The Effect of Brexit on the Probabilities of Default of the FTSE 100's Companies

Inês Margarida Frazão de Almeida Miguel

Dissertation written under the supervision of professor Nuno Silva

Dissertation submitted in partial fulfilment of requirements for the MSc in Finance, at the Universidade Católica Portuguesa, January 2022.

Title: The Effect of Brexit on the Probabilities of Default of the FTSE 100's Companies
Author: Inês Margarida Frazão de Almeida Miguel
Keywords: Probabilities of Default, Brexit, Maximum Likelihood Estimation, Structural Credit Risk Models

Abstract

The main goal of this dissertation is to understand whether Brexit had any impact on the probabilities of default of the FTSE 100's companies, as well as to perceive if this impact was any different when considering only firms that are a part of the financial sector. In this research, the firms' distance to default was computed using the Merton Model, calibrated applying the Maximum Likelihood Approach (Duan, 1994). Then, it was studied whether the distance to default changed more than expected in a number of days, following the classification performed by Korus and Celebi (2019). Two regression analysis were performed. The first one took as dependent variable the daily change in firms' distance to default, computed from the probabilities of default previously obtained. As explanatory variables, a dummy variable comprising the Brexit-related event days was considered along with several control variables. Using a sample of 56 FTSE 100's companies, during the period of January 2013 and December 2020, the Brexit dummy was not found to be significant at a 5% level. In the second regression, the Brexit dummy variable was considered only for the financial sector firms. Again, the Brexit dummy was not found to be significant at a 5% level. Consequently, this dissertation was not able to show the existence of a significant relationship between Brexit and the probabilties of default of the FTSE 100's companies.

Título: O efeito do Brexit nas Probabilidades de Falência das empresas do FTSE 100

Autora: Inês Margarida Frazão de Almeida Miguel

Palavras-Chave: Probabilidades de Falência, Brexit, Estimação de Máxima Verossimilhança, Modelos Estruturais de Risco de Crédito

Resumo

O objetivo desta tese consiste em compreender o impacto causado pelo Brexit nas probabilidades de falência das empresas do FTSE 100, bem como analisar se este foi diferente quando se tem em consideração apenas se essas empresas fazem parte do sector financeiro. Nesta dissertação, as distâncias de falência de cada empresa foram calculadas usando o modelo de Merton, calibrado através da aplicação do Método de Máxima Verossimilhança (Duan, 1994). Posteriormente, foi estudado se esta métrica teria uma variação maior do que o esperado em certos dias, seguindo a classificação dos autores Korus and Celebi (2019). De modo a calcular este impacto, duas regressões foram feitas. A primeira assume como variável dependente a variação das distâncias de falência, obtidas através das probabilidades de falência previamente calculadas. Relativamente a variáveis explicativas, uma *dummy* representativa dos dias relacionados com o Brexit foi considerada, juntamente com outras variáveis de controlo. Através de uma amostra de 56 empresas pertencentes ao índice FTSE 100, entre janeiro 2013 e dezembro 2020, a *dummy* Brexit não foi considerada significativa para um nível de confiança de 5%. Relativamente à segunda regressão, a *dummy* Brexit teve em conta apenas o sector financeiro. Novamente, esta a *dummy* não foi considerada significativa a um nível de 5%. Consequentemente, esta dissertação não conseguiu provar a existência de uma relação significativa entre o Brexit e as probabilidades de falência das empresas do FTSE 100.

To everyone in my life…

Table of Contents

1. Introduction

Brexit Background

On Thursday 23 June 2016, against the advice of former Prime Minister David Cameron and his government, nearly 52% of the United Kingdom's population voted in favour of leaving the European Union, hereby initiating the Brexit process. Due to several bureaucratic and political issues, only as recent as of 31 January 2020 did the UK withdraw from the EU after 47 years of membership, making it the first of the 27 to leave this union.

"Some people think that it [Brexit] is the end of the world. It's not. On the contrary, it's a massive opportunity for this country." – *Boris Johnson*

Despite being mainly perceived as a political event, during this four and a half years of uncertainty surrounding a "deal, no-deal" Brexit, the UK has seen several severe negative impacts on its economy, especially on its stock market (Ramichet et al., 2017). Only one day after the announcement (24th June 2016), the Pound Sterling was down 10% in comparison to US Dollar and 7% in comparison to Euro, and the FTSE 100 - index that follows London Stock Exchange's largest 100 companies by Market Capitalization - had fallen by 3%. Furthermore, in January 2021, the FTSE 100 was replaced as Europe's largest stock market, showing the strong position in which the UK standed as a member of the EU. In addition to this, the effects of Brexit were not only exclusive to the UK, as European countries were also severely impacted by this event. Like the FTSE 100, European stock market indices were also part of the collateral damages of Brexit, suffering a severe impact (Belke et al., 2016). However, this does not describe the full extent of what has already occurred due to this event. Its consequences were impactful, especially when we consider the decline in the confidence and perception of the stability of the UK, causing many companies to flee from it and look for another place to set their hub in Europe. This led not only to a neverseen relocation of almost 450 financial service companies, but also funds that amount up to £100 billion.

However, researchers believe that this event will not only have short-term consequences, but also severe long-term ones, such as a decline in UK's overall productivity (Gourinchas and Hale, 2017) – a key representation of economic growth and competitiveness. This display of short-term impacts of Brexit can all be translated into a sharp decline in UK's in its whole stability as a country, as well as in its influence in the banking and finance industry (Stoupos and Kiohos, 2021).

Motivation

Since this is a rather recent event, there is a lack of published research, and the currently existing one focuses mainly on analysing the short-term economic impact of Brexit on topics that are usually perceived as being pivotal by the masses, such as stock returns (Oehler, Horn and Wendt, 2017) and macroeconomical factors like GDP level (Baker et. al, 2016), leaving behind what I believe to be one of the most interesting and impactful topics of all to analyse – Credit Risk.

This dissertation aims to understand the impact of Brexit on the Credit Risk of the FTSE 100's companies, using the well-known Merton Model estimation. More specifically this research aims to understand whether the perception of credit risk of these companies was significantly affected by key news related to Brexit. By using this model, this research is able to understand the daily changes. This is particularly important as other models, such as credit ratings, do not carry this advantage. Since the models' origin (1974) several authors have proposed different methods in order to calibrate it, aiming to improve its accuracy. However, most of them fail to be consistent with the original model as well as to originate confidence intervals for the estimation parameters. In this dissertation the calibration method chosen was the Maximum Likelihood Approach (Duan, 1994) as it adresses these issues that other approaches are unable to accomplish. Unfortunately, no model is fully able to achieve perfection. In the case of the Maximum Likelihood Approach, it produces rather large confidence intervals for the expected asset return. This is a parameter that is relevant in the asset process under the true probability measure but does not appear in equity formulas derived under the risk-neutral measure. In order to overcome this, this research will set the expected asset return in accordance to the Capital Asset Pricing Model (CAPM), following Sharpe (1970), in an attempt to improve the precision of the parameters estimated. A linear regression will then be computed using the daily distance to default as the dependent variable, two Brexit dummies and several variables of interest, in order to fully understand the impact of Brexit on FTSE 100.

Korus and Celebi (2019) studied the impact of Brexit on the British pound exchange rates. In their research they analysed the impact of several event days regarding Brexit, in accordance to Walker (2018), whilst having as the dependent variable the change of the exchange rate of the British pound *vis-à-vis* the euro. This dissertation is then an extension of the authors' work, but taking the probability of default as the dependent variable.

Taking all of this into consideration, with this disseration I expect to fully be able to answer the following research questions:

- ***H1:*** *Key news regarding Brexit increased the probability of default of the FTSE100 companies.*
- ***H2:*** *The probabilities of default of FTSE 100's companies in the financial sector were more impacted by Brexit than those of other sectors.*

Thesis Outline

Throughout the remainder of this dissertation the subsequent structure will be followed. Chapter 2 reviews the existing and publicly available literature regarding the effects of Brexit on the UK. Chapter 3 presents the Merton model. Chapter 4 displays the data and proposed regression. Chapter 5 presents the results obtained. Chapter 6 introduces the main limitations of this thesis. Finally, Chapter 7 discusses the conclusions obtained.

2. Literature Review

Credit Risk

In order to understand credit risk we must first understand the meaning of default – failure to repay a debt on a loan or a security. This might arise due to the borrower's inability to make the required interest or principal payments on its debt, or because it violates a debt covenant (Berk and DeMarzo, 2017). Credit risk can therefore be defined as "the risk that counterparties in loan transactions and derivatives transactions will default" (Hull, 2018).

There are two main approaches to measure credit risk: reduced-form models and structural models. While reduced-form models assess endogenous variables in terms of observable exogenous variables, structural models frequently include unobservable parameters and are derived from theory. Structural models have a theoretical structure in which there is a reason for default to occur and the determinants are naturally derived from this theoretical structure, whilst in reduced-form models there is no clear reason for default and the determinants simply aid in quantifying the probability of default.

Credit ratings are offered by the main rating agencies, such as Moody's, S&P and Fitch. These scores aim to reflect the creditworthiness of corporate bonds by creating categories based on rating classes, centred around financial strength, forecasts and past history. The Investment grade class can be translated as "good" borrowers, meaning lower risk due to a lower probability of default, typically BBB- (Baa3) or above. Speculative grade, BBB- (Baa3) or below, are perceived as "bad" borrowers, as this rating implies that the company is less likely to pay back its creditors when in comparison to an investment grade company. Unfortunately, ratings are more often than not only assigned to large and publicly traded companies, leaving out several firms that the use either reduced-form or structural models in order to obtain their ratings.

One of the reduced-form approaches used to assess firms' credit risk is linear discriminant analysis – using financial rations to distinguish between "good" and "bad" firms – being the Altman's Z-Score[1] (Altman, 1968) the most popular discriminant score. According to this model, the higher the score, the less likely is for a company to default. Regression models (similar to linear but with more recent methodologies) and Inductive models (based on

[1] Despite its simplicity and accuracy, Altman's Z-Score is perceived as being rather backward-looking due to being based on historical data. Consequently, it assumes a fixed weight allocation, when in fact the effect of any variable is more than likely to change over time.

structural characteristics of the firm driven by economic theory) are other two more complex types of credit scoring models also used to compute probabilities of default.

