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The impact of the COVID-19 crisis on bank corporate credit risk management in the US and the UK

Bachelor's thesis

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Declaration of Authorship

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Abstract

The thesis deals with bank corporate credit risk management during the COVID-19 crisis in the US and the UK. As a proxy of corporate credit risk, we employ corporate aggregate probability of default provided by Credit Benchmark. To measure the impact of the crisis on corporate aggregate probability of default, we use variables representing macroeconomic and financial market environments. Furthermore, as proxies for the COVID-19 shock and governments' fiscal measures, we employ COVID-19 stringency index and dummy variable(s), respectively. Our data set consists of 60 monthly observations, and by its structure is suitable for time series analysis. The analysis is based on Ordinary Least Squares, Two Stage Least Squares, and Generalized Method of Moments estimations. The results show that fiscal measures "artificially" decreased change of corporate aggregate probability of default in both countries. We recommend that the respective bank credit risk managers incorporate proxies representing fiscal measures in their estimation of through-the-cycle probability of default that serves as an input for calculating regulatory capital. Besides, a variable representing stringency index is found to be significant in the US's model. Thus, we recommend using such a proxy as input for stress testing in the US.

Keywords	bank, COVID-19 crisis, credit risk management, probability of default
Title	*The impact of the COVID-19 crisis on bank corporate credit risk management in the US and the UK*
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Abstrakt

Tato teze se zabývá bankovním korporátním úvěrovým rizikem v USA a VB během COVID-19 krize. Jako proxy proměnnou korporátního úvěrového rizika používáme korporátní agregátní pravděpodobnost defaultu, kterou nám poskytla společnost Credit Benchmark. Abychom změřili dopad krize na korporátní agregátní pravděpodobnost defaultu, používáme proměnné, které zastupují prostředí makroekonomie a finančního trhu. Navíc jako proxy proměnné šoku COVID-19 krize a vládních fiskálních opatření používáme index přísnosti vládních opatření při řešení COVID-19 pandemie a dummy proměnné. Náš dataset obsahuje 60 měsíčních pozorování a svoji strukturou je vhodný na analýzu časových řad, kde konkrétně používáme metodu nejmenších čtverců, dvoustupňovou metodu nejmenších čtverců a obecnou momentovou metodu. Výsledky ukazují, že fiskální opatření ,,uměle"snížily změnu korporátní agregátní pravděpodobnosti defaultu v obou zemích. Doporučujeme příslušným bankovním rizikovým manažerům specializovaným na úvěrové riziko, aby zahrnuli proxy proměnné fiskálních opatření do odhadu „through-the-cycle"pravděpodobnosti defaultu, která slouží jako vstupní veličina při výpočtu regulatorního kapitálu. Dále jsme zjistili, že proměnná reprezentující index přísnosti vládních opatření při řešení COVID-19 pandemie je statisticky významná v modelu USA. Na základě toho doporučujeme použití takové proxy proměnné v příslušných zátěžových testech v USA.

Klíčová slova	banka, COVID-19 krize, řízení úvěrového rizika, pravděpodobnost defaultu
Title	*Dopad COVID-19 krize na řízení korporátního úvěrového rizika v bankách v USA a VB*

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Data note

We do not attach our data set because probability of default from Credit Benchmark is not publicly available. Thus, we do not provide R code either, as it would not work without the data.

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Acronyms

AIC	Akaike Information Criterion
ASFR	Asymptotic Single Risk Factor
BCBS	Basel Committee on Banking Supervision
BOE	Bank of England
CDF	Cumulative Distribution Function
CUE	Continuous Updating Efficient
DJIA	Dow Jones Industrial Average
DR	Default Rate
EL	Expected Loss
EAD	Exposure at default
FASB	Financial Accounting Standards Board
FAVAR	Factor-Augmented Vector Autoregressive
FED	Federal Reserve Board
FRED	Federal Reserve Economic Data
FTSE 100	Financial Times Stock Exchange 100
GMM	Generalized Method of Moments
IASB	International Accounting Standards Board
IFRS 9	International Financial Reporting Standard 9
IV	Instrumental Variable
IMF	International Monetary Fund
LGD	Loss Given Default
LOGIT	Logistic Regression
MDA	Multiple Discriminant Analysis
OfNS	Office for National Statistics
OLF	One Latent Factor
OLS	Ordinary Least Squares
OECD	Organization for Economic Co-operation and Development
PIT	Point-in-Time
PD	Probability of Default
RC	Regulatory Capital
RWA	Risk-Weighted Amount
SUR	Seemingly Unrelated Regressions
TTC	Through-the-Cycle
TTC-PD	Through-the-Cycle Probability of Default
2SLS	Two Stage Least Squares
VaR	Value at Risk
VAR	Vector Autoregression
WCDR	Worst Case Default Rate
WHO	World Health Organization

1 Introduction

The thesis deals with bank corporate credit risk management during the COVID-19 pandemic from which the whole world has been suffering for more than a year. As of the beginning of May 2021, more than 140 million cases have been confirmed, with more than 3 million deaths. Governments worldwide have been reacting by opening and closing their economies depending on the epidemic situation, which leads to enormous uncertainty. There is no doubt that the virus causes not only human suffering health-wise but also economy-wise. This creates various tasks for economists. Firstly, they should recognize and measure the harm caused to market participants. Secondly and hopefully, they should provide necessary remedies to make everyone suffer as least as possible.

Already in March 2020 (i.e., at the beginning of the COVID-19 crisis), Baldwin & Di Mauro (2020) warned about the potential distress that the pandemic could cause to households, firms, banks, governments, and simply to all subjects in the economy. When lockdowns and the other accompanying measures end, Koulouridi *et al.* (2020) warn that banks will face a lending environment they have never encountered. They stress that evaluating and monitoring credit risk is key in such a crisis despite the potential unreliability of data. Furthermore, it is generally known that banks played an important part during the last great crisis, today known as the Global financial crisis of 2007-2009. Thus the proper credit risk management is more than appropriate.

All these arguments motivated us to this thesis: "The impact of the COVID-19 crisis on bank corporate credit risk management in the US and the UK". As a proxy of corporate credit risk, we use corporate aggregate probability of default (PD) provided by Credit Benchmark, a London-based company specializing in this industry. To measure the impact of the current crisis on corporate aggregate PD, we use macroeconomic variables, financial market

variables, and both proxies for the shock caused by COVID-19 and fiscal measures that were employed by both countries. Such proxies are COVID-19 stringency index (we refer to as stringency index), which was proposed by Hale *et al.* (2020), and dummy variable(s). Based on the literature, we built the following hypotheses:

- **Hypothesis 1**
  - *Fiscal measures were not significant determinants of change of corporate aggregate probability of default in the US*
- **Hypothesis 2**
  - *Fiscal measures were not significant determinants of change of corporate aggregate probability of default in the UK*
- **Hypothesis 3**
  - *Growth of stringency index was not a significant determinant of change of corporate aggregate probability of default in the US*
- **Hypothesis 4**
  - *Growth of stringency index was not a significant determinant of change of corporate aggregate probability of default in the UK*

Even now, more than a year since the crisis started, the body of research regarding this topic is almost non-existent. We hope that the results provided will motivate further research on this issue.

The rest of the thesis is organized as follows: Theoretical background is described in Section 2. Section 3 provides an overview of the literature. The methodology is described in Section 4. With respect to analysis, data are described minutely in Section 5, whereas Section 6 summarizes the whole empirical analysis, contribution, policy recommendations, and further research opportunities. Last but not least, the general results are encapsulated in Section 7.

2 Theoretical background

This section deals with the regulatory framework regarding risk management. First of all, we present the brief history of Basel regulation introduced by the Basel Committee on Banking Supervision (BCBS) since it was created. The emphasis is put on the provisions regarding PD and credit risk. Nevertheless, we also discuss other risks that banks need to tackle to get an overall view of the topic. Secondly, we also touch upon International Financial Reporting Standard 9 (IFRS 9). Lastly, we provide a short overview of how PD can be modeled.

2.1 Credit risk management and regulation in banking

In general, there are two contracting parties that need to agree upon a loan. The lender (the creditor) provides the borrower (the obligor) with money (credit) that needs to be fully repaid after a pre-specified period of time. However, there always exists the risk that contractual payment will not be made by the borrower, and the creditor is the one who bears the risk. This risk is referred to as credit risk, and creditors put a price on this risk that increases the overall contractual payment over the repaying period. BCBS defines credit risk, its goal, and its proper management the following way:

> Credit risk is most simply defined as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms. The goal of credit risk management is to maximise a bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters. Banks need to manage the credit risk inherent in the entire portfolio as well as the risk in individual credits or transactions. Banks should also consider the relationships between credit risk and other risks. The effective management of credit risk is a critical component of a comprehensive approach to risk management and essential to the long-term success of any banking organisation. (BCBS, 2000a)

Both terms lending and borrowing of money, have accompanied our civilization ever since. Already in the eighteen century, Smith (1776), in his book

"The Wealth of Nations" stressed the importance of the utilization of borrowed money (in this context, capital) for the expansion of businesses. The main idea was that this capital could accelerate economic growth. Adam Smith actually did not state it this way, but he demonstrated this economic principle on examples of craftsmen and people of other professions who, by borrowing money, could skip the phase of gradual saving a sufficient amount of money for further expansion of their businesses. Obligors, in this context craftsmen, were better off as they had the needed money immediately, and also creditors were better off as they ended up with a greater amount of money if everything went well. Moreover, Smith emphasized that this process could prompt faster economic growth. Nevertheless, he already outlined an argument that can be in today's perspective seen as the reason for credit risk management. Simply not all borrowers always repay their loans. He listed two reasons. Firstly, he highlighted that some borrowers could not afford the loan in general as they did not have a proper financial background or did not have the proper reason (e.g., they simply used these newly acquired resources for immediate consumption that is from the point of economy as a whole not necessary). These borrowers were far more likely to default. Secondly, he mentioned that even some borrowers, who had the proper background to afford the loan in normal conditions and also proper business plan, defaulted too. He attributed this empirical finding to the fact that sometimes when too many people obtained loans and produced their products without the necessity to have enough prior savings, then there was an excess of supply over demand for all of these products, and someone necessarily defaulted. These two arguments given by Smith could be even in today's perspective viewed as the foundation for current risk assessment despite its far more complicated structure. The first one can be viewed as borrower's idiosyncratic risk and the other one as the systematic risk that is the same for all borrowers. These types of risk are further discussed in the following sections.

In today's world, banks are the entities that serve as creditors from whom to

borrow money. They provide credit to corporates, households, other banks, and also governments. They are part of the financial system as a whole. Mejstřík *et al.* (2015) mention that a well-functioning financial system is a cornerstone of the economy that, in case of a failure, usually spreads the "contagion" to the rest of the economy resulting in a financial crisis. Following bank runs in the early 30s, many local authorities established insurance of deposits in banks. This serves as one of the reasons for regulation of banks because when knowing that the deposits are insured, banks generally take more risk as a result (see, for example, Anginer *et al.* (2018)). Dow (1996) and Hull (2012) discuss this as a reason for regulation too. Mejstřík *et al.* (2015) further add other reasons for regulation of banks, such as information asymmetry (in a debtor-borrower relationship), high leverage of banks (it is more profitable to finance loans from liabilities than equity), and systemic risk. All these factors support the idea of proper regulation.

2.1.1 Basel regulation in banks

As Hull (2012) mentions, the regulation was mainly based on o national level by setting an acceptable ratio of capital to assets before 1988. Nevertheless, as time went by, this was not enough because of the different severity of regulation across states, e.g., zombie banks in Japan in the 80s (Kane, 1989). Hull (2012) further adds why this regulation was insufficient as the ratio of capital to assets did not take into account the increasing complexity of products (e.g., derivatives do not enter classical balance sheet, which results in a lower denominator in the ratio).

The BCBS was formed in 1974. The original members were Belgium, Canada, France, Germany, Italy, Japan, Luxembourg, Sweden, Switzerland, the Netherlands, the United States, and the United Kingdom. In its press release, BCBS (1975) defined its target as assistance to member central-bank governors in surveillance and exchange of information. Later, BCBS (1987) further announced its works on criteria for capital measurements and standards

that would strengthen the stability of the banking system and that would be unified across the member states. Following this, the BCBS (1988) introduced the accord "International Convergence of Capital Measurement and Capital Standards" which was the first major result of mutual collaboration across member states. The aim was to set international standards for capital adequacy to cover better credit risks a bank could encounter while doing its usual business.

