0.0000	1.000000 -----				
MARKET_CAPITAL_BN	0.118424 0.0000	-0.003977 0.8256	0.217777 0.0000	1.000000 -----			
QUICK_RATIO	-0.259943 0.0000	0.018087 0.3163	0.017407 0.3349	-0.066777 0.0002	1.000000 -----		
RISK_FREE_RATE	-0.052938 0.0033	0.083083 0.0000	-0.762008 0.0000	-0.206013 0.0000	-0.023926 0.1850	1.000000 -----	
ROIC	-0.104602 0.0000	0.005077 0.7785	-0.044909 0.0128	0.120767 0.0000	-0.116875 0.0000	0.052734 0.0035	1.000000 -----