However, Altman and Saunders (1996) argue that there are 3 sources of criticism to these models. First, they believe that linear probability assumptions are most likely not accurate for the model, as real-world conditions are non-linear, consequently leading to a less accurate forecast in comparison to models that relax the underlying assumption of linearity amongst explanatory variables. Furthermore, they consider that some approaches are far too linked to a theoretical model. Finally, since they are all based on book value data, they fail in capturing more subtle and fast-moving changes in borrower conditions.

Machine Learning

More recently, machine learning models have been gaining popularity by using advanced analytical techniques that enable the automation of some human-held activities. Machine learning can be defined as the "branch of artificial intelligence that allows computers to learn without being explicitly programmed" (Hull, 2018).

Based on the work of Hykin (1999), neural networks are machine learning systems centered around the model of a biological neuron. The premises for this assumption are that as the biological neural network changes itself to perform cognitive tasks, the artificial neural networks can modify their internal parameters to perform computational tasks.

There are 3 main types of machine learning mechanisms: supervised learning (involves linear and logistic regression); unsupervised learning (involves clustering techniques); reinforcement learning. In the first one, the computer is given data both regarding the inputs and the desired outputs and develops rules to map them. As for unsupervised learning, the computer aims to find the structure or the hidden patterns in data. In the final type of machine learning, the computer program interacts with a dynamic environment to perform a certain goal. Reinforcement learning trains the network as it introduces both prizes and penalties according to the network response.

According to Angelini et al. (2007), the main advantage of neural network systems is that the derived model does not make any assumption on the relationships among input variables. However, there is a theoretical limit of these models as they are black-box systems and there is a lack of transparency of the resulting models. Regarding their application to credit risk, despite being able to achieve a high predictive accuracy rate, they lack in the reasoning being their decisions and the estimated credit-scoring models fail in successfully integrating the actual decision environment.

Another vastly used machine learning technique is decision trees, for which there are two major groups: classification and regression trees. Within the classification trees the response variable is categorical, either assuming Yes/1 or No/0, while on the regression trees the response variable is either continuous or numerical. The main difference among these two types of decision trees is that classification trees are built with unordered values with dependent variables while regression trees take ordered values with continuous values. Furthermore, regression trees have 3 main advantages: unbiased splits; each node contains a single regression model fit; few limitations for its algorithms. In 2006, Simha and Satchidananda discovered that these methods are not only of simple understanding, but also provide good results, with an overall default precision of 90%.

A more popular approach is the use of Support Vector Machine (SVM). This machine learning algorithm can be applied for both classification and regression tasks, but is more commonly used for the former. Unlike neural networks, in SVM the solution does not get trapped in local minima. According to Danenas et al. (2011), this model relies on identifying special data points (support vectors) that separate the provided cases by transforming input space into linearly separable feature space and later answering the classification question.

Structural Models

Structural models distinguish themselves by being forward-looking and theoretically sound, whilst using securities prices as an input. The origin of this approach can be traced back to Black and Scholes (1973) and Merton (1974), when the authors developed a new approach, under certain assumptions, in order to estimate probabilities of default. This approach assumes that shareholders have an European call option on the firms' assets, whose strike is equal to its debt. This model will be further discussed in the next Chapter.

Several models have since then been implemented in order to try to deal with some of the gaps of the original Merton model. Black and Cox (1976) developed an extension to Merton model in which they let default occur at any time when the value of the assets falls below a certain threshold K[2], with the most famous one being the exogenous model associated with covenants. This differs from the original model as Merton assumes that default can only occur at maturity.

[2] Threshold K is associated with the minimum value of Assets enforced by a bond covenant.

In 2002, Brockman and Turtle proposed the use of down-and-out call[3] (DOC) to model equity with strike equal to debt. Leland (1994) and Leland and Toft (1996) extended the model and define that equity is modelled as a perpetual DOC, with strike equal to default point. Furthermore, the authors discuss that in order to compute the optimal capital, factors such as taxes, bankruptcy costs and payout rates must be taken into consideration.

Structural models have a few drawbacks. Particularly, they fail by assuming that capital markets are reasonably efficient and that movements in the assets' prices are informative, leaving room for improvement by further research.

Nonetheless, structural models such as the Merton model, the simplest one, are seen as the foundation for Moody's KMV, which aims to address the original model's limitations: simplistic debt structure; normally distributed returns; difficulties in estimating the asset value and its volatility. KMV computes the default point[4] by taking into account that firms have debt with differing maturities. This approach analyses the distance-to-default through an empirical distribution rather than a normal one. However, this tends to result in higher probabilities of default when Merton's output is close to 0, and lower probabilities of default when the output of the Merton model is too high.

Brexit's consequences

As previously mentioned, we must understand that Brexit is a rather recent event. Thus, there is an obvious lack of both published research articles and information regarding this topic. This is even more accentuated by the fact that credit risk is not perceived as the most appealing topic to analyse by the vast majority of researchers when in comparison to macroeconomic factors and stock returns - research topics of most of the available articles. Nonetheless, taking all of the available research into account, most authors agree that the expected effects of Brexit are negative and substantial.

The political uncertainty surrounding Brexit can be credited as its main pitfall. Baker et al. (2016) conducted research using some of the main movements in policy to date, such as 9/11 attacks and the failure of Lehman Brothers, in order to understand their impact in economic uncertainty, discovering that they are indeed linked to greater stock price volatility. I strongly believe that Brexit can also be perceived as an important movement in policy, hereby implying

[3] Exotic option based both on strike price and barrier price. The payout of this option is then determined by how its price behaves in comparison to the previously designated barrier price.
[4] Level at which a company is assumed to enter in default.

its association with an increase in stock price volatility. What is more, this impact might not even be coherent amongst different industries. Boutchkova et al. (2012) argue that the effect on volatility depends on the industry the company is in. Industries that rely more on trade, contract enforcement and labour are the ones to show greater return volatility when local political risks are higher. This spikes curiosity as it leads us to believe that this political situation might have led to a heterogenous impact across the different sectors, worth analysing whether the assumption of the financial one being the most affected still holds.

In 2016, Raddant analysed that the volatility in the UK market, after the Brexit referendum peaked, which can be explained by the increase in uncertainty surrounding the "deal, no-deal" situation the countries involved were facing. However, the author also shows that it had fallen to its pre-vote levels within 3 weeks, with the industrial sector having the fastest recovery and the financial sector the slowest. This is also in line with the discrepancy in sectors analysed by Boutchkova.

Taking into account the fact that this dissertation will follow the approach of the Merton Model, volatility is of utmost importance, as an increase in volatility is expected to have a negative impact on the risk of a company, potentially leading to an increase in its probability of default. Furthermore, Caporale et al. (2018) applied long-memory techniques in order to understand the impact of Brexit on the FTSE100 Implied Volatility index, concluding that there were significant changes in the degree of persistence – measure of uncertainty. When considering more long-term focused studies, Bloom et al. (2019) argue that Brexit generated a large, broad and long-lasting increase in uncertainty.

What is more, according to the research of Kadiric and Korus (2019), the announcement of the Brexit referendum is associated with increasing credit spreads in both the UK and Euro Area, being the former the most affected. This is particularly interesting because credit spreads are a measure of the risk of default and are expected to capture relevant information about default rates (Merton, 1974). Consequently, it is anticipated that the increase in credit spreads caused by Brexit would also be mirrored by an increase in the probabilities.

Nevertheless, there are still some who argue that Brexit will have a positive effect on UK's economy. Minford (2019) writes on his ongoing research that there are several economic benefits that can be linked to long-term gains when a "Clean Brexit" – leaving the Single Market and Customs Union – occurs.

3. Merton Model

In this dissertation, the Merton Model was chosen to compute the probabilities of default of the FTSE 100 companies. In order to viably estimate the variable in question, the Maximum Likelihood Approach (Duan, 1994) was implemented, as well as Capital Asset Pricing Model (Sharpe, 1970).

The model

In 1974, Merton applied option pricing theory, based on the work of Black and Scholes (1973). He used stock prices as an input to determine a company's probability of default, bond spread, and the value of a firm's debt and assets. According to the authors, equity can be identified as an European call option on the firm's assets, with a strike equal to the face value of debt. This consequently opens a door when studying credit risk.

While the model distinguishes itself due to its effectiveness in showing the variables that drive a company's probability of default and enables us to compute it clearly and objectively, it still has several limitations regarding its inputs: only recognizes default at debt maturity, use as input the firm's asset value and volatility; oversimplifies the firm's capital structure by assuming that a company has only a constant zero-coupon bond as liabilities.

In order to understand the reasoning behind their conclusion we must first understand the intuition behind this model. The asset value of a company is the sum of its equity value and liabilities value, and when the assets of a firm are lower than its liabilities, a firm enters in default. When this occurs, since equityholders have limited liability[5], the value of equity goes to zero. Consequently, shareholders will prefer to default rather than repaying creditors, therefore implying that whenever the value of liabilities is greater than that of assets they will always choose to default.

A long call option (1) gives the holder the right, but not the obligation, to buy the underlying asset (S_T) for a certain price (strike price, K) at a certain future date (Hull, 2012 – Options, Futures and Other Derivatives). When the strike price is higher than the price of underlying asset shareholders will not want to exercise our option and consequently the payoff is going to be 0. However, if the price of the underlying is above the strike they will obviously want to exercise it as it would be perceived as buying it "cheap". Changing into a firm perspective, we

[5] Limited liability implies that the investor's liability is limited to his/hers initial investment. This is particularly important in the case of default as this means that they are not obliged to put down extra capital in order to pay for the firm's debts.

can then understand that when the assets are lower than liabilities the shareholders will not want to exercise their option on equity with a strike price equal to the face value of debt, but if the opposite occurs they will, receiving the difference between the firm value and the liabilities. Furthermore, risky debt can then be modelled as a risk-free debt plus a short put on the firm's assets, giving the holder the right to sell the underlying asset, at a certain price, at a certain date.

(1) $$payoff_{long\ call} = \max(S_T - K, 0)$$

	Equityholders	**Debtholders**
Scenario 1: Assets > Debt (S_T>K)	Assets - Debt	Debt
Scenario 2: Assets < Debt (S_T<K)	0	Assets

As previously stated, this is a model, implying that it simplifies reality in order to make things manageable. The Merton model follows the following assumptions (Löffler and Posch, 2007): no transaction costs; no bankruptcy costs; no taxes; unrestricted borrowing and lending at the risk-free rate; no short-selling restrictions; no uncertainty about liabilities; log-normally distributed assets.