The accord introduced the Cooke Ratio that allows for both on- and off-sheet credit exposures. All these exposures are divided into three categories, namely on-balance sheet assets, off-balance sheet items without derivatives (e.g., guarantees), and exposures from over-the-counter markets. For all three groups, a risk-weighted amount (RWA) is calculated. The items of higher quality are given lower weight and vice versa. Furthermore, a new definition of capital, which divides it into two components, was established. It was Tier 1 Capital, which is of higher quality from those two, and Tier 2 Capital. The requirement for banks was that the ratio of RWA to total capital would be higher or equal to 8%:

$$CAD = \frac{CAP}{RWA} \geq 0.008 \tag{2.1}$$

where CAD denotes Capital adequacy, CAP denotes the sum of Tier 1 and Tier 2 capitals and RWA as explained above. Nevertheless, this ratio had to be higher or equal to 4% when only Tier 1 capital was in nominator. Although the 1988 accord did not take into account netting that can significantly reduce exposure for institutions having bilateral netting agreements in the over-the-counter market, it was later added to the original accord in the "1996 Amendment as referred by Hull (2012).

BCBS (1996) in the "1996 Amendment" further introduced regulatory capital for market risks that a bank face in trading activities. Generally, banks had to use the standardized approach, which was based on assigning regulatory capital separately for each type of instruments traded. Nevertheless,

Hull (2012) mentions that this approach was not that sophisticated and did not take into account correlation among instruments. Banks of greater importance and sophistication were allowed to use internal models based on JP's Morgan Value at Risk (VaR) model. Furthermore, this amendment presented fair value accounting (marking to market) for items that are held for trading purposes. Loans and other debt securities that were expected to be held until maturity were still valued at historical costs. The credit risk assessment remained intact and applied to all exposures as the original accord apart from a few items from the trading book that were newly regulated as market risk. Last but not least, the formula for regulatory capital that took into account market risk was changed in the following way:

$$CAD = \frac{CAP}{creditRWA + marketRWA} \geq 0.008 \tag{2.2}$$

Already at the end of the previous century, BCBS (1999) discussed new possibilities for credit risk assessment that would rely more on banks' internally calibrated models. The committee tested these models and proved that they could be more accurate than any general-based models. Nevertheless, they stressed that by that time, there was no known procedure that would ensure proper comparability across institutions from a regulatory perspective. As such framework was later determined (we refer to this later), the new accord Basel II was introduced. The accord became effective in most countries in years prior to the start of the Global Financial Crisis of 2007-2009. Nevertheless, in the US, it became effective in April 2008. Ex post, it can be said that the accord was actually predetermined to be unsuccessful because its launch overlapped with the aforementioned crisis that is considered as one of the biggest in history (IMF, 2008).

At the dawn of the new century, BCBS (2006) introduced the revised framework for Basel II that stemmed from the original proposal by BCBS (1998) and included the procedure for stress testing that serves as the desired measure for comparability of internal models. In the text, we refer to the Basel

II accord as BCBS (2006) because it includes all key documents regarding Basel II as a whole, although the parts of the document were introduced separately and sooner.

BCBS (2006) based the new accord on three pillars, i.e., Minimum Capital requirements, Supervisory review, and Market discipline. Supervisory review could be understood as instructions for regulatory bodies how to deal with regulation in their country. Market discipline is mainly concerned with the disclosure of capital adequacy allocation and risk assessment procedures.

As far as Minimum Capital requirements are concerned, market risk procedures were left unchanged. Moreover, the accord newly took into account operational risk and included it in the formula for calculation of regulatory capital. Operational risk can be viewed as the risk that is associated with the failure of banks' internal procedures, policies, or systems. BCBS (2006) specified tree approaches for calculating the RWA for operational risk, i.e., The Basic Indicator Approach, The Standardized Approach, The Advanced Measurement Approach. Last but not least, the accord changed the calculation of capital requirements for credit risk because the original Basel I weights were in a way ineffective and unfair (Ahmed & Khalidi, 2007). The original risk weights took into consideration only the difference between general groups of assets (e.g., corporate debt X residential debt) but not the difference between assets of one group (e.g., corporate debt X corporate debt). Gordy (2003) further emphasizes that the original Basel I accord did not consider the quality of the collateral, which was not the case in Basel II. Moreover, Chatterjee (2015) states that the original Basel I framework gave incentives to "risk shifting" because of mispriced risks. Based on this, he further states that banks tended to hold riskier assets because of greater profitability. This rings true because if a bank needs to hold the same amount of capital for the corporate bond that belongs to investment grade and for the corporate bond that belongs to speculative grade, the bank should choose the riskier one as high-risk products are, generally, associated with greater potential profit. Keeping this into mind, the new approach had to be more

sensitive to this problem. In fact, the Basel committee was aware of this problem, as already mentioned, but it had to find the common framework for comparison. As time went by, the committee agreed upon this common framework that is based on Vasicek (2002) and introduced it with newly revised requirements for credit risk that enabled more sophisticated banks to use internally calibrated models for calculations of regulatory capital for credit risk (BCBS, 2006). Furthermore, BCBS in this document introduced conditions and guidelines for stress testing.

The new Basel II formula, which was introduced by BCBS (2006) and which considered all credit, market, and operational risks, was as follows:

$$CAD = \frac{CAP}{creditRWA + marketRWA + operationalRWA} \geq 0.008 \quad (2.3)$$

Furthermore, BCBS (2006) introduced in the accord three approaches for calculation of RWA for credit risk, i.e., The Standardized Approach, The Foundation IRB Approach, and The Advanced IRB Approach. The Standardized Approach is, by definition, very similar to Basel I calculations with only adjusted risk weights. The new risk weights now take into account the cross-sectional differences between one group of assets. For example, risk weights for corporations range from 20% to 150%. Interestingly, as mentioned by authors, namely Witzany (2017) and Hull (2012), it is better for a bank to hold an asset that is unrated rather than one that has a bad rating as for the unrated one, the risk weight is lower. Nevertheless, BCBS (2006) allows this diversification among cross-sections to be determined by external rating agencies that are approved by a supervisor in a given country. Lessons from the Global financial crisis of 2007-2009 fully showed how dangerous this external rating could be because of conflict of interests (Mullard, 2012). Whether a bank use The Standardized Approach or IRB Approaches is determined by its importance for the system and its sophistication. So, the less sophisticated banks stick to The Standardized one.

Both IRB Approaches are based on Vasicek (2002) work "Loan portfolio

value". As BCBS (2005) emphasizes, the regulatory requirements for unexpected losses should be based on a model that is portfolio invariant, i.e., determination of required capital depends only on the risk associated with that loan and not on the portfolio it is added. Gordy (2003) proves that only Asymptotic Single Risk Factor (ASRF) models can be portfolio invariant and shows that they are derived based on the law of large numbers. BCBS (2005) states that due to the given reasons, these models are used in the Basel risk weight function. Furthermore, the committee in the document stresses that in large portfolios with many exposures, the individual risk (idiosyncratic) risks are likely to offset each other to zero. This results that only systematic risks, which are in ASRF models represented by only one factor, significantly influence portfolio losses. The ASRF model underlying IRB Approach is originally based on Merton (1974) single asset model to credit portfolio. Vasicek (2002) shows that the model can be further adjusted to serve as an ASRF credit portfolio model. This model uses through-the-cycle probability of default (TTC-PD) as an input because it should "smooth" the business cycle and reflect the long-term conditions. This TTT-PD is then transformed by Vasicek's formula into default rate that is conditional on systematic factor. The formula further takes as an input the correlation among financial products in a portfolio. For the derivation of Vasicek's formula, we mostly follow Hull (2012) as it is slightly simplified from the original Vasicek's framework and uses the notation that better serves the purpose. Based on the following formula, Basel's II regulatory capital can be derived. Regulatory capital serves as important input into the RWA formula for both IRB Approaches.

Vasicek (2002) firstly assumes that all loans in the portfolio have the same pairwise correlation, have the same maturity, the same PD, and since he applies the law of large numbers that the size of the portfolio is as huge as possible. Furthermore, he assumes that all loans in the portfolio once default (although the default might occur in the distant future) and that the cumulative distribution function (CDF) for time to default is the same

for each loan. So, define T_i as the time when the loan i is defaulted and let PD to be the probability of default by time T:

$$PD = Prob(T_i < T) \tag{2.4}$$

Hull (2012) remarks the difficulties of defining the structure of correlation among variables that are not normally distributed or it cannot be assumed for sure. In the context of Vasicek's formula, Vasicek (2002) uses as a solution multivariate factor copula model:

$$U_i = \sqrt{\rho}F + \sqrt{1-\rho}Z_i \tag{2.5}$$

where

$$PD = Prob(T_i < T) = Prob(U_i < U) \tag{2.6}$$

He uses this model to define copula correlation among all $U_1, ..., U_n$. In the model, he assumes that each U_i is equi correlated variable from a standard normal distribution that is mapped from each T_i on a percentile-to-percentile basis. So, the default for obligor i occurs when the value of U_i decreases below U that Vasicek (2002) shows to be a function of TTC-PD ($U = N^{-1}[PD]$). In equation (2.5), ρ corresponds to the pairwise correlation between loans in portfolio (that is implicitly the same for all loans because of equi correlation structure), F corresponds to systematic factor representing the whole macroeconomic environment, whereas Z corresponds to idiosyncratic factor. Then the term $\sqrt{\rho}F$ corresponds to loan's i exposure to a systematic factor, and the term $\sqrt{1-\rho}Z_i$ corresponds to idiosyncratic exposure. Moreover, all $F, U_1, ..., U_n$ are mutually independent, again because of the equi-correlation of U_i.

The systematic factor F directly affects the PD by time T, which comes from equations (2.5) and (2.6). The higher the F is, the better the economic conditions, and as a result, every U_i with its T_i will also be high. $Prob(T_i < T) = Prob(U_i < U)$ is low in this scenario. If F is low, the situation is reversed. Based on Vasicek's formula, Hull (2012) defines the "worst case

default rate," $WCDR(T, X)$ for a certain portfolio to be the default rate during time period T that has probability X of not being exceeded:

$$WCDR(T, X) = N\left(\frac{N^{-1}(PD) + \sqrt{\rho}N^{-1}(X)}{\sqrt{1-\rho}}\right) \tag{2.7}$$

This formula is derived conditional on systematic factor F. Now, we show how Vasicek's formula can be derived.

Probability that $U_i < U$ conditional on F is:

$$Prob(U_i < U|F) = Prob(\sqrt{\rho}F + \sqrt{1-\rho}Z_i) \tag{2.8}$$

From equation (2.5), Z_i can be expressed as:

$$Z_i = \frac{U_i - \sqrt{\rho}F}{\sqrt{1-\rho}} \tag{2.9}$$

Based on equation (2.9), the formula (2.8) above can be rewritten in the following way:

$$Prob(U_i < U|F) = Prob\left(Z_i < \frac{U - \sqrt{\rho}F}{\sqrt{1-\rho}}\right) = N\left(\frac{U - \sqrt{\rho}F}{\sqrt{1-\rho}}\right) \tag{2.10}$$

The procedure is correct because both U and F are treated like constants. From equation (2.6) it holds that $PD = Prob(T_i < T) = Prob(U_i < U)$, thus it can be written:

$$Prob(T_i < T|F) = N\left(\frac{U - \sqrt{\rho}F}{\sqrt{1-\rho}}\right) \tag{2.11}$$

Because $U = N^{-1}[PD]$, the equation can be rewritten:

$$Prob(T_i < T|F) = N\left(\frac{N^{-1}(PD) - \sqrt{\rho}F}{\sqrt{1-\rho}}\right) \tag{2.12}$$

Random variable F has a standard normal distribution, therefore according to Hull (2012), $Prob(F < N^{-1}(Y)) = Y$. From that, we know that value Y belongs to the interval of $[0, 1]$. To serve the purpose better, we further follow Hull (2012) and define $X = 1 - Y$, which is equivalent to $Y = 1 - X$. From

the properties of standard normal distribution, it holds that $-N^{-1}(Y) = -N^{-1}(1-X) = N^{-1}(X)$. Based on this, the "worst case default rate," $WCDR(T, X)$ during time T that will not be exceeded with probability X equals exactly the right-hand side of the equation (2.7). Furthermore, DR (default rate) can be defined in the exact same manner because Vasicek (2002), Chatterjee (2015), and Hull (2012) all remark that the equation holds for all percentiles. Hull (2012) further demonstrates how Vasicek's model can be further adjusted. He shows that when DR is the default rate and $G(DR) = N^{-1}(X)$ is the CDF for DR, then equation (2.7) can be transformed to define probability density function for the default rate:

$$DR(T, X) = N\left(\frac{N^{-1}(PD) - \sqrt{\rho}G(DR)}{\sqrt{1-\rho}}\right) \tag{2.13}$$

Now $G(DR)$ can be expressed from equation (2.13) as:

$$G(DR) = N\left(\frac{\sqrt{1-\rho}N^{-1}(DR) - N^{-1}(PD)}{\sqrt{\rho}}\right) \tag{2.14}$$

When differentiating equation (2.14) with respect to DR, we obtain:

$$g(DR) = \sqrt{\frac{1-\rho}{\rho}} \exp \frac{1}{2}\left[(N^{-1}(DR))^2 - \left(\frac{\sqrt{1-\rho}N^{-1}(DR) - N^{-1}(PD)}{\sqrt{\rho}}\right)^2\right] \tag{2.15}$$

where $g(DR)$ is the probability density function for default rate. Knowing the value of ρ and TTC-PD, one can obtain the exact probability distribution function of default rate that lays the foundation for Basel II terms, namely regulatory capital, expected loss, unexpected loss, and value at risk (VaR) that we will discuss shortly.

In order to derive the RWA formula, we use Vasicek (2002) results, and according to BCBS (2006), define expected loss (EL) as:

$$EL = \sum_{i=1}^{n} EAD_i LGD_i PD_i \tag{2.16}$$

where EAD_i is exposure at default, i.e., the amount of money that is ex-

pected to be owed by contracting party i when it defaults. LGD_i is loss given default, i.e., what proportion of EAD_i will be lost in case of default of contracting party i. Finally, PD_i is the expected probability of default of contracting party i over the next year. Vasicek (2002) assumes that in one portfolio, all loans have the same PD. If this scenario holds, then this PD is the same as Vasicek's $DR(T, X)$. Although in practice, each PD_i in the portfolio is marginally different from one another, Gordy (2003) shows that due to the size of the portfolio, it does not cause any problems. He further demonstrates that the formula for the VaR can be approximately defined if the dependence across exposures is driven only by a single systematic factor (dependence is represented by the pairwise correlation of ρ), if the portfolio is large, and if each exposure is negligible. The VaR, according to him, is approximated as:

$$VaR \approx \sum_{i=1}^{n} EAD_i LGD_i WCDR_i \tag{2.17}$$

where as mentioned:

$$WCDR_i = N\left(\frac{N^{-1}(PD_i) + \sqrt{\rho}N^{-1}(G(DR)}{\sqrt{1-\rho}}\right) \tag{2.18}$$

From these two equations, regulatory capital (RC) can be calculated in the following way:

$$RC = \sum_{i=1}^{n} EAD_i LGD_i WCDR_i - \sum_{i=1}^{n} EAD_i LGD_i PD_i = VaR - EL \tag{2.19}$$

The stress testing is based on assuming various scenarios in the economy via independent variables in equation (2.19). On the ground of the impact of such a scenario on regulatory capital, a central bank can have a better overview of the condition of its commercial banks and can also directly compare them.

Now we stick to the calculation of risk-weighted assets for corporate, sovereign, and bank exposures as the thesis is concerned with the determinants

of PD for corporates. BCBS (2006) recommends Lopez (2004) empirical results to determine ρ as a function of PD:

$$\rho = 0.12\frac{1 - exp(-50 \cdot PD)}{1 - exp(-50)} + 0.24\left[1 - \frac{1 - exp(-50 \cdot PD)}{1 - exp(-50)}\right] \tag{2.20}$$

By plugging a few numbers from interval $[0, 1]$, it can be seen that the relationship is supposed to be negative, i.e., as PD increases, the ρ decreases and vice versa. Despite this, Lee *et al.* (2009) find that there is no strong decreasing relationship between ρ and PD and recommended Basel committee to revisit this relationship for future usage in banks. This is further supported by Dietsch & Petey (2004) and Kupiec (2009). On the other hand, the research of both Chernih *et al.* (2006) and Blümke (2015) is consistent with Lopez (2004). Nevertheless, the formula defined by BCBS (2006) still holds. BCBS (2006) further defines the formula for calculation of the RWA for corporates as:

$$RWA = 12.5 \cdot RC \cdot MA \tag{2.21}$$

where MA is maturity adjustment and is defined by them as:

$$MA = \frac{1 + (M - 2.5) \cdot (0.11852 - 0.05478 \cdot ln(PD))^2}{1 - 1.5 \cdot 0.11852 - 0.05478 \cdot ln(PD))^2} \tag{2.22}$$

Maturity adjustment can be understood as allowance for longer-lasting instruments, i.e., the longer the instrument lasts, the greater the uncertainty about the future financial position of the contracting party it encompasses.

Up till now, we have not distinguished the Foundation IRB approach from the Advanced IRB approach. According to BCBS (2006), banks that use the Foundation IRB approach can estimate TTC-PD (although a minimal value to 0.003% is set), and all EAD, LGD, and M are set by the committee. On the other hand, the committee allows banks that use the Advanced IRB approach to further estimate on their own EAD, LGD, and M, but they are still subjected to specific requirements that we do not delve into. Nevertheless, the committee recommends the usage of the Advanced IRB approach for banks based on permission from the local authority.

BCBS (2006) specifies that banks should cover expected losses by provisions. On the other hand, unexpected losses should be covered by economic capital. In equation (2.18), it is assumed that $G(DR) = 0.999$, which is, in other words, a scenario that we are 99% sure that will not be worse. Such a situation should, based on statistical theory, happen once in 1000 years, but lessons from 2007-2009 show that this is not the case. Chatterjee (2015) suggests that for such VaR, it is too expensive to hold capital from the point of view of banks. This assumption seems reasonable because of the aforementioned reasons, namely insurance of deposits. Furthermore, other financial institutions might also relied on the concept of Too Big To Fail, firstly mentioned by Stewart McKinney in 1984 (Farber, 2012) as supported by Stern & Feldman (2004). Already in 2004, they warned about potential bail-outs that would happen if systematically important financial institutions become insolvent. Ex-post, they were right, as can be seen in the cases of Fannie Mae, Freddie Mac, and AIG. Despite bailouts, the crises from 2007-2009 again showed how the financial "contagion" could spread into economic "contagion" in terms of GDP, unemployment, inflation, etc. In other words, this empirical evidence further supports the proper regulation of banks and, more generally, of the whole financial system.

As a reaction to the financial crisis, BCBS (2009b) introduced the "Revisions to the Basel II Market Risk Framework" (from now on, we refer to this as BCBS (2011b) because of later adjustments to the framework). BCBS (2011b) admitted that huge losses financial institutions incurred were in the trading book. Thus, the committee implemented Incremental Risk Capital Charge, Comprehensive Risk Capital Charge, and Stressed Var. Incremental Risk Charge aimed at the equalization of capital charge for unsecuritized items that are of similar type, but one is on the trading book, and the other one is on the banking book. Prior to this amendment, it was more advantageous to hold them in the trading book rather than in the banking book, as mentioned by BCBS (2009a). The Stressed VaR, by its definition from BCBS (2011b), significantly increased capital requirements for market

risks because it at least doubled the overall market risk requirements for more sophisticated banks. The Comprehensive Risk Capital Charge was, according to the committee, aimed at so-called correlation trading activities. Hull (2012) gives examples of tranches that are more prone to losses in a stressed market environment as correlations of the underlying assets increase.

The "Revisions to the Basel II Market Risk Framework" became effective by the end of 2011 (BCBS, 2011b). It can be viewed as a quick reaction to the crisis. Concerning Basel III, it is rather a long-term reaction because all segments of the revised framework have not been completely implemented up to date (BCBS, 2020a). BCBS (2011a) regarded Basel III as the key response to the Global financial crisis that should make the banking system far more resilient. The committee firstly introduced the new Basel III accord right after the crisis (BCBS, 2010). In the accord, BCBS defined a new capital charge for liquidity risk where banks have to calculate Liquidity Coverage Ratio and Net Stable Funding Ratio. Hull (2012) argues that at the beginning of the financial crisis in 2007, even banks that met required capital levels experienced difficulties because of improper management of liquidity risk. BCBS (2011a) also redefined and adjusted requirements and definitions of capital, i.e., now there is Tier 1 equity capital, Additional Tier 1 capital, and Tier 2 capital with no Tier 3 capital as in Basel II, which we not discussed previously. These adjustments, by their final definition, result in stricter capital requirements. Furthermore, BCBS introduced a capital conservation buffer that further increased Tier 1 equity capital and also a countercyclical buffer that is very similar to conservation buffer, but its implementation depends on the discretion of national authorities. Both Hull (2012) and BCBS (2014) argue that prior to the crisis in 2007-2009, there was an excessive increase in both on- and off-balance sheet leverage in banks while they still managed to hold capital requirements properly. Therefore, BCBS (2011a), as a part of the accord, also presented a new capital requirement - leverage ratio. The leverage ratio is an additional capital requirement that is calculated as the ratio of Tier 1 capital over exposures that include,

for example, on-balance-sheet exposures, derivatives exposures, and others. BCBS (2014) further states that high leverage significantly amplified the crisis.

BCBS (2017) claims that counterparty credit risk that is associated with derivatives can be decomposed into two parts. Firstly it is the risk of counterparty's default, and this risk has already been accounted for in previous accords. Secondly, it is the risk that the counterparty becomes less creditworthy and is called credit valuation risk. BCBS (2017) further highlights that during the Global financial crisis in 2007-2009, credit valuation risk was a significant source of unexpected losses. Therefore, as a part of Basel III, BCBS (2011a) further introduced credit value adjustment that takes this risk into account. Hull (2012) stresses that regulators are aware of the problems regarding huge bail-outs of systematically important institutions. According to BCBS (2011a), G-SIB and SIFI stand for systematically important banks and systematically important financial institutions, respectively. These institutions are, according to the accord, required to hold further capital as a safety net. For example, BCBS (2013) defined that G-SIBs have to hold extra equity capital of either 1%, 1.5%,2%, 2.5%, 3%, 3.5% of risk-weighted assets depending on the importance.

2.1.2 IFRS 9

Following the Global financial crisis in 2007-2009, International Accounting Standards Board (IASB) published a new accounting standard IFRS 9, that replaces the International Accounting Standard 39. PwC (2017b) discusses that the aim of the standard was to become less complex than its predecessor and to detect credit losses on loans and receivables in time.

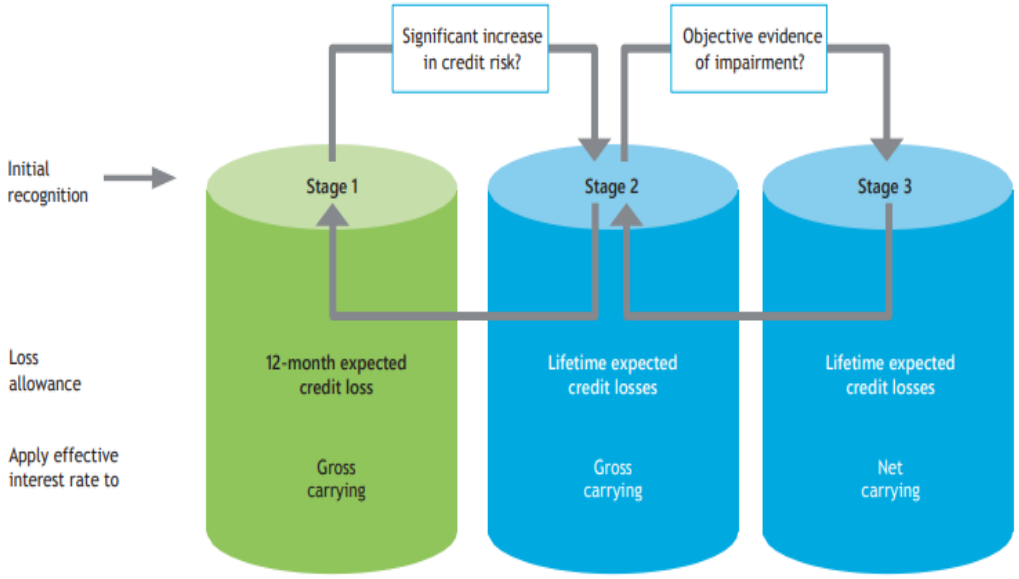
The standard was presented in three phases, each of which deals separately with classification and measurement, impairment, and hedging. Because the thesis deals with credit risk, we mainly discuss the impairment phase. While describing, we follow the description of IFRS 9 from PwC (2017b), Deloitte

(2017), and BDO (2018). Furthermore, we use notation from PwC (2017b).