According to this model, the market value of the firm's assets follows a stochastic process[6] called the Geometric Brownian motion (2). This implies that it is dependent on an expected instantaneous yield on the assets (drift) and on the Wiener process. This process can be classified as a stochastic process in continuous time that follows the following properties: $W_0 = 0$; it has independent stationary increments taken from a Normal distribution with mean 0 and variance d_t[7]; continuous paths. Furthermore, the drift can be perceived as the predictable component, whereas the Wiener process represents the unexpected shocks' portion of the equation. Another disadvantage of the model related to this is that it is unable to estimate the occurrence of jumps to default as a consequence of following a geometric Brownian motion. Mathematically,

(2) $$dV_t = \mu V_t dt + \sigma V_t dW_t \quad, 0 \leq t \leq T$$

[6] Family of random variables defined on a fixed probability space (Ω , $\mathcal{F}$, P) with *t* as an indicator of time
[7] Defined as the smallest imaginable period of time

where:

dV_t represents the change in the value of the firm (Assets)

μ represents the firm's asset drift

σ represents the asset volatility

W_t represents the Wiener process

However, in order to solve this we have two unknowns, the value of the firm and its volatility. In 1944, Kiyosi Ito developed what we know today as the Ito's lemma - method of integrating and differentiating time dependent functions of a stochastic process.

Applying it to log (V_t) and integrating it, we are then able to define asset value:

(3) $$\Leftrightarrow V_t = V_0 e^{(\mu - \frac{1}{2}\sigma_A^2)t + \sigma_A W_t}$$

The value of equity (E_t) can then be computed by using the Black and Scholes (1973) formula for European call options:

(4) $$E_t = V_t N(d_1) - Le^{-r(T-t)} N(d_2)$$, with $$d_1 = \frac{(\ln\left({V_t}/{L}\right) + \left(\mathrm{r} + {\sigma_A^2}/{2}\right))(\mathrm{T-t})}{\sigma\sqrt{T-t}}$$

$$d_2 = d_1 - \sigma_A \sqrt{T-t}$$

$$L = \frac{Fe^{-rT}}{V_0}$$

For listed companies, we typically assume that the value of equity is the market capitalization of that firm. As the value of the stock is not dependent on the asset volatility (σ_A), the asset value is not directly observable. However, this is not the only unknown, we are also unaware of the value of the asset volatility.

As previously mentioned, a company enters in default when its value is lower than its liabilities. Consequently, the probability of default of a company can be understood as the probability of the market value of the company's assets being lower than its debt:

(5) $$PD = prob\ (V_T \leq L)$$

Considering that we have already established the equation for the asset value (3), we can then rewrite the previous equation:

(6) $$PD = prob\left(\ln(V_0) + \left(\mu - \frac{1}{2}\sigma_A^2\right)t + \sigma_A W_T\right) \leq \ln\ (L))$$

Even though equity is not dependent on the asset volatility, the probability of the value of assets being lower than its debt is.

(7)
$$\varepsilon_T = \frac{W_{(T)} - W_{(0)}}{\sqrt{T}} \ , \qquad \frac{W_{(T)}}{\sqrt{T}} \sim N(0,1)$$

It follows that:

(8)
$$PD = prob\left(-\frac{\ln\left(\frac{V_0}{L}\right) + \left(\mu - \frac{\sigma_A}{2}\right)t}{\sigma_A\sqrt{t}} \geq \varepsilon\right)$$

$$\Leftrightarrow PD = N\left(-\frac{\ln\left(\frac{V_0}{L}\right) + \left(\mu - \frac{\sigma_A}{2}\right)t}{\sigma_A\sqrt{t}}\right)$$

$$\Leftrightarrow PD = N(-d_2)$$

Using a risk-neutral approach we can interpret distance to default (9) as the expected number of standard deviations the asset price must change for default to be triggered T years in the future (Hull – Risk). Therefore, we can describe the distance-to-default as being equal to the value of d_2:

(9)
$$DD = \frac{(\ln\left({V_t}/{L}\right) + \left(\mathrm{r} - {\sigma_A^2}/{2}\right))(\mathrm{T}-\mathrm{t})}{\sigma\sqrt{T-t}} = d_2$$

Consequently, the probability of default and the distance to default are related, and their relationship can be defined by:

(10)
$$PD = N(-DD)$$

As can be seen in the graph below and understood from (10), the lower our distance to default is, the more likely the company is to default. Furthermore, the more volatility there is, the higher the chances that the value of assets (A) ends up below nominal debt at time T. This occurs due to an increase in difficulty in understanding what is going to happen in the long-term, consequently leading to an increase in the probability of default. We can also see that as time goes by, the volatility tends to increase, also increasing the probability of default, as the uncertainty surrounding log(A) evolves in proportion to the square root of the change in time. Finally, the more debt we have, the higher the horizontal line in the graph is going to be, leading to an increase in the probability of default too.

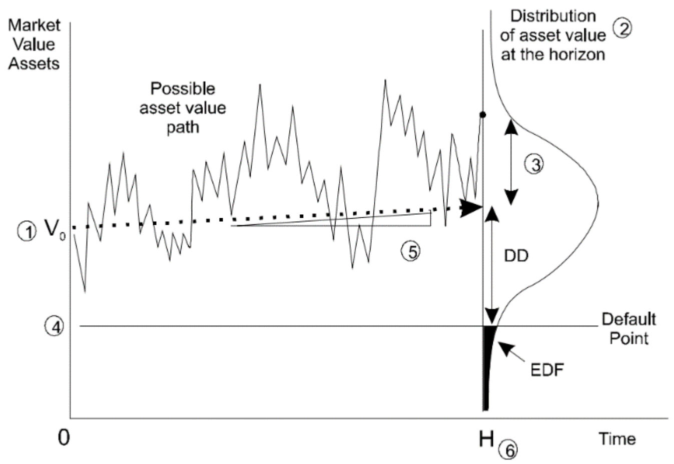


Figure 1 – Estimating the probability of default (Crosbie et al., 2003)

Model Calibration

The expected asset return

A risk-neutral world is defined as "an imaginary world where investors require no compensation for bearing risks" (Hull, 2018). Apart from its potential impact on the asset value (exogenous), under the Merton model equity is not dependent on the agents' preferences and consequently there is no need to estimate the expected return on assets. Despite this, the expected asset return is needed to compute real-world probabilities of default. This implies the need for this parameter estimation, which will be done through the use of the CAPM.

First introduced by Sharpe (1963), the CAPM is an equilibrium pricing model. Based on Markowitz's portfolio, this model follows the following assumptions: rational investors; perfect markets; normally distributed returns. If all these assumptions are true, then every financial asset should offer an expected return which is consistent with its degree of systematic risk[8].

Since systematic risk reflects the covariance of its return with the market index return, beta – indicator of the degree of systematic risk – expresses the sensitivity of a security's return to the mean market return.

(11) $$\beta_i = \frac{\sigma_{i,M}}{\sigma_M^2}$$

[8] Risk inherent to the entire market, which is not diversifiable.

where:

β_i represents the degree of systematic risk

$\sigma_{i,M}$ represents the covariance of the individual security's rate of return with the market portfolio's return

σ_M represents the variance of the market portfolio

Consequently, we can then define the expected return of an individual security in equilibrium:

(12) $$E(R_i) = R_f + \beta_i(E(R_M) - R_f)$$

where:

$E(R_i)$ represents the expected return of an individual security

R_f represents the risk-free rate

$E(R_M)$ represents the expected return of the market

We can then apply this equation in order to provide for more accurate estimates, and only rely on the Maximum Likelihood approach to obtain σ_A and A.

Assets and σ_A

In 1994, Duan proposed the Maximum Likelihood approach as a method to solve the unknows in the Merton Model - μ_A and σ_A. The aim of this method is to find the parameter values that turn the observed equity into its most likely occurred value.

The density of the value of a firm ($\emptyset^A(v_i|v_{i-1}, \mu, \sigma)$) can be defined as:

(13)

$$\emptyset^V(v_i|v_{i-1}, \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma\sqrt{t_i - t_{i-1}}} \exp\left(-\frac{(logv_i - logv_{i-1} - \left(\mu - \frac{1}{2}\sigma^2\right)(t_i - t_{i-1}))^2}{2\sigma^2(t_i - t_{i-1})}\right.$$

Since equity can be perceived as a function of asset value, we can define its density ($\emptyset^E(v_i|v_{i-1}, \mu, \sigma)$) as:

(14) $$\emptyset^E(v_i|v_{i-1},\mu,\sigma) = \emptyset^V(v_i|v_{i-1},\mu,\sigma) * \frac{1}{\partial E/_{\partial V}}$$

Consequently, the likelihood function of the asset value and corresponding asset volatility for the given observed equity prices can be defined as:

(15) $$L(s_1,\dots,s_n\,|s_0,\mu,\sigma) = \prod_{i=1}^{n} \emptyset(v_i(\sigma)|v_{i-1}(\sigma),\mu,\sigma)\frac{1}{C_i'(v_i(\sigma);\sigma)} \quad \text{, with}$$

$$s_i = C_i\ (v_i(\sigma);\sigma)$$

$$v_i(\sigma) = C^{-1}(s_i;\sigma)$$

where:

L represents the likelihood function

$s_1,\dots,s_n$ represents the observed equity values

C_i represents the price of the call option with maturity t_i

Taking into account the fact that asset returns are i.i.d.[9] our log-likelihood function $(log\ L(s_1,\dots,s_n\,|s_0,\mu,\sigma))$ is the following:

(16) $$log\ L(s_1,\dots,s_n\,|s_0,\mu,\sigma) = \prod_{i=1}^{n} \emptyset^A(v_i|v_{i-1},\mu,\sigma)\frac{1}{C_i'(v_i(\sigma);\sigma)}$$

$$\Leftrightarrow log\ L(s_1,\dots,s_n\,|s_0,\mu,\sigma) = -\frac{1}{2}n\log 2\pi - n\log\sigma - \frac{1}{2}\sum_{i=1}^{n}\log(t_i - t_{i-1}) -$$
$$\frac{1}{2\sigma^2}\sum_{i=1}^{n}\frac{(logv_i(\sigma)-logv_{i-1}(\sigma)-\left(\mu-\frac{1}{2}\sigma^2\right)(t_i-t_{i-1}))^2}{t_i-t_{i-1}} - \sum_{i=1}^{n} logv_i(\sigma) - \sum_{i=1}^{n}\log N(d_1\,(\sigma))$$

This method distinguishes itself from other approaches to solving the Merton model's issues, as it results in estimators that are known to be statistically efficient in large samples. Unlike the system of equations method, by using this methodology one is able to obtain a constant asset volatility, hereby increasing its consistency with the hypothesis stated by the model. Furthermore, it also benefits from the fact that sampling distributions are readily available for computing confidence intervals (Duan, Gauthier and Simonato, 2005).