IFRS 9 presents the new impairment measure for loans and receivables that is based on the expected credit loss model. The allowance is the output from the model and is calculated by assuming various default scenarios that might occur in the future. For each of these scenario, the shortfalls the entity would incur are discounted either by effective interest rate or by credit-adjusted effective interest rate. Each of these shortfalls is then multiplied by the probability of such an event. The allowance is then the sum of these weighted discounted shortfalls, and its changes are directly recognized in profit and loss. There is a General Approach for calculation of the allowance that determines whether the loss allowance equals to 12-month expected credit loss (expected credit losses that result from defaults on financial instruments that might happen within one year after the reporting date) or to lifetime expected credit losses (expected credit losses that result from all possible defaults on the financial instrument within its life). For trade receivables that do not contain significant financial component (according to IFRS 15), it is required to calculate a loss allowance for lifetime expected credit losses. Apart from these "IFRS 15 contract assets" and purchased or originated credit-impaired assets (we address this later), the allowance equals 12-month expected credit loss unless there is a significant increase in credit risk that is defined as a significant increase in the probability of default on the instrument since the initial recognition. The standard allows various approaches in assessing whether the credit risk has increased significantly or not. Nevertheless, it strictly assumes that credit risk has increased significantly when the contracting party is past due more than 30 days with payments. The impairment model for General Approach can be summarized in figure 1.

From the chart, it can be further seen that there are actually three stages of an asset in the portfolio. For the first stage, the allowance equals 12-month expected credit loss, and interest income is calculated by applying the effective interest rate (the interest rate that discounts expected cash flows

Figure 1: The impairment model for General Approach



Source: Deloitte (2017)

to the initial carrying amount of an asset) to the gross carrying amount of an asset (the amortized cost of a financial asset before adjusting for loss allowance). If the asset is not credit-impaired while purchased, it belongs to stage one at initial recognition. On the other hand, when there is a significant increase in credit risk, the allowance equals lifetime expected credit loss, and the asset is in stage two. Nevertheless, the interest income is still calculated by applying the effective interest rate to the gross carrying amount of an asset. Lastly, when the asset becomes credit impaired, it goes to stage three, and the allowance still equals lifetime expected credit loss, but the interest income is calculated by applying the effective interest rate to the net carrying amount of an asset (the amortized cost of a financial asset with adjustment for loss allowance). Thus the interest is lower than in the previous two stages. Importantly, as assets can move up from stage one gradually to stage three, they can also move the other way if their credit conditions improve. In general, the effective interest rate also serves as a discount rate when calculating the expected loss for this group of assets.

As already indicated, there are exceptions to this approach. Firstly, the

"IFRS 15 contract assets" can only operate in stage two and stage three, otherwise it is the same. Secondly, purchased or originated credit-impaired assets are treated differently because they are already impaired when bought. They are associated with credit-adjusted effective interest rate. Although the credit-adjusted effective interest rate is calculated in a similar fashion as the effective interest rate, it must be generally lower because future expected cash flows explicitly reflect the uncertainty of the instrument. The credit-adjusted effective interest rate serves as a discount rate for calculating of expected credit loss for purchased or originated credit-impaired assets. For these assets, the allowance always equals the lifetime expected credit loss, and interest income is calculated by applying the credit-adjusted effective interest rate to the net carrying amount of an asset.

PwC (2017b) stressed that the effect of IFRS 9 on credit risk management would be noticeable because impairment losses on receivables and loans would be earlier recognized. Furthermore, they said that new classification and measurement categories would cause more volatility in the income statement because more assets would be measured at fair value. Lastly, they emphasized that new disclosure requirements might lead financial institutions to adopt new systems that would process the necessary data.

Nevertheless, the thesis is concerned both with the UK that has adopted IFRS 9 and also with the US that neither has adopted IFRS 9 nor will in the future. Even though the US has always had its own accounting standards, PwC (2017b) mentions efforts both from IASB and from the Financial Accounting Standards Board (FASB) to create the joint standards that unfortunately failed. PwC (2017a) directly compared credit impairment under IFRS 9 and US GAAP (the standard proposed by FASB) with results that both standards adopted a similar "expected credit loss" model. On the other hand, they emphasized that the main difference in impairment between standards is that under US GAAP, the allowance always equals the lifetime expected credit loss, i.e., there is no 12-month expected loss. This can be understood that US GAAP is in general stricter than IFRS 9.

2.1.3 Models for estimating default probabilities

There is a huge number of models that aim to estimate PD. Chan-Lau (2006a) divides these models based on available data into two categories: market-based models and fundamental-based models. Market-based models are, according to him, founded on security prices, whereas fundamental-based models rely on general factors, such as accounting information, rating information, systematic factors, and economic factors.

Chan-Lau (2006b) emphasizes that market-based models are especially useful for estimating PD when obligor's securities or referencing credit derivatives are frequently traded on secondary markets. These models are based on reverse-engineering asset pricing formulas from which risk-neutral PDs are extracted. He gives examples of securities, namely credit default swap, bond, and equity, that can serve this purpose. Furthermore, he states that although credit default swaps are considered to be the best indicator of credit risk from all securities, they are not traded in all markets. Thus for less developed markets, other, more common securities have to be used. Last but not least, he stresses that these models generate risk-neutral PDs. Nevertheless, he shows how to derive the real-world PDs from risk-neutral based on the marginal utility of wealth.

In another paper, Chan-Lau (2006a) discusses fundamental-based models where he classifies the models the following way:

- Macroeconomic-based models
  - The estimation of PD is based on macroeconomic variables. See, for example, Zsigraiová (2014), Jakubik & Schmieder (2008), and Virolainen (2004).
- Credit scoring (accounting-based) models
  - Such models are, for example, Moody's KMV Model and Altman's Z-Score.

- Ratings-based models
  - See Rösch (2005).
- Hybrid models
  - These models are the mixture of above approaches.

In the thesis, we mainly analyze the relationship between PD, its macroeconomic determinants, and its financial market determinants. Therefore, in this section, we stick to macroeconomic-based models as they are most closely related to what we are doing.

Lowe (2002) for BCBS suggested discussion in this macroeconomic area because probability of default increases in worsen economic conditions, which results in higher capital requirements that are usually, as mentioned by Darracq Pariès *et al.* (2020), difficult to meet. Lowe (2002) also points out that the level of capital should not decrease further during financial imbalances. Chan-Lau (2006a) says that this has given grounds for the implementation of econometrics models that explains probability of default given macroeconomic variables. He further divides macroeconomic-based models depending on whether explanatory variables are exogenous or endogenous.

In general, the concept of endogeneity in econometrics means that at least one explanatory variable is correlated with error in a given time period. Chan-Lau (2006a) further elaborates this idea on macroeconomic-based models where he states that these models allow macroeconomic explanatory variables to be correlated with financial distress as a shock in the error term. Such an endogenous model might, for example, be the vector autoregression (VAR) that, after estimation, requires to use impulse response analysis in order to find out the effect of a shock to each macroeconomic variable on PD. Such analysis was, for example, employed by Hoggarth *et al.* (2005), Hamerle *et al.* (2011), and Alessandri *et al.* (2018).

On the other hand, there are macroeconomic-based econometrics models that assume exogenity in explanatory variables. Chan-Lau (2006a) defines

probability of default depending on the macroeconomic environment for these exogenous models in the following way:

$$p_t = f(y_t) \tag{2.23}$$

where p_t is PD at time t, that can be either firm-specific, industry-specific, or country-specific, and y_t is an economic factor that originates from all macroeconomic variables to represent the conditions as a whole. He further states that variable y is usually modeled in a way that the higher the y is, the better the economic conditions are. Therefore, f must be a decreasing function of y. Last but not least, Chan-Lau (2006a) defines y as a function of macroeconomic $X = (X_1, X_2, ..., X_n)$, and a random shock V:

$$y_t = g(X_t, V_t) \tag{2.24}$$

To be able to estimate PD, Chan-Lau (2006a) says that proper macroeconomic variables must be chosen as a set of explanatory variables. Furthermore, function g must be specified for the construction of economic indicator, whereas function f must be specified for linking this factor to PD. Such a model is, for example, employed by Virolainen (2004), who models PD of several sectors in the Finnish economy. Other authors, for example, Jakubík (2006) employs another type of exogenous model - the latent factor model. He employs one latent factor (OLF) model to estimate PD of the Finnish economy.

2.2 Implications of the COVID-19 crisis for banks

Firstly, we touch upon COVID-19 as a disease. Secondly, we mention the expectations about the COVID-19 crisis at its beginning. Then, the section discusses both fiscal and monetary measures employed by the US and the UK. We also remark on their efficiency. Last but not least, we discuss regulation loosening and summarize the potential harm all these factors might cause to credit risk management in banks.

To date, the whole world has been suffering from a coronavirus pandemic for more than a year with a huge number of victims. It can be argued that lock-downs, closed borders, and quarantines, as we have got familiarized in recent year, is something that no one had ever imaged of in this century. The disease was officially named Coronavirus Disease 2019 (COVID-19) by the World Health Organization (WHO) (Sohrabi *et al.*, 2020).

It is reported that COVID-19 started as an epidemic in the city of Wuhan, Hubei province, China (Santos, 2020). The disease then spread to the whole world by the movement of people till the WHO declared it a global pandemic on March 11th. Gralinski & Menachery (2020) initially designated the virus the virus causing this disease as 2019-nCoV. Zhou *et al.* (2020) later found evidence that the virus is genetically similar to the SARS-CoV virus that caused SARS outbreak in 2003. As a result, the WHO (2020) named the virus Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2).

No one can argue that this original health crisis, which infected the world economy, has and will have an impact on the banking system as well. Already in March last year, Baldwin & Di Mauro (2020) mentioned that the COVID-19 crisis did not seem to be "V-shaped", i.e. short and sharp, but rather "U-sharped", i.e., longer. One year later, it can be said that they were right because quarantines still take place, public and private containment measures, namely factory closures, school closures, and travel restrictions, are still the most frequent measures when the number of positive cases increases.

Furthermore, they identified how these measures result in both supply- and demand-side shocks that negatively influence both households and companies worldwide and further remarked that globalization only amplified the overall impact. Generally, in a crisis that stems from the real economy, banks and other financial institutions are prone to suffer too because they either are lenders of institutions and households or operate with financial instruments that are derived from the value of the aforementioned companies. Moreover, IMF (2020) already in April that year warned that global financial conditions had tightened abruptly with the onset of the COVID-19 pandemic and that resilience of all financial institutions might be tested during the rise of systematic risk. Zhang *et al.* (2020) confirmed this. Baldwin & Di Mauro (2020) and Gbohoui & Medas (2020) stressed that both governments and central banks would need to run coordinated fiscal and monetary policies to mitigate the consequences as much as possible. On the other hand, research of these authors was published before most of the fiscal and monetary measures, which are discussed later, were in place. Therefore, these authors could not know about any of these measures. Despite that, we still discuss their work just to have an overall understanding of the COVID-19 situation.

Governments and their respective central banks were aware of the seriousness of the situation and adopted both monetary and fiscal measures that are unprecedented (BCBS, 2020b). For example, the Federal Reserve Board (FED) cut its federal funds rate nearly to zero, introduced unlimited quantitative easing, directly lent to commercial banks and significant corporates, and also deployed Commercial Paper Funding Facility (Cheng *et al.*, 2021). The US government, on the other hand, provided US citizens and firms with paid sick leave, unemployment and food assistance, tax rebates, tax deferrals, loan guarantees, loan grants, etc. With regards to the UK, their both fiscal and monetary measures were of similar character as the UK's but only differing in amount IMF (2021).

König & Winkler (2020) provide empirical analysis on how government per-

formance during the pandemic influences economic growth. As a proxy for government performance, they used the Economist Intelligence Unit (EIU, 2020) and the COVID-19 Misery index (the index created by the authors) that both reflect governments' pandemic management. They tried to explained cross-country differences of revisions in GDP growth projections for 2020 from the OECD, the IMF, and the World Bank while controlling for necessary independent variables. The results were mostly unambiguous as, in most cases, they found that the better the government handles the pandemic, the less bad the GDP projection for 2020 is for a particular state. In the context of the US and the UK, they remarked that both countries' performance in terms of both indices was rather average or less than average in the sample of all countries for which data were available. Moreover, their data set ends in July. Thus it does not reflect later "waves" of the pandemic. Despite this, their results do not say that both fiscal and monetary measures in the UK and US were ineffective but that all these measures could have had a bigger impact. TheCityUK (2020) also claims that the measures definitely eased the pain in the UK in the short run, but they stress that the question is what will happen in the long run. Bullard *et al.* (2020) also consider these measures to be helpful in the US during the first wave of the pandemic. Taking this into account, there is no doubt that both fiscal and monetary measures but especially such unorthodox fiscal measures prevented many corporates shutdowns. As we show later, PD in both countries rose despite the newly deployed fiscal measures during the year. The question that arises is what the situation would like if it were not for these measures? We will come back to this question later.

TheCityUK (2020) stresses that the real challenge is to prevent corporate defaults when they need to start repaying the extra debt they took on them as well as tax deferred. Goodhart *et al.* (2020) mention that low interest rates prevalent across the world post the crisis in 2007-2009 led to further accumulation of debt and search for yield in the private sector. With the extra debt taken on during 2020, they conclude that the financial position of

the private sector is even less resilient. Nevertheless, they add that position of banks has improved due to toughened regulation. In spite of this, when the current financial support from both governments end, many corporations will find themselves in trouble in meeting their obligations unless, as TheCityUK (2020) points out, governments react to prevent this from occurring.

With regard to regulation, there have also been some measures to ease the pain of banks. With respect to the UK, The Bank of England (BoE) announced in March 2020 its measures to address the challenges of COVID-19 (BoE, 2020). Some of them were, for example, cancellation of annual 2020 stress test for largest banks, reducing countercyclical buffer rate to 0%, and recommendations regarding classification in IFRS 9. They explicitly stated that the act of a subject to take repayment holidays is not, on its own, a sufficient condition to move a loan to Stage 2 in the impairment model for the General approach during the pandemic. The FED was not falling behind as they allowed higher leverage ratios (FED, 2020b) and the extension of the transition to the US GAAP accounting standard (FED, 2020a). Mossadams (2020) argues that this allows banks to have lower provisions. Moreover, both central banks in the respective documents appealed to their commercial banks to provide their clients with as much support as possible while, at the same time, keeping in mind lending standards.

To summarize this section, there is no doubt that the challenge for risk managers is enormous. On one hand, they must not be too restrictive while approving loans not to further worsen the crisis. On the other hand, they must stick to the imposed regulatory framework again not to worsen the crisis or even not cause future crises. At the same time, they need to keep track of the effect of employed fiscal measures on PD because it is evident that they have kept the economy alive. This idea is supported by Kongsamut *et al.* (2020), who explains the potential increase in credit risk when the policy interventions regarding COVID-19 unwind. Risk managers need to track these possible scenarios, take them into consideration, and prepare for potential further increase in PD.

3 Literature review and hypotheses

This section discusses the merits of macroeconomic-based models for PD modeling. We further list various authors who have dealt with the topic and divide their research based on the methodology employed. Lastly, we summarize the literature and present the motivation for our hypotheses.

BCBS (2006) claims that estimates of PD, and in the case of the Advanced IRB Approach also estimates of LGD and EAD, should be the key parameters for risk management practices, credit approval processes, internal capital allocations, and corporate governance for all banks that are subjected to regulation. Furthermore, they highlight that it is clear that estimates for internal usage might be slightly different from those for capital allocation regarding IRB Approaches. Nevertheless, they emphasize that banks have to provide regulators with documentation that reasonably justifies these nuances. Last but not least, they stress that banks should perform sound stress testing procedures to test for various unexpected negative shocks that have an impact via all PD, LGD, and EAD on regulatory capital requirements. We have already mentioned this in "Theoretical background".

Chan-Lau (2006a) explicitly recommends macroeconomic-based models for stress testing purposes. The merits of these models for probability of default estimation are significant. They mainly use as dependent variable aggregate PD where the aggregation is based on asset characteristics, i.e., a bank can aggregate PD of all corporates bonds that are rated B. As already mentioned, BCBS (2005) states that in a large portfolio of similar exposures, the idiosyncratic factors offset each other. This statement allows risk managers to drop independent variables that represent idiosyncratic factors in their models for stress testing. Because BCBS (2006) considers as a stress test trying various macroeconomic scenarios that might occur, these macroeconomic-based models are, in fact, forecasting models. Therefore, fewer potential independent variables are preferable in order to avoid overfitting.

Rösch (2005) explains that after introducing the Basel II accord, there are two main types of credit risk models. Firstly, they are the through-the-cycle (TTC) models that we already discussed in the context of PDs in the case of Vasicek (2002) formula. Secondly, they are the point-in-time (PIT). He explains that these (PIT) models carry the most current information regarding the situation of the borrower. Therefore, they can be used to forecast the most likely future conditions for a pre-specified period of time (BCBS, 2000b). Rösch (2005) mainly focuses on comparing the performance between these two types of models with respect to PD and ρ. He finds evidence that PIT credit risk models exhibit lower correlations, which results in more precise estimates of PD. On the other hand, he further says that TTC credit rating models are frequently used by rating agencies because the aim of these ratings is to be forward-looking. Hamerle *et al.* (2011) further add that also banks frequently stick to TTC rating models both because of regulation purposes (Basel II) and also because of internal purposes. Nevertheless, he provides empirical evidence that these models perform better when macroeconomic variables are added, i.e., when, as Zsigraiová (2014) points, there are made to be PIT models. She also highlights that there are many authors who link PD with macroeconomic and also financial environments. Such authors are Koopman & Lucas (2005), Hamerle *et al.* (2004), Pederzoli & Torricelli (2005) and Marcucci & Quagliariello (2009). Koopman & Lucas (2005) had enough evidence to reject GDP growth to be a significant determinant of corporate PD. Besides or instead of growth variables, they recommend the inclusion of credit spread. On the other hand, Marcucci & Quagliariello (2009) finds that the effect of GDP on PD differs according to the state of the economy. They also state that the effect further differs depending on the quality of the portfolio.

There are several studies that test the significance of specific macroeconomic and financial market variables. Firstly, there are authors who use models of logistic form. For example, Virolainen (2004) tries to explain the relationship between corporate PD and macroeconomic variables where he divides

the Finnish corporate sector into six industries. For the estimation, he uses seemingly unrelated regression (SUR). He finds that GDP growth, interest rate, and loan to GDP ratio are significant determinants of PD. In Italy, Fiori *et al.* (2009) followed Virolainen's analysis, but they represent macroeconomic environment by latent factors employed by principal component analysis. They find most of them to be significant. Agrawal & Maheshwari (2014) use both logistic regression (LOGIT) and multiple discriminant analysis (MDA) to evaluate the impact of changes in both macroeconomic variables and financial market variables on Indian corporate PD. As a proxy of PD, they use monthly stock returns for firms in the sample. They conclude that inflation and growth of the stock market index are both significant determinants of Indian corporate PD.

On the other hand, Zsigraiová (2014) says that various authors employed VAR model and lists them. Nevertheless, Jakubík (2006) does not recommend it because of the potential non-linear structure of the underlying model. Instead, he favours non-linear models that are founded on the work of Merton (1974). As such, he employs latent factor model, in particular, OLF model on Finnish data. Other authors who employ latent factor models are Hamerle *et al.* (2003), Jakubik *et al.* (2007), Jakubik & Schmieder (2008), Hamerle *et al.* (2011) and Zsigraiová (2014).

For example, Jakubik & Schmieder (2008) use the OLF model on both Czech and German data to find the key macroeconomic determinant of aggregate PD and also compare the sensitivity of particular macroeconomic shocks on aggregate PD. They state that although they are significant differences in PD in both countries, similar macroeconomic variables can be employed. After the fitting of the models, they do stress tests with results confirming that Czech's aggregate PD is more susceptible to macroeconomic shocks than Germany's. Lastly, they confirm that the effect of particular macroeconomic variables differs depending on the development of a particular economy. This makes it impossible to summarize comprehensively the relationship between macroeconomic variables and PD across countries and also its sectors.

As another example, we describe the results of Zsigraiová (2014), who employs both the OLF model and factor-augmented vector autoregressive (FAVAR) model on several sectors of the Czech economy in order to compare the forecasting power of these two models. OLF performs better than FAVAR in her analysis, which further demonstrates the superiority of latent variable models and, in general, non-linear models for aggregate PD modeling.

Lastly, there is also a study by Antonsson (2018), which only aims to find key macroeconomic determinants of Swedish retail aggregate PD with no intention to predict. She uses Ordinary Least Squares (OLS) estimation with the results that GDP growth and repo rate are both significant determinants. On the other hand, she does not consider the non-linear relationship as Jakubík (2006) recommends. Thus, there might be room for improvement.

All in all, all these studies provide evidence of the importance of macroeconomic and financial variables for PD modeling. Although none of these authors examine the relationship between PD, macroeconomic and financial environments either in the UK or in the US, the results can still serve as a benchmark for our analysis.

To summarize it, the recent literature has mainly sought to find key macroeconomic determinants of PD in particular countries and sectors. Furthermore, it has also tried to find the best models for forecasting and then using these models to compare the reaction of PD to certain macroeconomic shocks between countries.

As we have discussed in the previous section, both the US and the UK employed unorthodox fiscal and monetary measures that aimed to ease the economic pain. We aim to build our hypotheses on this fact. Furthermore, in our analysis, we use the COVID-19 stringency index, proposed by Hale *et al.* (2020), as a proxy of the COVID-19 shock.

Now we can state our hypotheses that were already mentioned in "Introduction".

- **Hypothesis 1**
  - *Fiscal measures were not significant determinants of change of corporate aggregate probability of default in the US*
- **Hypothesis 2**
  - *Fiscal measures were not significant determinants of change of corporate aggregate probability of default in the UK*
- **Hypothesis 3**
  - *Growth of stringency index was not a significant determinant of change of corporate aggregate probability of default in the US*
- **Hypothesis 4**
  - *Growth of stringency index was not a significant determinant of change of corporate aggregate probability of default in the UK*

First of all, we stated our hypotheses in a negative way due to statistical interpretation as it is easier to have a simple null hypothesis for statistical inference, although, ex-ante, we expect the opposite. Moreover, the hypotheses are stated only in "two-sided" alternatives and not in "one-sided" because we want to be sure when rejecting the null hypothesis.

With respect to fiscal measures, we employ dummy variables as their proxies. Their distribution is explained in later sections. We believe that the inclusion of such proxies in macroeconomic-based PD models at the time of COVID-19 is helpful as it is highly likely that fiscal measures "artificially" decreased the change of aggregate corporate PD.

On the other hand, growth of stringency index might be useful as well because it is improbable that in such a "mess", which originated around COVID-19, the change of aggregate corporate PD rose only due to the deterioration of macroeconomic and financial market environments. Growth of stringency index represents the real economy.

4 Methodology description

In this section, we describe our methodology approach. We start with Ordinary Least Squares (OLS) estimation, then continue with Two Stage Least Squares (2SLS) estimation and finish with Generalized Method of Moments Estimation (GMM). Furthermore, we provide arguments for such a choice of methodology approach.

For both countries, we estimate the time series process $[(x_{t1}, ..., x_{tk}, y_t) : t = 1, ..., n]$ by the linear model of the following type:

$$y_t = \beta_0 + \beta_1 \cdot x_{t1} + ... + \beta_k \cdot x_{tk} + e_t \tag{4.1}$$

By n, we denote the number of time periods, and $[e_t : t = 1, ..., n$ represents the series of disturbances. We estimate the model by OLS. Wooldridge (2016) lists various assumptions regarding this estimation method.