[9] Independ identically distributed.

Regardless, these confidence intervals tend to be small for the asset volatility (σ_A) and too large for the asset drift (μ_A). In fact, μ_A estimations tend to reflect past performance rather than the asset expected return. As an alternative to estimating this parameter through maximum likelihood, I opted for assuming the CAPM and only estimating the value of sigma.

Other parameters

The debt used for the calibration of this model is taken from the balance sheet of each company. This information can be easily obtained through platforms such as Refinitiv Eikon. However, since its frequency is annual rather than daily, which is this dissertation's approach, there is a need to adapt it. This can then be implemented through the use of interpolation.

Furthermore, the risk-free rate can be defined as the as the interest rate at which money can be borrowed or lent without risk for that given period (Berk and DeMarzo, 2017). In this dissertation the United Kindgom 5 Year Benchmark is used as a proxy for the risk-free rate.

4. Data and Methodology

Sample Construction

Firstly, the time period covered by this dissertation spans from January 2013 to December 2020. The starting date of 1st January 2013 was used as to not only achieve consistency with the table of event days that is later going to be used on study, but also to avoid biases from the sub-prime crisis period. The final date of 31st December 2020 was then chosen, as otherwise there would be limitations in obtaining data for further dates, hereby putting at risk this research.

Firms were chosen based on the following criteria:

1. *Be a FTSE 100 Index constituent on both dates.*
2. *Have non-zero debt.* This is particularly important because as debt is a vital variable in the Merton Model, the results otherwise obtained by their use would be wrongly estimated and would consequently lead to bias.
3. *Achieve convergence when estimating using the Maximum Likelihood Approach*[10]. Note that most of the companies that did not converge had an extremely unstable debt, hereby violating the premises of the model in use.
4. *Do not have residuals above 10**$\sigma_{Residuals}$.

As this dissertation assumes a daily frequency, the final sample consists of 113'344 observations, representing the 56 firms (Appendix 9.1) that are part of the FTSE100 Index included in this analysis over the course of 2024 days.

Merton Model Inputs

All data for this dissertation was retrieved either using the Refinitiv Eikon API or the Yahoo Finance API for Python. By using this programming language, one is able to access several libraries and built-in functions, leading to an easier implementation of the desired credit risk concepts.

Debt

Firstly, the value of Debt was obtained. As this is financial information available on the Balance Sheet of every company, its frequency is typically yearly. These yearly values were retrieved from Eikon using the Total Debt Outstanding[11] as data item, and then interpolated in order to

---

[10] Both Rolls Royce and Imperial British Tobacco have achieved convergence when applying the algorithm, but as their values were not feasible, due to sudden debt increases and extremely unstable asset value, they have been excluded from the sample. Further evidence can be seen in Appendix 9.3.
[11] Setting United Kingdom pound (GBP) as the currency.

obtain daily values for the entire time-period in analysis. For this variable, an average value of approximately 21’588 million GBP was obtained in the sample, with the maximum value of 361’962 million GBP being obtained by the company Barclays PLC (BARC.L) on the first analysis day, and the minimum being achieved by Admiral Group PLC (ADML.L) with a debt of 0.1 million GBP.

Interest Rate

Regarding the interest rate, the Risk-free rate is need in order to estimate μ_A. As the frequency of this item is already daily, one just needs to retrieve from Eikon the daily rates for the selected bond, which was United Kindgom 5 Year Benchmark (‘GB00BNNGP668’). As it can be seen from the graph below, as our sample moves into 2020 years, the risk-free rate assumes negative values, achieving a minimum value of -0.001380 on 4th August 2020. As a consequence of the economic downturn, accelerated by the COVID-19 pandemic, the Central Bank lowered the interest rates to negative values in order to incentivize consumption when people would rather save than spend money. Similar behaviour had already been seen upon the 2008 financial crash (Subprime crisis).

Figure 2 – Risk-free rate variation during the analysis period

Market Price of Risk

The Market Price of Risk (Appendix 10.2) can easily be computed from observable factors. Mathematically:

$$MPR = \frac{\beta * ERP}{\sigma_E} \tag{17}$$

where:

MPR represents the Market Price Risk

β represents the computed beta for each company

ERP represents the Equity Risk Premium

σ_E represents the equity volatility

As can be seen from (17), one key input to the calibration of the MPR is the Beta of each company. Consequently, daily returns for each company in the sample, as well as for the market portfolio ('FTSE')[12] were computed. Then, by using the formula in (11), the daily β_i for each company was reached (Appendix 10.1).

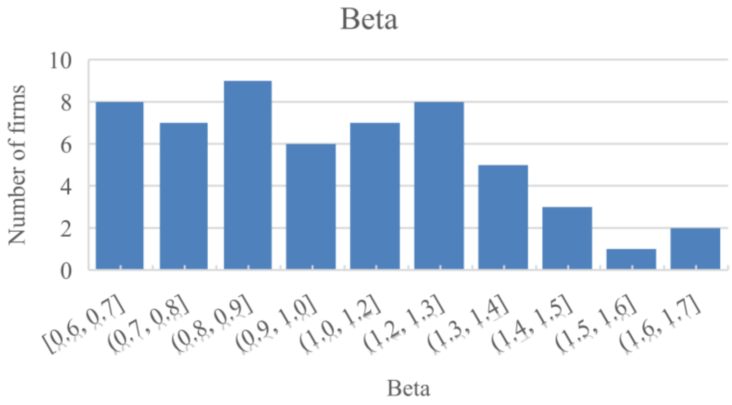


Figure 3 – Beta for each company

Another component of the MPR is the Equity Risk Premium (ERP). To obtain more accurate values of this metric, Professor Damodaran's website was used as a resource. However, since there were only yearly values available for the United Kingdom, interpolation was required to achieve the frequency of this dissertation (daily).

Regarding the equity volatility, this value was derived from the stock returns previously obtained and annualized.

[12] Benchmark as market portfolio.

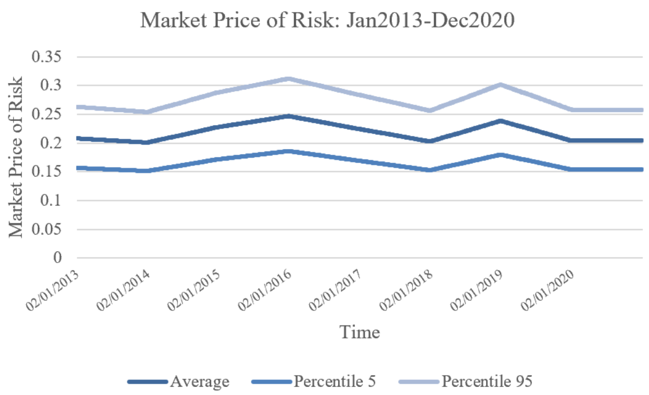


Figure 4 – Market price of risk during the analysis period

Asset Drift (μ_A)

In order to estimate the values of the asset drift (μ_A), one must first obtain the values of its components. Note that the value of the asset volatility is going to be obtained during the Maximum Likelihood Estimation optimization, whilst the value of MPR can be achieve through the above explanation.

(18) $$\mu_A = r_f + \sigma_A * MPR$$

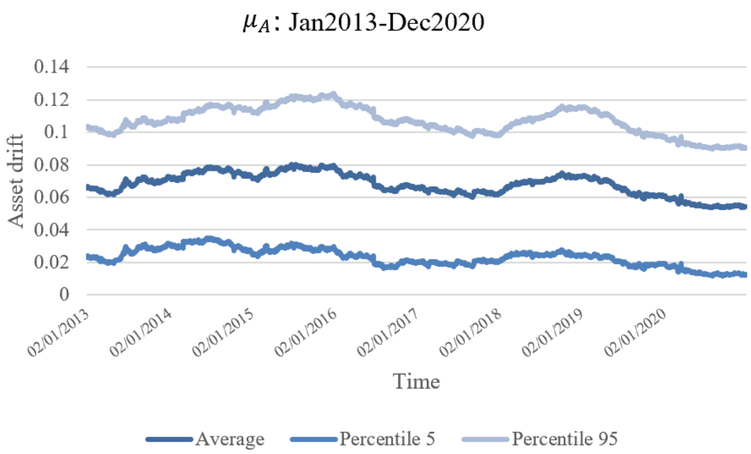


Figure 5 – Asset drift during the analysis period

Assets and Sigma

Even though the value of assets (Appendix 10.4) is not observable, one can simply derive it as it is implicit in the equity function of the model and conditional to the values of its parameters:

(19) $$Equity_{Obs} = Equity_{Function}$$

$$\Leftrightarrow Equity_{Obs} = V_t N(d_1) - Le^{-r(T-t)} N(d_2)$$

Consequently, by finding the root of the equation (point at which it reaches the value of 0), whilst taking into account the values of daily market capitalization as input for $Equity_{Obs}$, one is able to obtain the daily value of the assets:

$$V = E + Le^{-r(T-t)} - Put \tag{20}$$

In order to obtain accurate values for the asset estimation, and help the algorithm to converge, bounds were set during the optimization. The lower bound was set to the equity value observed, whilst the upper bound was set to $E + Le^{-r(T-t)}$.

As previously mentioned, the volatility of each company is obtained through the Maximum Likelihood Approach (Appendix 10.7). This can easily be obtained by maximizing the equation in (16) for each company, whilst computing the asset value. Consequently, this approach can be translated into the following steps:

1. The initial guess for the values of sigma was set to 0.2.
2. Maximize the function in (16) by iterating over the values of sigma, whilst computing the value of the assets until convergence is achieved with success.
3. Through the equation in (20) obtain the asset values for each of the 2024 days across the 56 firms. This takes as input the daily market capitalization (Equity Observed), daily debt, and asset drift implied by the CAPM method and the optimal asset volatility.

By definition, the estimated sigma obtained is constant throughout the entire time-period in analysis. The lowest value of sigma, 0.01204, was obtained for Lloyds Banking Group PLC (LLOY.L). Regarding the highest value of sigma observed, Standard Chartered PLC (STAN.L) obtained a sigma of 0.72002, due to its constant changing values of market capitalization, despite having a relatively steady debt.