Firstly, it is linearity, stationarity, and weak dependence. We argue in the upcoming sections why this assumption holds in our analysis. With regard to stationarity, we test it by the Augmented Dickey-Fuller test, originally proposed by Dickey & Fuller (1979). Since the data set we work with is at least differenced, there is no need to account for the time trend or the intercept in the test. Furthermore, due to the length of the data sets (60 observations for each process), we allow for only three lags of the variable of interest not to suffer from small sample bias (Wooldridge, 2016). Concerning weak dependence, we cannot test it, but we implicitly assume that the assumption holds when the null hypothesis of the Augmented Dickey-Fuller test is rejected, i.e., when we find enough evidence to reject the null hypothesis of non-stationarity on a given significant level.

Secondly, it is multicollinearity. Since we work with differenced variables, this should not be the problem in our regressions. Nevertheless, to be sure, we check this in the data description section via correlation matrix of all variables employed.

Thirdly, we need contemporaneous exogeneity. We are a bit skeptical that this assumption holds as we work with macroeconomic and financial market variables. In reality, probably all of these are "slightly" endogenous, but based on economic logic, we suspect which variables ruin the regressions and treat them accordingly by using instrumental variable(s) (IV). As IVs for the case of the US, we employ UK's variables and vice versa since, ex-ante, we expect that these IVs at time t are not correlated with the error in the regression of a particular country at time t. Presumably, it is not true, but we still believe that this correlation is negligible, which would improve the estimation anyway. Furthermore, as we can have less endogenous variables than exogenous, we employ 2SLS regression as our instrumental variable regression because 2SLS regression is, in the case of overidentifying restrictions, more efficient than standard instrumental variable regression (Wooldridge, 2016).

Moreover, we use standard test associated with 2SLS regression, namely the Weak instruments test, the Hausman test and the Sargan test. The weak instrument test is based on the work from Bound *et al.* (1995), who firstly identified the problem of weak instruments. The test is based on the joint significance of variables using the F-test. Therefore, the null hypothesis is that the instruments are jointly insignificant while regressed on the potentially endogenous variable. The test also works when there is more than one endogenous variable, as the standard F-test is not sufficient in this case. For further details, see Stock *et al.* (2005). The Hausman test was originally proposed by Hausman (1978). The null hypothesis is that both OLS and instrumental variable (in our case 2SLS) regression results are consistent, whereas the alternative is that only instrumental variable regression results are consistent. On the other hand, it does not necessarily mean that the rejecting of the null hypothesis says that 2SLS regression results are consistent because the test is based on determining the significance of the difference between 2SLS and OLS estimates. Thus, it might occur that 2SLS are even more biased, and the test rejects the null hypothesis due to this

fact. Taking this into account, it is worthy to use the Sargan test in case of more instrumental variables than endogenous variables (i.e., overidentifying restrictions). The test was originally proposed by Sargan (1958) and later was elaborated by Hansen (1982). The null hypothesis is that at least one instrument is valid. We do not delve into the depth of the construction of this test. Further detail can be found in respective papers. On the other hand, we are cautious when interpreting this test because of the results from Roodman (2009), who warns about to high P-value of the test. Furthermore, the test is only valid under homoskedasticity and no serial correlation.

With regard to homoskedasticity and serial correlation assumptions. We decided to use only errors that are robust to both of these issues because, as Wooldridge (2016) warns, the standard test for AR(p) correlation only detects serial correlation in adjacent errors. As a result, other forms of serial correlation are not found. Furthermore, he points out that in case of any kind of serial correlation, standard tests for heteroskedasticity are not valid. Taking this into account, we do not rely on the results of these tests, and we do not try to correct for any specific form of either the serial correlation or the heteroskedasticity in both OLS and 2SLS regressions. Instead, we assume that we are facing both of these problems and use robust errors.

Therefore, we further employ GMM estimation that was originally proposed by Hansen (1982). He shows that both OLS and 2SLS estimators are special types of GMM estimator. Wooldridge (2001) mentions that in the presence of heteroskedasticity and serial correlation, the GMM estimator is more efficient than the 2SLS procedure with robust standard errors. As already indicated, we assume that both of these problems are present, which makes the application of GMM suitable.

Now we briefly derive key characteristics of GMM estimator in the context of instrumental variable regression and follow the derivation from Greene (2012). Hansen (1982) based the GMM estimator on additional moment restrictions with the hope to improve efficiency. In such a case, there are more

moment conditions than parameters. Further, to set moments conditions closely to zero, he used the quadratic loss function.

Now we delve into the derivation itself. Firstly, let us assume that we have L exogenous variables with K independent variable in the original equation to estimate and $L > K$. Let us define U as a vector of L moment conditions:

$$U = \begin{bmatrix} \frac{1}{n} \cdot [\sum_{t=1}^{n} m_1(y_t, x_{t1}, ..., x_{tk}, \beta)] \\ \frac{1}{n} \cdot [\sum_{t=1}^{n} m_2(y_t, x_{t1}, ..., x_{tk}, \beta)] \\ \vdots \\ \frac{1}{n} \cdot [\sum_{t=1}^{n} m_L(y_t, x_{t1}, ..., x_{tk}, \beta)] \end{bmatrix} \tag{4.2}$$

According to Hansen (1982), the GMM estimator of β (β is vector of all $\beta_0, ..., \beta_k$) is based on minimizing Q_n:

$$Q_n(\beta) = U^T W_N U \tag{4.3}$$

W_N in the equation denotes positive definite $L \times L$ weighting matrix. With respect to this matrix, Hansen (1982) further assumed that $W_n \xrightarrow{p} W$, which is too positive definite matrix. The condition for minimization is standard, i.e., calculating $\frac{\partial Q_n(\beta)}{\partial \beta}$, equalling this derivation to zero and expressing β.

Hansen (1982) defined the consistent and asymptotically normally distributed GMM estimator as:

$$\sqrt{N}(\hat{\beta}_{GMM} - \beta) \xrightarrow{d} N(0, CSC^T) \tag{4.4}$$

where

$$C = (G^T W G)^{-1} G^T \tag{4.5}$$

$$G = E[\frac{\partial m_i(y_t, x_{t1}, ..., x_{tk}, \beta)}{\partial \beta^T}] \tag{4.6}$$

$$S = E[m_i(y_t, x_{t1}, ..., x_{tk}, \beta), m_i(y_t, x_{t1}, ..., x_{tk}, \beta)^T] \tag{4.7}$$

for each $i = 1, ..., L$.

Hansen (1982) further proved that the best W is such that $W = S^{-1}$.

What remains is to consistently estimate G, W, and S to obtain the estimate of variance matrix of GMM estimator, which is essential for statistical inference. In our analysis, we employ the Continuous Updating Efficient (CUE) GMM estimator that solves the already mentioned. The choice of this estimator is based on the results of Hansen *et al.* (1996). They firstly proposed the estimator and then showed that in small samples, the CUE estimator is superior to others, such as Iterated Efficient and Two Step Efficient GMM estimators.

Besides, we also employ the Hansen J-test proposed by Hansen (1982). The aforementioned Sargan test is a special case of this test as in the case of no serial correlation and heteroskedasticity, the tests are identical. The results of these tests must undoubtedly differ in our regressions as the Hansen J-test takes into account both heteroskedasticity and serial correlation that we expect to be present in our models. Therefore, it might happen the Sargan does not have enough evidence to reject the null hypothesis on a particular model when employing 2SLS regression, whereas the Hansen J-test does have enough evidence to reject the null hypothesis in GMM estimation with the same assumption about the instruments in both procedures.

Last but not least, it is not granted that the independent variables influence the dependent variable in a static way. The reason for this is that most of our independent variables represent the macroeconomic and the financial market environments. Therefore, as recommended by Witzany (2017), we employ univariate analysis to choose the best lag of each independent variable based on the Akaike Information Criterion (AIC), which was proposed by Akaike (1974). A similar approach was, for example, used by Zsigraiová (2014).

5 Data description

In this section, we deal with describing both dependent and independent variables with reasoning why we chose them. Furthermore, we provide comments on descriptive statistics of each variable employed. Last but not least, we show the distribution of each variable and their mutual relationship.

5.1 Employed variables

The data used for the empirical analysis comes from various sources. As Zsigraiová (2014) points out, estimation of PD using macroeconomic variables is usually done using quarterly data. As we are provided with monthly data on PD, our results should be more granular. Moreover, because we are only interested in the ceteris paribus effect (i.e., we do not want to predict), we are not that concerned with a higher number of independent variables. Therefore, we also employ variables that represent the financial market. Last but not least, due to the stated hypothesis, interpretation purpose and, stationarity problems, all continuous variables are differenced, and variables, which do not represent percentage value, are also divided by their value in the previous period.

In order to cover both the ups and downs of the business cycle, BCBS (2006) requires the data set for inference regarding the probability of default to be at least five years. This is satisfied because the covered period spans from December 2015 to November 2020. This also means that a few first months of the COVID-19 crisis are included. Zsigraiová (2014) also works with the data set that includes crisis, in particular the Global Financial crisis of 2007-2009. Just like us, she also included a proxy for the crisis in her models. This further supports the inclusion of growth of stringency index into our models. Now we clarify our choice of particular variables employed.

5.1.1 Change in log odds ratio

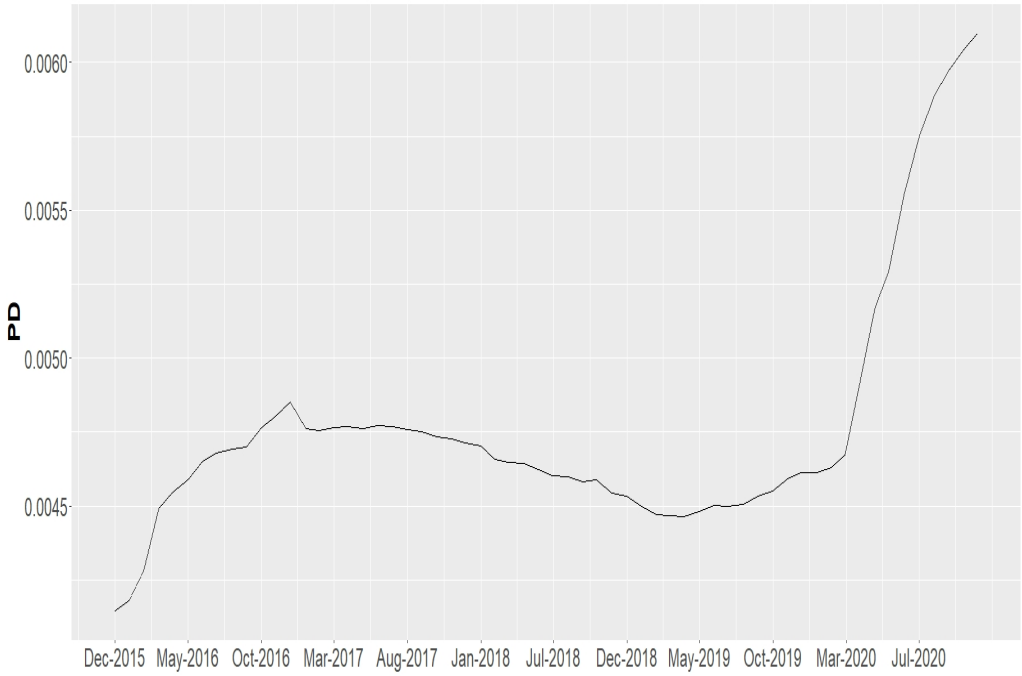
Firstly, we use as the dependent variable change in log odds ratio. Log odds ratio at time t is defined as: $log\_odd_t = log(PD_t/(1 - PD_t))$. From this, we define change in log odds ratio at time t as:

$$\Delta log\_odd_t = log\_odd_t - log\_odd_{t-1} \tag{5.1}$$

We work with log odds instead of classical PD because the relationship between PD and independent variables is generally modeled in a non-linear way. This comes from the fact that as a standard procedure for rating, banks use logistic regression (Witzany, 2017), and the idea is further supported by Jakubík (2006), who explicitly recommends non-linear models for estimation of PD using macroeconomic variables. By using the dependent variable in log odds ratio form, we "linearize" the relationship between the dependent variable and independent variables. Thus, we can use standard linear estimation procedures. It would be daring to assume that fiscal measures actually decreased PD. This can be seen in figures 2 and 3. Corporate PD rose since March 2020 till the end of the sample in both countries.

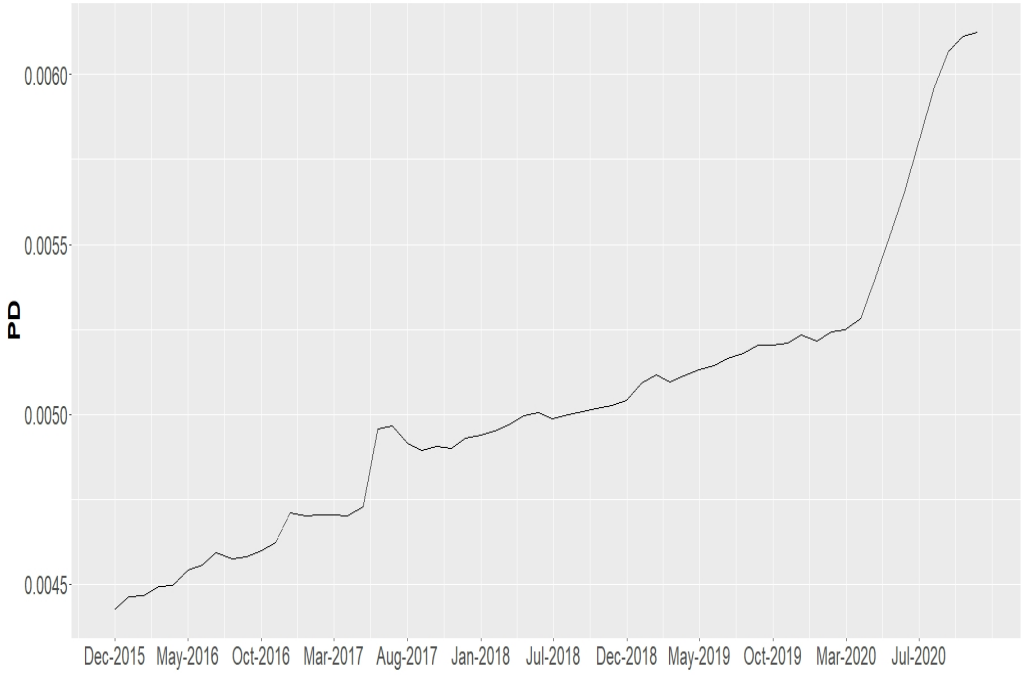
Taking this into account, it makes more sense to think whether the fiscal at least slowed the growth of PD (log_odd). Therefore, we decided that we want to explore whether fiscal measures slowed the change of PD (log_odd). This means that we have to work with the difference of this variable. Furthermore, as the data set of PDs consists of only 60 observations, we use cubic spline interpolation that uses polynomial of 3rd degree to approximate two further observations of PD prior to December 2015 in order to keep as many observations as possible due to differencing and the potential inclusion of lag of the dependent variable into regression as an independent variable. The explanation of the method can be found, for example, in McKinley & Levine (1998). Zsigraiová (2014) also uses this method in her work, but her goal is to approximate monthly observations from quarterly. Surely, in this context, it is not a perfect solution because it approximates observations ac-

Figure 2: Aggregate corporate PD in the US



Source: Author's computation

Figure 3: Aggregate corporate PD in the UK



Source: Author's computation

cording to the trend around the beginning of the data set but it should not cause any problems as the data sets for both countries are "well-behaved" at their beginnings.

The time series of Δlog_odd for both the US and the UK can be seen in Appendix 1. These charts show that the shock of the COVID-19 crisis is evident for both the US and the UK as Δlog_odd increased very sharply in March 2020 in the respective countries. On the other hand, we see that since then, Δlog_odd started decreasing, i.e., log_odd rose less sharply.

What makes this analysis unique is the time series of PD. Normally, such time series must be somehow derived from other variables and factors because, as such, the variable PD is not available. Zsigraiová (2014) lists various approaches how PD can be extracted from data related to defaults.

We use aggregate corporate PD for the US and the UK from Credit Benchmark, a London-based company. They define its business as:

> Credit Benchmark brings together the credit risk assessments of the world's leading financial institutions to deliver greater visibility into the credit quality of individual entities. Using an innovative approach, Credit Benchmark aggregates, anonymizes and publishes monthly consensus credit indicators on sovereigns, financial institutions, corporates and small and medium enterprises. (Credit Benchmark, 2021)

Credit Benchmark (2019)[1] explains that dynamism in the banking process of lending causes statistical inference issues of survivor bias, selection bias, and like-for-like comparisons. They add that a good aggregate should be resilient to these problems to provide a relevant benchmark. As a result, they use the basket approach that, as they refer, should address noise from selection and survivor bias. For further details, see Credit Benchmark (2019).

[1]This document is available upon request. The concept of the given document can be seen at this link: `https://www.creditbenchmark.com/credit-index-bank-sourced-credit-indices/`

5.1.2 Fiscal dummy variables

For both countries, we employed dummy variable(s) that should represent the effect of the fiscal measures deployed by the Governments. IMF (2021) provides up-to-date evidence of particular measures that both US's and UK's Governments employed. For the US, we choose to employ two dummy variables, $fiscal\_1$ and $fiscal\_2$. First one, $fiscal\_1$ equals zero from the beginning of the sample till March 2020. In April 2020, it starts to equal 1 and remains this way until the end of the sample. The choice of the distribution of this variable is obvious because the biggest "package" of fiscal measures became effective in April 2020. We use this dummy in a static way because the US's Δlog_odd is determined by other independent variables (mainly macroeconomic and financial market ones) with almost no delay. This feature is explained in the following section. With regard to $fiscal\_2$, this dummy equals zero from the beginning of the sample until June 2020. From that moment, i.e., from July 2020 the dummy equals 1 till the end of the sample. We employ this second dummy as we are interested in whether the effect of fiscal measures changed after three initial months.

To sum it up for the US, we expect that $fiscal\_1$ will have a negative impact on Δlog_odd. With respect to $fiscal\_2$, the effect might be either positive or negative. If positive, it would indicate that the effect of fiscal measures on their own vanished after the initial three months (assuming that $fiscal\_1$ is negative). If negative, it would mean that fiscal measures started to be even more effective as time went by. Nevertheless, we will discuss this in-depth during the empirical analysis.

As far as the UK is concerned, we employ only one dummy representing fiscal measures. We denote this dummy as $fiscal$. It equals zero from the beginning of the sample until June 2020. From July 2020 till the end of the sample, it equals one. Although most of the measures became effective also in April 2020 as in the US, we choose this approach that is different from the case of the US because Δlog_odd is determined by later lags of

other independent variables. In other words, if some harm happens to the economy, it takes more time to be reflected in Δlog_odd for the UK than the US. Again, we explain this feature in the following section. Based on this, it makes no sense to employ a second dummy for the UK as we would simply "run out" of the sample.

Last but not least, these dummy variables might also partly represent the effects of unconventional monetary policy actions. Nevertheless, this is only a matter of the definition of these variables and should not change the potential impact of the analysis.

5.1.3 Real economy variables

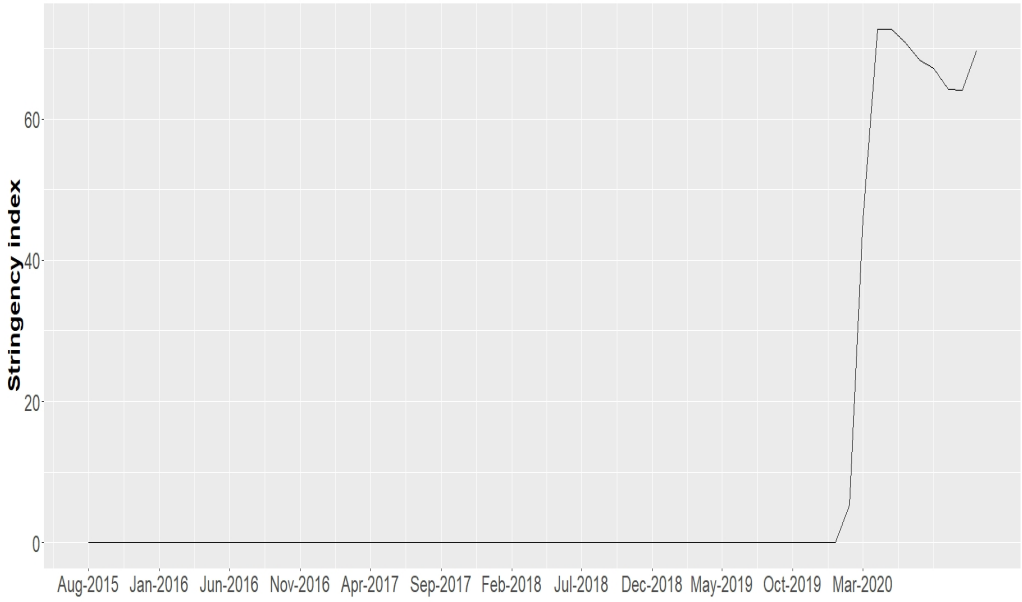
5.1.3.1 Change in COVID-19 stringency index

As already noted, we decided to include COVID-19 stringency index that reflects the strictness of the restrictions imposed by the government in a particular country as a proxy for the COVID-19 crisis. As noted, the index was proposed by Hale *et al.* (2020). It takes on values from zero to one hundred, where one hundred is the strictest scenario possible. We refer to this index at time t as: $stringency\_index_t$. In figures 4 and 5, it can be seen that the index really follows all the measures as we remember them. As far as indices are concerned in this thesis, we intend to use them in growth rates, i.e., $100 \cdot (index_t - index_{t-1}/index_{t-1})$. In spite of this, we decided not to apply this formula for this particular index because we would give it "extreme" variance advantage" over other independent variables. Hence, we define change in COVID-19 stringency index at time t as:

$$\Delta stringency\_index_t = \frac{stringency\_index_t - stringency\_index_{t-1}}{100} \tag{5.2}$$

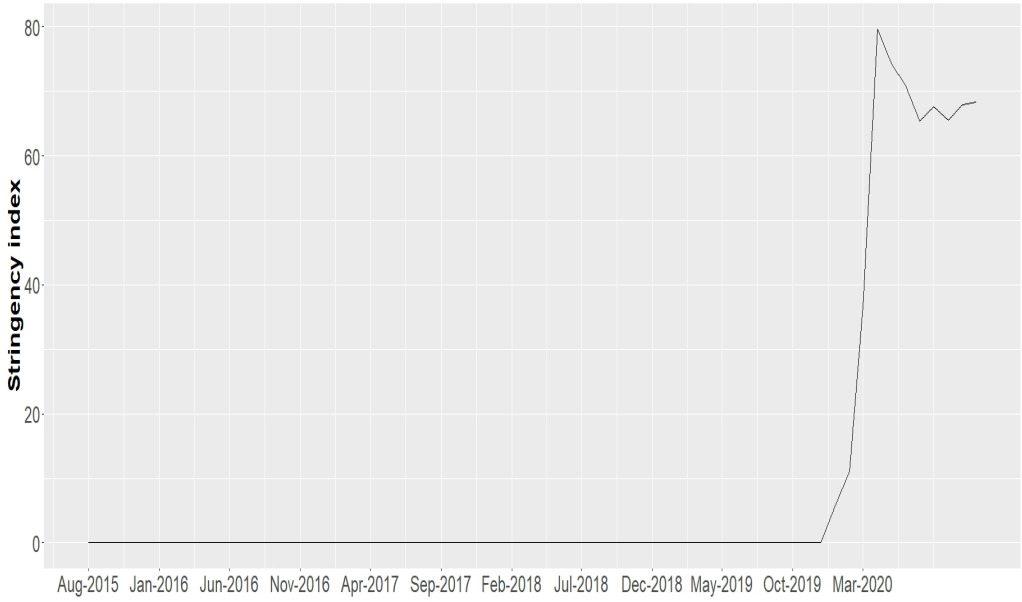
This definition is, on the other hand, "unfair" to this index because it removes most of its variation. Nevertheless, if it is significant among other variables, then we are even more sure about its suitability in such macroeconomic-based models with data sets that cover the period of COVID-19.