As can be seen from the graph below there are a few companies that have an extremely low estimate for the value of sigma. It is then worth mentioning that these are mainly financial sector companies, more specifically banks. This occurs due to the fact that banks often have extremely high values of debt, caused by the banks' crucial activity – deposits. Notice that considering banks' very high leverage and moderately high equity volatility, when applying the Merton model to this industry it tends to attribute low figures to asset volatility estimates. This is then compatible with the idea that banks typically hold very diversified portfolios but dismisses the skewness that often arises due to deep recessions.

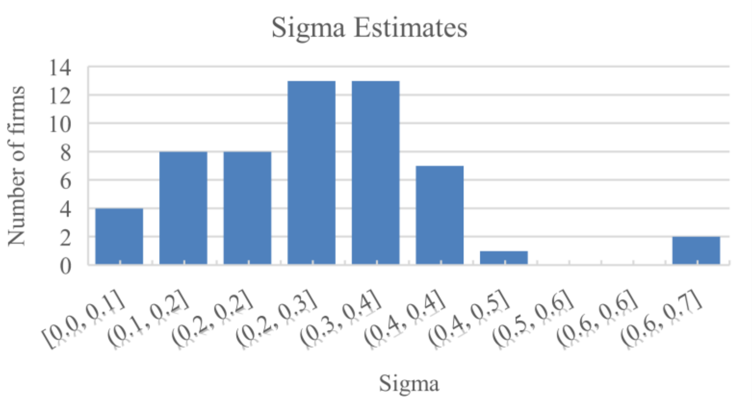


Figure 6 – Sigma estimates obtained through Maximum Likelihood Estimation

As previously mentioned, the asset value is computed when optimizing the value of sigma. HSBC Holdings PLC (HSBA.L) is the company in the sample with the highest value of assets, 353’815 million GBP. On the other hand, the lowest value of 1’889 million GBP was achieved by Evraz PLC (EVRE.L).

As can be seen from Graphic 6, financial companies in this sample tend to have higher levels of debt over assets, even obtaining levels above 1 for this ratio, as can be seen by the trendlines. Furthermore, financial sector companies with higher levels of this ratio tend to have either extremely low or high values of sigma, once again this is verified amongst banks.

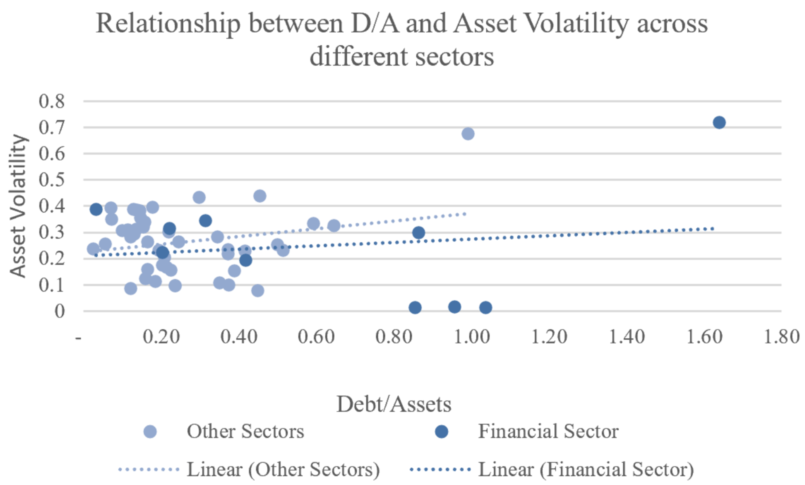


Figure 7 – Relationship between average daily Debt/Assets and Asset Volatility across different sectors

Probabilities of Default

Finally, as all the inputs needed are now obtained, the real-world probabilities of default according to the Merton Model can now be computed (Appendix 10.8), in accordance with equation (9). As previously mentioned, the regression in this dissertation uses distance-to-default (Appendix 10.9) as the dependent variable, which can be derived from (10).

	Count	***Mean***	***Standard Deviation***	***Min***	***Max***	***25%***	***50%***	***75%***
Debt	113344	21588	52390	0.1	361962	1233	4258	12300
Asset	113344	44099	62803	1889	353815	8257	17616	51632
$\boldsymbol{\sigma_A}$	56	0.26166	0.13734	0.01204	0.72002	0.16499	0.26334	0.33490
$\boldsymbol{\mu_A}$	113344	0.06801	0.03175	0.00115	0.19638	0.04648	0.06858	0.08578
$\boldsymbol{PD_{RW}}$	113344	0.05961	0.15426	0.00000	0.98557	0.00000	0.00093	0.01839
$\boldsymbol{PD_{RN}}$	113344	0.09476	0.20054	0.00000	0.99609	0.00004	0.00455	0.05635
$\boldsymbol{DD_{RW}}$	113344	3.6058	2.6816	-2.1855	20.3096	2.0883	3.1125	4.4500
$\boldsymbol{DD_{RN}}$	113344	3.1023	2.6799	-2.6597	19.7419	1.5861	2.6080	3.9433

Table 1 – Descriptive statistics for the probabilities of default and their inputs (million GBP)

As can be seen from Table 1, when comparing real-world probabilities of default to risk-neutral ones, we can argue that the former are lower on average. Furthermore, the company to achieve the highest probability of default was ITV PLC (ITV.L) in December 2015, while multiple companies reached the lowest value of 0 during several days in our analysis.

Regression Analysis

Main Regression

In this dissertation, a panel data regression was performed for the 56 companies from January 2013 until December 2020 (2024 analysis days). As this regression focuses on the difference in the variables across days, this results in the final number of 2023 analysis days.

Panel data refers to data containing the time series observations of several individuals, involving a cross-sectional dimension (*i*) and a time series dimension (*t*), hence why it is appropriate for this dissertation. By using panel data, there is a more accurate inference of model parameters (Hsiao et al., 1995), the analysis is better able to control the impact of omitted variables and dynamic relationships (Pakes and Griliches, 1984), and both the computation and statistical inference are simplified (Arrelano et. Al, 1999). In this dissertation fixed entity effects were also applied in order to control for the average differences across firms in both observable and unobservable predictors.

To analyse the impact of the news related to Brexit on the probabilities of default of the FTSE 100 companies, the distance-to-default was chosen as the dependent variable. Jessen and Lando

(2014) argue that Merton model's probabilties of default are too low, and that by using the distance-to-default we are able to observe similar, but inverse, effects with improved regression fit. According to Chan-Lau (2021), the distance-to-default is used to rank the firms according to their riskiness, and once established, empirical mapping to default rates are associated to objective measures of default risk . Nonetheless, according to Duffie and Lando (2021), if the distance-to-default is not accurately measured then the default intensity will not solely be dependt on it, but also on other covariates that might expose extra information regarding the firm's probability of default.

Following the classification approach of Korus and Celebi (2019), this dissertation has a Brexit dummy that aims to analyse the impact of news related to Brexit in the perception of credit risk. The Brexit dummy will take the value of 1 for event days that are perceived to be key by authors and 0 otherwise. This dummy will be used as independent variable, whilst other control variables will also be applied to the regression. The full description of the events can be seen in Appendix 9.2.

As the risk-free also has an impact on the probability of default of a firm, this dissertation also includes it in its analysis. This occurs because this variable is a key component in determining several of the Merton Model inputs, hereby impacting the value of distance-to-default. Consequently, the UK 3 month Benchmark Rate ('GB00BHMD2B06') was chosen to represent the short-term risk free, whereas the UK 10 year Benchmark Rate ('GB00BMGR2809') represents the long-term rate. Furthermore, one must bear in mind that both are only applicable as long as they are not highly correlated.

As all of the companies analyzed are part of the FTSE100 Index, it also makes sense to include the other main stock index returns as control variables, as these might also have some impact in the variable in analysis and be affected by Brexit. As a consequence, the S&P 500 was chosen to represent America and the STOXX Europe 600 to represent Europe.

Even though finacial ratios are typically used in this type of analysis, one must take into account the fact that these variables have an yearly frequency. Consequently, this would imply that in order to be used in this dissertation, they would have to be interpolated to obtain a daily frequency and would possibly lead to biased results.

Furthermore, while other studies might include the FTSE 100 returns, as the chosen companies are part of it, it would most likely also lead to biased results.

Variable	Function	Definition
ΔDistance-to-default	Dependent variable	Distance measure
Brexit Dummy	Independent variable	Brexit dummy
ΔSP500 Returns	Control variable	S&P 500 Index returns
ΔSTOXX 600 Returns	Control variable	STOXX Europe 600 returns
ΔUK 3M Benchmark	Control variable	Short-term risk-free rate
ΔUK 10Y Benchmark	Control variable	Long-term risk-free rate

Table 2 – Variable definition for main regression analysis

Consequently, this regression can be represented by the following equation:

$$\widehat{\Delta DD}_{i,t} = \alpha_{i,t} + \beta_1 BrexitDummy_t + \beta_2 \Delta SP500_t + \beta_3 \Delta STOXX600_t + \beta_4 \Delta UK3M_t + \beta_5 \Delta UK10Y_t$$

In Table 3, one can see displayed the basic descriptive statistics for the inputs required for the regression analysis performed in this dissertation. Regarding the change in distance-to-default variable, with an average of -0.0004, the highest value of 2.0724 was observed for Natwest Group PLC (NWG.L). The lowest value observed, -3.2110, was from Lloyds Banking Group PLC (LLOY.L)

	Mean	***Std.***	***Min***	***Max***	***25%***	***50%***	***75%***
$\Delta \boldsymbol{DD}$	-0.00044	0.05120	-3.21097	2.07238	-0.01279	-0.00005	0.01255
$\Delta \boldsymbol{SP500}$	0.00043	0.01077	-0.12765	0.08968	-0.00311	0.00069	0.00510
$\Delta \boldsymbol{STOXX}$	0.00018	0.01067	-0.12191	0.08070	-0.00427	0.00058	0.00539
$\Delta \boldsymbol{UK\_3M}$	-0.00645	0.22392	-2.00747	2.33940	-0.01379	0.00000	0.01303
$\Delta \boldsymbol{UK\_10Y}$	-0.00115	0.06124	-0.38926	0.57234	-0.02160	-0.00203	0.01890

Table 3 – Descriptive statistics of regression inputs for main regression analysis

A Correlation Matrix was then built in order to avoid multi-collinearity problems in the model. As none of the values obtained are close to 1, such issues are not present in this analysis.

As can be seen from Table 4, when looking at the correlation matrix, one can see that the Brexit dummy is positively related to the dependent variable in study (change in distance-to-default), but with a relatively low coefficient. Consequently, this indicates that as one increases, the other one decreases. Furthermore, one can argue that the change STOXX Europe 600 is the variable with the highest correlation coefficient when considering the main study variable. This implies that as the change in the retuns of this index increases, so does the change in distance-to-default and vice-versa. The same applies for both changes in the risk-free benchmark rates and the S&P 500 returns.

	ΔDD	BD	$\Delta SP500$	ΔUK_3M	ΔUK_10Y	$\Delta STOXX$
ΔDD	1	-0.001490	0.256254	0.391298	0.006649	0.172934
BD	-0.001490	1	0.017188	0.004560	0.007240	-0.005607
$\Delta SP500$	0.256254	0.017188	1	0.607894	0.009813	0.224393
ΔUK_3M	0.391298	0.004560	0.607894	1	0.012263	0.257856
ΔUK_10Y	0.006649	0.007240	0.009813	0.012263	1	-0.001639
$\Delta STOXX$	0.172934	-0.005607	0.224393	0.257856	-0.001639	1

Table 4 – Correlation coefficients for main regression analysis

Alternative Approach

As it is widely known, the financial sector represents close to 7% of the United Kingdom's economy[13], hereby making it a crucial sector worth to further analyse. Furthermore, as previosuly mentioned in Chapter 2, the financial sector has been perceived as one of the most affected by Brexit. To further understand the impact of Brexit on this sector and consequently be able to answer H3 defined in Chapter 1, I decided to perform a second regression analysis.

This new regression differs from the previous one in the sense that new variables, that aim to understand the direct impact of the Brexit announcements in the probabilities of default of the financial sector companies, which amount to 10 companies, are now being introduced. Consequently, a financial sector dummy was created, assuming the value of 1 when the company's sector is Financial and 0 otherwise.

Variable	Function	Definition
ΔDistance-to-default	Dependent variable	Distance measure
Brexit Dummy * Financial Sector Dummy	Independent variable	Interaction between Brexit Dummy and Financial Sector Dummy
ΔSP500 Returns	Control variable	S&P500 Index returns
ΔSTOXX 600 Returns	Control variable	STOXX Europe 600 returns
ΔUK 3M Benchmark	Control variable	Short-term risk-free rate
ΔUK 10Y Benchmark	Control variable	Long-term risk-free rate

Table 6 – Variable definition for financial sector regression analysis

Consequently, we can express this analysis through the following equation:

[13] Latest data available in 2019.

$$\widehat{\Delta DD}_{i,t} = \alpha_{i,t} + \beta_1 BrexitDummy_t * FinancialSectorDummy_t + \beta_2 \Delta SP500_t + \beta_3 \Delta STOXX600_t + \beta_4 \Delta UK3M_t + \beta_5 \Delta UK10Y_t$$

As can be seen from Table 7, the new dummy that represents the interaction between the Brexit events and the financial sector has a different correlation with the variable of interest when in comparison to the original independent variable. The BD*FD (Brexit Dummy * Financial Sector Dummy) has a small, yet positive, correlation with the change in distance-to-default hereby implying that they have similar behaviours.

	ΔDD	$BD * FD$	$\Delta SP500$	ΔUK_3M	ΔUK_10Y	$\Delta STOXX$
ΔDD	1	0.003804	0.256254	0.391298	0.006649	0.172934
$BD*FD$	0.003804	1	0.007232	0.001919	0.003046	-0.002359
$\Delta SP500$	0.256254	0.007232	1	0.607894	0.009813	0.224393
ΔUK_3M	0.391298	0.001919	0.607894	1	0.012263	0.257856
ΔUK_10Y	0.006649	0.003046	0.009813	0.012263	1	-0.001639
$\Delta STOXX$	0.172934	-0.002359	0.224393	0.257856	-0.001639	1

Table 7 – Correlation coefficients for financial sector regression analysis

5. Results

Main Regression

By using the variables stated in Table 3, one was able to perform a regression analysis, obtaining the following estimation for the change in the distance-to-default:

$$\widehat{\Delta DD}_{i,t} = -0.00076 - 0.0016 BrexitDummy_t + 0.1004 \Delta SP500_t + 1.7179 \Delta STOXX600_t + 0.0005 \Delta UK3M_t + 0.0632 \Delta UK10Y_t$$

From the regression above, it is possible to state that on average, and assuming that the other variables are constant, when we are in the presence of a key Brexit day (BrexitDummy=1), the change in distance-to-default is 0.0016 standard deviations lower than in a regular day (BrexitDummy=0).

Regarding the control variables, all of them have positive coefficients. This implies that for every 1% increase in either of them, the change in distance-to-default will increase by their beta coefficients, assuming no other changes.

Assuming a significance level of 5%, one can argue that the change in the STOXX Europe 600 returns, as well as the change in the S&P 500's returns and the change in the UK 10 Year Benchmark are significant. Consequently, it is possible to assume that these variables contribute to the explanation of the dependent variable in this model. Furthermore, this can be concluded based on the fact that, as can be seen from Table 8, these control variables achieve a p-value lower than 0.05. Unfortunately, the Brexit dummy is not significant, which can imply that no statistical evidence can be found as to whether key Brexit news are associated with a decrease in the changes in distance-to-default.

In this regression, an R^2 of 0.1590 was achieved. This metric aims to measure how much variation in the dependent variable is being explained with the remaining ones. Consequently, this model only explains 15.90% of the variation in the distance-to-default. Even though this metric is rather low, one must take into account the fact that there is always a possibility that random factors that affect the dependent variable exist, hereby distancing the value of obtained from 1[14].

[14] Perfect fit, meaning that all of the variance in the dependent variable is explained by the variables in the model.

	Parameter	*Standard Error*	*T-stat*	*P-value*	*Lower CI*	*Upper CI*
Constant	-0.0007	0.0001	-5.0186	0.0000	-0.0010	-0.0004
Brexit Dummy	-0.0016	0.0033	1.0281	0.3039	-0.0030	0.0097
ΔS&P500	0.1004	0.0164	6.0976	0.0000	0.0678	0.1321
ΔSTOXX600	1.7179	0.0166	103.30	0.0000	1.6855	1.7506
ΔUK 3M	0.0005	0.0006	0.7912	0.4288	-0.0007	0.0017
ΔUK 10Y	0.0632	0.0024	26.722	0.0000	0.0586	0.0679
					$\boldsymbol{R^2}$	**0.1590**

Table 8 – Main regression analysis output

Alternative Approach

Setting up the second regression in accordance with Table 6, the following results were obtained:

$$\Delta\widehat{DD_{i,t}} = -0.0007 + 0.0033BrexitDummy_t * FinancialSectorDummy_t + 0.0999\Delta SP500_t + 1.71814\Delta STOXX600_t + 0.0005\Delta UK3M_t + 0.0633\Delta UK10Y_t$$

It is now possible to see that the new Brexit dummy has a different effect on the dependent variable, when in comparison to the first regression. One can argue that when we are in the presence of a key Brexit day and taking into account only the financial firms, holding everything else constant, the change in distance-to-default is 0.0033 standard deviations higher than if we were to analyse a non-financial company in a regular day. Furthermore, the control variables present no significant change when considering the main regression previously performed.

As far as significance is concerned, once again the Brexit independent variable was not significant at a 5% level. What is more, the remaining control variables have the exact same p-value as before, hereby individually maintaining their level of significance equal to the one in the first regression analysis performed.

Regarding the R^2, this metric also remained the same. Consequently, it is possible to say that this second regression performed is able to explain the variation in the distance-to-default as much as the previous model.

	Parameter	*Standard Error*	*T-stat*	*P-value*	*Lower CI*	*Upper CI*
Constant	-0.0007	0.0001	-5.0186	0.0000	-0.0010	-0.0004
BD * FD	-0.0033	0.0033	1.0281	0.3039	-0.0030	0.0097
ΔS&P500	0.0999	0.0164	6.0976	0.0000	0.0678	0.1321
ΔSTOXX600	1.7181	0.0166	103.30	0.0000	1.6855	1.7506
ΔUK 3M	0.0005	0.0006	0.7912	0.4288	-0.0007	0.0017
ΔUK 10Y	0.0633	0.0024	26.722	0.0000	0.0586	0.0679
					R^2	**0.1590**

Table 9 – Financial regression analysis output

6. Limitations

As this dissertation included several constraints, it is more than likely that there will be various limitations adding bias to the results obtained.

The main limitation is most likely the sample size used. For this dissertation I decided to focus on the FTSE 100, as it is the main index in the United Kingdom. However, I now understand that perhaps if I were to have chosen a bigger index, it might have led to more robust conclusions. One possibility would be to use the FTSE 350. This would also help in understanding the true impact on the financial sector, as the number of financial companies would also be larger.

Another limitation could be the Brexit dummy itself. Even though this dummy was defined in accordance with the existing research performed by Korus and Celeris (2019), the authors might have missed several key dates or even failed in understanding the relance of the ones categorized as so. As a consequence, it might be relevant to perform further research using a different classification method.

Finally, several of the FTSE 100 companies violate the premises of the Merton Model. For instance, this model assumes that debt stays constant. However, this was not the case for several companies. The COVID-19 pandemic also contributed to a significant increase in debt for several firms. Consequently, a further analysis using a different method of obtaining the probabilities of default might also be appropriate.

7. Conclusions

The aim of this dissertation was to analyse the effect of Brexit on the probabilities of default of the FTSE 100's companies. Through the use of the Merton Model with parameters estimated using Maximum Likelihood Approach, this metric was obtained for 56 companies integrating the index from January 2013 and December 2020. Two research questions were considered. The first one was whether Brexit-related news led to an increase in the companies' probabilities of default, whilst the second question of this dissertation aimed to understand whether these news impacted financial firms more heavily or not.

Regarding the first research question, the Brexit dummy was found to have a positive correlation with the change in distance-to-default, hereby implying a negative one with probabilities-of-default. This idea was confirmed by our panel data model, where the independent variable of interest (Brexit dummy) did not achieve significance for a level of 5%.

Regarding the second research question, since the added Brexit was also not significant at a 5% level, one cannot argue that, in key Brexit days, companies in the financial sector have had any observable impact in their probabilities-of-default' changes.

8. Bibliography

1. Altman, E., Saunders, A. (1996). Credit Risk Measurement: Developments over the last 20 years. *Journal of Banking & Finance*. Accessed September 12, 2021. https://doi.org/10.1016/S0378-4266(97)00036-8

2. Baker, J., et al. (2016). The short-term economic impact of leaving the EU. *National Institute Economic Review, 236*, 108-120. Accessed September 11, 2021. https://doi.org/10.1177/002795011623600114

3. Baker, S.R., Bloom, N., Davis, S.J., (2016). Measuring economic policy uncertainty. *Q. J. Econ.* 131 (4), 1593–1636. Accessed September 11, 2021. https://doi.org/10.3386/w22740

4. Berk, J. B., DeMarzo, P. M. (2011). *Corporate finance*. Boston, MA: Prentice Hall.

5. Black, F., Cox, J. C., (1976), "Valuing Corporate Securities: Some Effects of Bond Indenture Provisions". *Journal of Finance*, 31, 351–367. Accessed September 12, 2021. https://doi.org/10.2307/2326607

6. Bloom, N., et al. (2019). The impact of Brexit on UK firms NBER Working Paper 26218, September. Accessed September 11, 2021. https://www.nber.org/system/files/working_papers/w26218/w26218.pdf

7. Caporale, GM., Gil-Alana, L., Trani, T. (2018). Brexit and Uncertainty in Financial Markets. *International Journal of Financial Studies* 6(1):21. Accessed September 11, 2021. https://doi.org/10.3390/ijfs6010021

8. Crosbie, P., Bohn, J. Modeling Default Risk. 2003

9. Duan, J., Gauthier, G., Simonato, J. (2004). On the equivalence of the KMV and maximum likelihood methods for structural credit risk models. Unpublished working paper. University of Toronto. Accessed September 11, 2021. http://neumann.hec.ca/~p240/Recherche/documents/20050617KMVmle.pdf

10. Gourinchas, P., Hale, G. (2017). Brexit: whither the pound? *FRBSF Economic Letter 2017*. Accessed September 11, 2021. https://www.frbsf.org/economic-research/files/el2017-11.pdf

11. Hull, J.C. (2012). *Risk management and financial institutions*. Hoboken, N.J: Wiley

12. Kadiric, S., Korus, A. (2019). The effects of Brexit on credit spreads: Evidence from UK and Eurozone corporate bond markets. *Int Econ Econ Policy* 16**,** 65–102. Accessed September 11, 2021. https://doi.org/10.1007/s10368-018-00424-z

13. Korus, A. , Celebi, K. (2019). The Impact of Brexit news on British pound exchange rates. *International Economics and Economic Policy*. 16: 161-192. Accessed September 30. https://doi.org/10.1007/s10368-018-00423-0

14. Lando, D. (2004). Credit risk modelling: Theory and application. *Princeton Series in Finance*. Princeton, N.J: Princeton University Press

15. Loffler, G., Posch, P.N. (2007). Credit risk modeling using Excel and VBA. Chichester: Wiley

16. Boutchkova, M., et al. (2012). Precarious Politics and Return Volatility. *The Review of Financial Studies*, Volume 25, Issue 4, April 2012. 1111–1154. Accessed September 11, 2021. https://doi.org/10.1093/rfs/hhr100

17. Minford, P. (2019) The effects of Brexit on the UK economy. *Cardiff Economics Working Papers*. No. E2019/1. Cardiff University. Cardiff Business School, Cardiff. Accessed September 11, 2021. https://doi.org/10.1111/twec.12771

18. Oehler, A., Horn, M., Wendt, S. (2017). Brexit: short-term stock price effects and the impact of firm-level internationalization. *Finance Res., Lett.22,* 175-181. Accessed September 11, 2021. https://doi.org/10.1016/j.frl.2016.12.024

19. Pielicchata, P. (2021). Brexit pushes 440 financial services firms to move some U.K. business to Europe. Accessed September 11, 2021. https://www.pionline.com/brexit/brexit-pushes-440-financial-services-firms-move-some-uk-business-europe

20. Stoupos, N., Kiohos, A. (2021). BREXIT referendum's impact on the financial markets in the UK. *Rev World Econ* 157, 1–19. Accessed September 25, 2021. https://doi.org/10.1007/s10290-020-00393-z

21. Raddant, M. (2016). The Response of European Stock Markets to the Brexit. *Kiel Policy Brief No. 100.* Kiel: Institute for the World Economy. Accessed September 11, 2021. https://www.econstor.eu/bitstream/10419/156089/1/882200887.pdf

22. Resti, A., Sironi, A. (2012). Risk Management and Shareholders' Value in Banking: From Risk Measurement Models to Capital Allocation Policies. Hoboken, N.J: Wiley.

23. Walker, N. (2018). Brexit timeline: events leading to the UK's exit from the European Union. *House of commons library.* Briefing paper n.07960. Accessed September 30, 2021. https://researchbriefings.files.parliament.uk/documents/CBP-7960/CBP-7960.pdf

24. Duffie, D., et al. (2007). Multi-period corporate default prediction with stochastic covariates. *Journal of Financial Economics* 83 (2007) 635–665. Accessed October 6, 2021. https://www.darrellduffie.com/uploads/pubs/DuffieSaitaWang2007.pdf

25. Chan-Lau, J. (2021). Scenario Analysis with the DD-PD Mapping Approach: Stock Market Shocks and U.S. Corporate Default Risk. IMF Working Paper WP/21/143, International Monetary Fund. Accessed October 6, 2021. https://www.elibrary.imf.org/view/journals/001/2021/143/article-A001-en.xml

26. Bottazzi, G., et al. (2011), Financial and economic determinants of firm default. Journal of Evolutionary Economics volume 21, 373–406. Accessed October 6, 2021. https://doi.org/10.1007/s00191-011-0224-6

27. Vassalou, M., Xing, Y. (2004), Default Risk in Equity Returns. *The Journal of Finance*, 59: 831-868. Accessed October 6, 2021. https://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.2004.00650.x

28. Malasari, D., et al. (2020). Financial Ratios and Probability of Default by Using the KMV-Merton Method in the Non-Financial Sector listed on the Indonesia Stock Exchange. Finance: Theory and Practice, 24, 1. Accessed October 16, 2021. https://doi.org/10.26794/258

29. 7-5671-2020-24-1-6-13

30. Syamsuddin, L. (2004). Corporate Financial Management. Jakarta: PT Raja Grafindo

31. Angelini, E., et al. (2008). A neural network approach for credit risk evaluation, *The Quarterly Review of Economics and Finance*, Volume 48, Issue 4, 733-755, ISSN 1062-9769. Accessed October 16, 2021. https://doi.org/10.1016/j.qref.2007.04.001.

32. Pulipaka, G. (2016). An essential guide to classification and regression trees in R Language. Medium. Accessed October 16, 2021. https://medium.com/@gp_pulipaka/an-essential-guide-to-classification-and-regression-trees-in-r-language-4ced657d176b

33. Simha, J.B., Satchidananda, S.S. (2006). Comparing Decision Trees with Logistic Regression For Credit Risk Analysis. SAS APAUGC, Mumbai.

34. Danenas, P., et al. (2011). Credit Risk Evaluation Model Development Using Support Vector Based Classifiers, *Procedia Computer Science*, Volume 4, 1699-1707. Accessed October 16, 2021. https://www.sciencedirect.com/science/article/pii/S1877050911002420

35. Putri, N., et al. (2021). Credit risk analysis using support vector machines algorithm. Journal of Physics: Conference Series, 1836(1):012039. Accessed October 16, 2021. https://iopscience.iop.org/article/10.1088/1742-6596/1836/1/012039/meta

36. Doumpos, et al. (2015). Combining accounting data and a structure model for predicting credit ratings: Empirical evidence from European listed firms. Journal of Banking and Finance, 50, 599-607. Accessed November 13, 2021. https://doi.org/10.1016/j.jbankfin.2014.01.010

9. Appendix 1

9.1. FTSE100 Companies

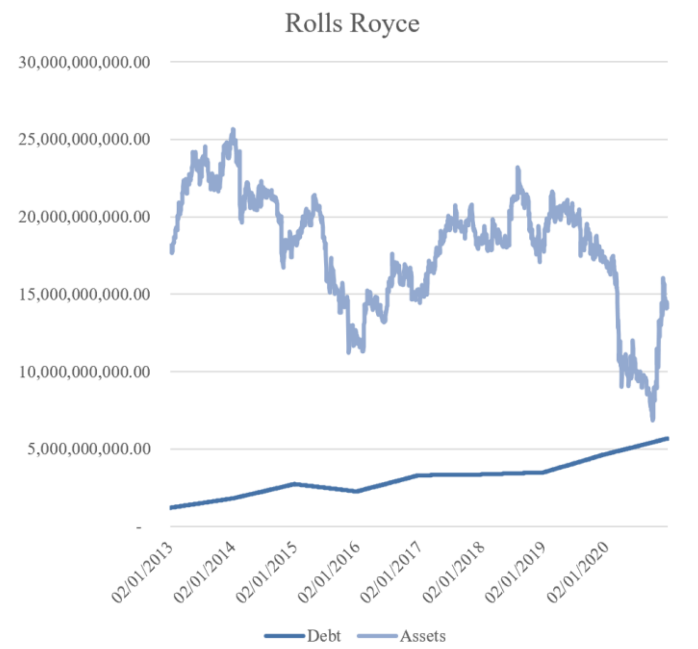
	Instrument	*Company Common Name*	*GICS Sector Name*	*ICB Industry code*
1	**AAL.L**	Anglo American PLC	Materials	55
2	**ABF.L**	Associated British Foods PLC	Consumer Staples	45
3	**ADML.L**	Admiral Group PLC	Financials	30
4	**ANTO.L**	Antofagasta PLC	Materials	55
5	**AV.L**	Aviva PLC	Financials	30
6	**AZN.L**	AstraZeneca PLC	Health Care	20
7	**BAES.L**	BAE Systems PLC	Industrials	50
8	**BARC.L**	Barclays PLC	Financials	30
9	**BATS.L**	British American Tobacco PLC	Consumer Staples	45
10	**BLND.L**	British Land Company PLC	Real Estate	35
11	**BNZL.L**	Bunzl plc	Industrials	50
12	**BRBY.L**	Burberry Group PLC	Consumer Discretionary	40
13	**BT.L**	BT Group PLC	Communication Services	15
14	**CPG.L**	Compass Group PLC	Consumer Discretionary	40
15	**CRDA.L**	Croda International PLC	Materials	55
16	**CRH.L**	CRH PLC	Materials	50
17	**DGE.L**	Diageo PLC	Consumer Staples	45
18	**EVRE.L**	EVRAZ plc	Materials	55
19	**EXPN.L**	Experian PLC	Industrials	50
20	**FERG.L**	Ferguson PLC	Industrials	50
21	**GLEN.L**	Glencore PLC	Materials	55
22	**GSK.L**	GlaxoSmithKline PLC	Health Care	20
23	**HSBA.L**	HSBC Holdings PLC	Financials	30
24	**ICAG.L**	International Consolidated Airlines Group SA	Industrials	40
25	**IHG.L**	InterContinental Hotels Group PLC	Consumer Discretionary	40
26	**ITRK.L**	Intertek Group PLC	Industrials	50
27	**ITV.L**	ITV PLC	Communication Services	40
28	**JMAT.L**	Johnson Matthey PLC	Materials	55
29	**KGF.L**	Kingfisher PLC	Consumer Discretionary	40
30	**LAND.L**	Land Securities Group PLC	Real Estate	35
31	**LGEN.L**	Legal & General Group PLC	Financials	30
32	**LLOY.L**	Lloyds Banking Group PLC	Financials	30
33	**MGGT.L**	Meggitt PLC	Industrials	50
34	**NG.L**	National Grid PLC	Utilities	65
35	**NWG.L**	Natwest Group PLC	Financials	30
36	**NXT.L**	Next PLC	Consumer Discretionary	40
37	**POLYP.L**	Polymetal International PLC	Materials	55
38	**PRU.L**	Prudential PLC	Financials	30
39	**RDSa.L**	Royal Dutch Shell PLC	Energy	60
40	**RDSb.L**	Royal Dutch Shell PLC	Energy	60
41	**REL.L**	Relx PLC	Industrials	40
42	**RIO.L**	Rio Tinto PLC	Materials	55

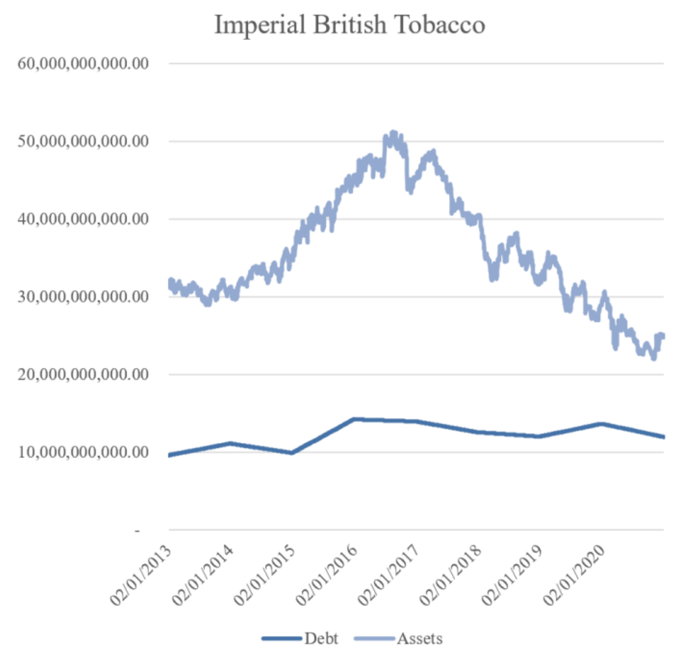
43	**RKT.L**	Reckitt Benckiser Group PLC	Consumer Staples	45
44	**SBRY.L**	J Sainsbury PLC	Consumer Staples	45
45	**SDR.L**	Schroders PLC	Financials	30
46	**SGE.L**	Sage Group PLC	Information Technology	10
47	**SMIN.L**	Smiths Group PLC	Industrials	50
48	**SN.L**	Smith & Nephew PLC	Health Care	20
49	**SSE.L**	SSE PLC	Utilities	65
50	**STAN.L**	Standard Chartered PLC	Financials	30
51	**SVT.L**	Severn Trent PLC	Utilities	65
52	**TSCO.L**	Tesco PLC	Consumer Staples	45
53	**ULVR.L**	Unilever PLC	Consumer Staples	45
54	**UU.L**	United Utilities Group PLC	Utilities	65
55	**WPP.L**	WPP PLC	Communication Services	40
56	**WTB.L**	Whitbread PLC	Consumer Discretionary	40

9.2. Key Brexit Days

Date	Event
23/01/2013	Announcement of an in-out referendum
22/02/2016	The Prime Minister announces the EU referendum date
23/06/2016	UK holds referendum on its membership of the EU
13/07/2016	Theresa May becomes the new UK Prime Minister
02/10/2016	Article 50 will be triggered before the end of March 2017
03/11/2016	High court rules UK parliament must have a say
17/01/2017	UK Prime Minister gives her Lancaster House speech
24/01/2017	Supreme Court rejects the UK Government’s appeal of the Gina Miller case
29/03/2017	UK Prime Minister triggers Article 50 of the Treaty on European Union
30/03/2017	UK Government publishes the Great Repeal Bill White Paper
18/04/2017	UK Prime Minister calls a General Election
08/06/2017	UK General Election results
19/06/2017	First round of UK-EU exit negotiations begin
22/09/2017	UK Prime Minister delivers her key Brexit speech in Florence
20/10/2017	European Council meeting to assess progress on the first phase of Brexit negotiations
08/12/2017	Joint Report concludes Phase 1 of negotiations and both sides move to Phase 2
02/03/2018	Prime Minister gives a speech at Mansion House
10/04/2019	Extension of Article 50
24/07/2019	Boris Johnson becomes the new UK Prime Minister
28/10/2019	Further Brexit extension
23/01/2020	European Union (Withdrawal Agreement) Act 2020 received Royal Consent
31/01/2020	UK left the EU and entered a transition period

9.3. IMB.L and RR.L





10. Appendix 2 – Python Fundamental Functions

10.1. Beta Function

```
def Beta(returns_companies,symbols_list):
    values_beta=[]
    X=returns_companies['.FTSE']
    for i in range(0,len(symbols_list)):
        y= returns_companies[symbols_list[i]]
        slope, intercept, r_value, p_value, std_err = stats.linregress(X, y)
        values_beta.append(slope)
    beta = pd.DataFrame (values_beta, columns = ['Beta'])
    return beta
```

10.2. MPR derived from the CAPM

```
def MPR(beta,ERP, vol_eq):
    return beta*ERP/vol_eq
```

10.3. Equity function

```
def equity_function(A,r,vol,D):
    t=5
    d1=(np.log(A/D)+t*(r+(vol**2)/2))/(vol*t**0.5)
    d2=d1-vol*t**0.5
    Nd1=si.norm.cdf(d1, 0.0, 1.0)
    Nd2=si.norm.cdf(d2, 0.0, 1.0)
    return A*Nd1-D*math.e**(-r*t)*Nd2
```

10.4. Asset function

```
def root_asset(A,obs,r,vol,D): #receives A as an inital guess
    def asset_function(A,obs,r,vol,D):
        t=5
        A= obs-(A*si.norm.cdf((np.log(A/D)+t*(r+(vol**2)/2))/(vol*t**0.5), 0.0, 1.0)-
D*math.e**(-r*t)*si.norm.cdf((np.log(A/D)+t*(r+(vol**2)/2))/(vol*t**0.5)-vol*t**0.5, 0.0,
1.0))
```

```
        return A
    L=(D*(math.e**(-r*5)))/A
    upperbound=obs+((math.e**(-r*5))*(L))+10**20
    root = optimize.brentq(asset_function,
obs,upperbound,args=(obs,r,vol,D),maxiter=100000)
    return root
```

10.5. ln Function

```
def lnV(A):
    return np.log(A)
```

10.6. N(d1) Function

```
def Nd1_function(A,r,vol,D):
    t=5
    d1=(np.log(A/D)+t*(r+(vol**2)/2))/(vol*t**0.5)
    Nd1=si.norm.cdf(d1, 0.0, 1.0)
    return Nd1
```

10.7. Maximum Likelihood Estimation Function

```
def maximum_likelihood_function(par,data,firmnumber):
    t=5
    deltat=1/(2024/7)
    def log(par):
        A,obs_df,rf_df,MRP_df,D_df=data #A is just an inital guess
        vol=par
        V=[]
        n=len(D_df)
        for i in range(0,n):
            D=D_df.iloc[i:i+1,firmnumber].values
            rf=rf_df.iloc[i:i+1,firmnumber].values
            MRP=MRP_df.iloc[i:i+1,firmnumber].values
            r=rf+vol*MRP
            obs=obs_df.iloc[i:i+1,firmnumber].values
```

```
            a=root_asset(A,obs,r,vol,D)
            V.append(a)
        #Get a list with the ln of the Assets
        lnVs = [lnV(i) for i in V]
        #Get a list with the difference between the ln of the Assets t and ln of the Assets t-1
        diff_list=[lnVs[i] - lnVs[i-1] for i in range(1,n)]
        diff_list.insert(0,0)
        #Get the function value
        loglikelihood_function=(-0.5*n*np.log(2*math.pi))-n*np.log(vol)-
0.5*np.sum(np.log(deltat))-((1/(2*vol**2))*np.sum([(diff_list[d]-((r-
0.5*(vol**2))*deltat)**2)/deltat for d in range(0,n)]))-np.sum(lnVs)-np.sum(lnVs)-
np.sum(np.log([Nd1_function(V[k],r,vol,D) for k in range(1,n)]))
        return -loglikelihood_function
    root_log = minimize(log, par, method='SLSQP',bounds=((0.01,1.5),))
    return root_log.x
```

10.8. Probability of Default Function

```
def PD(A,D,r,vol):
    def D1(A,D,r,vol):
        t=5
        return (np.log(A/D)+t*(r+(vol**2)/2))/(vol*t**0.5)
    def D2(A,D,r,vol):
        t=5
        return (np.log(A/D)+t*(r+(vol**2)/2))/(vol*t**0.5)-vol*t**0.5
    return si.norm.cdf(-D2(A,D,r,vol), 0.0, 1.0)
```

10.9. Distance to Default Function

```
def distance_to_default(A,D,r,vol):
    t=5
    return (np.log(A/D)+t*(r+(vol**2)/2))/(vol*t**0.5)-vol*t**0.5
```