Figure 4: Stringency index in the US



Source: Author's computation

Figure 5: Stringency index in the UK



Source: Author's computation

The time series of $\Delta stringency\_index$ for both the US and the UK can be seen in Appendix 1. The variables increased sharply for both countries at the beginning of the COVID-19 crisis. Therefore, it seems reasonable to expect its significant effect on Δlog_odd based on descriptive statistics.

5.1.4 Macroeconomic variables

As Chan-Lau (2006a) says, modeling default probabilities is challenging due to the availability of data. Although we aim to model PD (Δlog_odd) for the corporate sector, we employ macroeconomic variables on an aggregate level for the whole country as independent variables due to the unavailability of sectoral data.

Based on the literature review and our judgment, we work in our analysis with the following macroeconomic variables: growth of real gross domestic product, inflation, change in interest rate, growth of exchange rate, change in unemployment rate.

We follow mostly the structure of these variables as it is provided in the literature. For example, Zsigraiová (2014) uses GDP in the form of growth rate as we do. Similarly, we follow her definition of inflation based on producer price index instead of consumer price index since we work with corporate PD (Δlog_odd). We further use other variables in different form as we believe it is more relevant in our regressions.

5.1.4.1 Growth of real gross domestic product

We suspect that growth of real gross domestic product will be an important variable for our analysis. Firstly, we define real gross domestic product at time t as: R_GDP_t. From this, we further define growth of real gross domestic product at time t as:

$$GDP\_gr_t = 100 \cdot \frac{R\_GDP_t - R\_GDP_{t-1}}{R\_GDP_{t-1}} \tag{5.3}$$

In general, we expect the relationship between GDP_gr and Δlog_odd to be negative. Many authors identify the relationship between PD and gross domestic product of any form to be significant. For example, Virolainen (2004), Koopman & Lucas (2005), Fiori *et al.* (2009), Zsigraiová (2014), and Antonsson (2018) all confirm this relationship to be negative. Furthermore,

BCBS (2006) in Basel II accord implicitly expects this relationship too because it specifies that banks should test the impact of a mild recession on PD (via a decrease in gross domestic product) and hence the effect on regulatory capital requirements.

To have the R_GDP_t with the same interpretation for both the US and the UK (i.e., R_GDP_t with the same base year), we create this variable manually from their nominal GDPs and deflators. Luckily for us, both deflators have the same base year - 2015, which is exactly what we want. All four variables are downloaded from Federal Reserve Economic Data (FRED) database. The links can be found in "Bibliography". Unfortunately, none of these variables is offered on quarterly basis. Thus the interpolation is needed. We again choose Cubic Spline Interpolation that uses polynomials of 3rd degree as we did in the case of aggregate PD with only difference in the purpose.

The time series of GDP_gr for the US and the UK can be seen in Appendix 1. This variable has been seriously hit by the crisis but also recovered very quickly for both countries. On the other hand, this did not happen in the case of Δlog_odd, which might slightly influence the significance of this variable in regressions for both countries.

5.1.4.2 Inflation

Another variable that we suspect is key to our analysis is inflation. Firstly, we define producer price index at time t as: PPI_t. Based on this, inflation at time t can be defined as:

$$inflation_t = 100 \cdot \frac{PPI_t - PPI_{t-1}}{PPI_{t-1}} \tag{5.4}$$

Because the rise of inflation is generally connected to redistribution of wealth from lenders to borrowers, we expect the relationship between $inflation$ and Δlog_odd to be negative. All Jakubik *et al.* (2007), Zsigraiová (2014), and Agrawal & Maheshwari (2014) found a negative relationship between PD and inflation. Producer price index for both countries was again downloaded

from FRED, and links can be found in "Bibliography".

The time series of $inflation$ for both countries can be seen in Appendix 1. In the case of the US, there is no doubt that the variable has been hit by the crisis. On the other hand, it is not that evident in the UK.

5.1.4.3 Change in interest rate

Interest rate is an important macroeconomic variable in each economy. We use 10-year monthly average of government bond interest rate for both countries where data are downloaded from OECD, and the link be found in "Bibliography". We refer to interest rate at time t as: $interest\_rate_t$. Furthermore, we define change in interest rate at time t as:

$$\Delta interest\_rate_t = interest\_rate_t - interest\_rate_{t-1} \tag{5.5}$$

The expected relationship between Δlog_odd and $\Delta interest\_rate$ is twofold. Firstly, $\Delta interest\_rate$ might be positively related to Δlog_odd because corporations find it more difficult to repay their loans when $\Delta interest\_rate$ increases. On the other hand, the relationship might also be negative because the reaction of central banks during crises is lowering the interest rate, which is subsequently displayed in all interest rates in the economy. This argument may also support the idea of endogeneity of $\Delta interest\_rate$ that could be either caused by simultaneity or reversed causality. Despite this, a variable representing interest rate in the economy has been frequently used in the analysis of PD. For example, all Virolainen (2004), Jakubík (2006), and Zsigraiová (2014) find the relationship between PD and such a variable to be negative. Based on the assumptions above and their results, we expect the relationship between Δlog_odd and $\Delta interest\_rate$ to be negative.

The time series of $\Delta interest\_rate$ for both countries can be seen in Appendix 1. The sharp decrease during March 2020 in the US proves how fast interest rates react to the decrease of central banks' interest rates. On the other hand, the variable also decreased in the UK but not that significantly.

5.1.4.4 Growth of exchange rate

For both countries, we use nominal exchange rate downloaded from the FRED (in the case of the US) and from the Office for National Statistics (OfNS), where the rate is defined as X USD/GBR for 1 EUR. Again, links for both sources can be found in "Bibliography". Exchange rate at time t is referred as: $exchange\_rate_t$. Thus, we define growth of exchange rate at time t as:

$$exchange\_rate\_gr_t = 100 \cdot \frac{exchange\_rate_t - exchange\_rate_{t-1}}{exchange\_rate_{t-1}} \tag{5.6}$$

We identify two factors that determine whether $exchange\_rate\_gr$ is a significant determinant of Δlog_odd.

Firstly, when a country is export-oriented, the increase of $exchange\_rate$, i.e., depreciation of the currency, makes the domestic product cheaper abroad, which makes domestic corporates less likely to default. In this scenario, we would expect the relationship between $exchange\_rate\_gr$ and Δlog_odd to be negative. On one hand, trade balance in both the US and the UK has been negative for many years. This should theoretically mean that neither the US nor the UK is export-oriented. On the other hand, the data on particular sectors are not available with respect to trade balance, so we cannot actually know which sectors have positive trade balance and which not.

Secondly, Niepmann & Schmidt-Eisenlohr (2017) say that $exchange\_rate\_gr$ might be a significant determinant of PD in a given country when there are many loans in foreign currency. This is reasonable because if domestic currency depreciates, the loan becomes more expensive, and the obligor is more likely to default. Nevertheless, they point out that borrowing in foreign currency is rather prevalent in emerging economies.

Based on the given arguments, we still expect the relationship between $\Delta exchange\_rate$ and Δlog_odd to be negative in both countries. However, we are not sure about the significance.

The time series of $exchange\_rate\_gr_t$ for both countries can be found in Appendix 1. The behavior of the variables for both countries is a bit messy, which makes it difficult to draw any conclusions from that despite its increase at the beginning of the crisis.

5.1.4.5 Change in unemployment rate

We use data for unemployment rate from FRED (the US) and OECD (the UK) with both links in "Bibliography". From now on, we refer to unemployment rate at time t as: $unemployment\_rate_t$. Accordingly, we define change in unemployment rate as:

$$\Delta unemployment\_rate_t = unemployment\_rate_t - unemployment\_rate_{t-1} \tag{5.7}$$

Zsigraiová (2014) emphasizes that the effect of unemployment rate on aggregate PD should be especially strong for the sector of household. Although we work with aggregate PD (Δlog_odd) for corporates, we still include $\Delta unemployment\_rate$ in our regressions. Furthermore, if the relationship exists, we expect it to be positive.

The time series of $\Delta unemployment\_rate$ for both countries can be found in Appendix 1. In the case of the US, the variable behaves similarly as $\Delta stringecy\_index$. Based on descriptive statistics, they should have a similar effect on Δlog_odd. On the other hand, the $\Delta unemployment\_rate$ in the UK increased too but not that significantly, so we are a bit skeptical about its significance in the respective regressions.

5.1.5 Financial market variables

As already indicated, we also employ this type of variables. The target is to improve the estimation, i.e., decrease a potential chance of bias.

Based on literature review and judgment, we work with the following financial market variables: change in spread, and growth of stock market index.

5.1.5.1 Change in spread

For both countries we use monthly average of spread between 3-Month LIBOR (based on either US dollars or UK pounds) and 3-Month Treasury Bill interest rates in a given country. Data are downloaded from FRED and Investing.com. As with other variables, the links can be found in "Bibliography". We refer to spread at time t as: $spread_t$. Consequently, we define change in spread at time t as:

$$\Delta spread_t = spread_t - spread_{t-1} \tag{5.8}$$

Koopman & Lucas (2005) recommend the inclusion of spread for PD modeling. They find the relationship to be positive. Taking this into consideration, we believe that $\Delta spread$ could have an impact on Δlog_odd and that the relationship will be positive. We think so because higher spreads are associated with uncertainty on the markets as banks are less willing to lend each other. This uncertainty must also influence the expectation of corporate PD. On the other hand, the significance of this variable might be low as we also include $\Delta interest\_rate$ in our regressions, although the underlying rate for this variable is 10-year monthly average of government bond interest rate.

Furthermore, we believe that we control for the effect of conventional monetary policy, which is performed by both the FED and the BOE, by inclusion of changes in 10-Year interest rate and in 3-Month spread.

The time series of $\Delta spread$ for both countries can be found in Appendix 1. At the beginning of the crisis, there has been a steep increase of the $\Delta spread$, followed by a quick recovery in both the US and the UK. So there is no doubt that this variable has been hit by the crisis too.

5.1.5.2 Growth of stock market index

Lastly, we include a variable that represents stock markets in given countries. We define it in growth rates. The choice of the following stock indices is arbitrary as we work with monthly observations and need to average them.

Thus, it does not matter which indices we choose due to loss of granularity.

For the US, we use the Dow Jones Industrial Average (DJIA) index, where data are downloaded from FRED. In the case of the UK, we use the Financial Times Stock Exchange 100 (FTSE-100) index with data being downloaded from the Wall Street Journal. Both links can be found in "Bibliography" too. We refer to the value of DJIA index at time t as: $DJIA_t$ and to the value of FTSE-100 at time t as: $FTSE_t$. Correspondingly, we define growth of DJIA index at time t as:

$$DJIA\_gr_t = 100 \cdot \frac{DJIA_t - DJIA_{t-1}}{DJIA_{t-1}} \tag{5.9}$$

and growth of FTSE-100 index at time t as:

$$FTSE\_gr_t = 100 \cdot \frac{FTSE_t - FTSE_{t-1}}{FTSE_{t-1}} \tag{5.10}$$

Stock market index was, for example, used by Hamerle *et al.* (2011) for forecasting default probabilities. Furthermore, Agrawal & Maheshwari (2014) also employed such a variable in their analysis and found a negative relationship. We include growth of stock market index in our regressions as we expect that this variable might also reflect the shock of COVID-19 on PD (Δlog_odd). The expected relationship between Δlog_odd and $DJIA\_gr$ ($FTSE\_gr$) is negative because the improvement of stock market should be reflected in lower corporate PD.

The time series of $DJIA\_gr_t$ and $FTSE\_gr_t$ can be found in Appendix 1. They were both shortly hit by the crisis, but since then, they have recovered.

5.2 Relationship between variables

We also report mutual correlations between each continuous independent variable. We want to make sure that there is no multicollinearity in the regressions. The correlations can be seen in table 1 and 2, with stars denoting the significance level. One star denotes 90%, two stars 95%, and three 99%.

Table 1: Correlation of US's continuous independent variables

	GDP_gr	$inflation$	$\Delta interest\_rate$	$exchange\_gr$	$\Delta unemployment\_rate$	$\Delta spread$	$DJIA\_gr$	$\Delta stringency\_index$
GDP_gr	1							
$inflation$	0.07	1						
$\Delta interest\_rate$	0.21	0.29**	1					
$exchange\_gr$	0.05	0.04	-0.17	1				
$\Delta unemployment\_rate$	-0.43***	-0.56***	-0.21*	-0.22*	1			
$\Delta spread$	0.16	-0.54***	-0.35***	0.11	0.29**	1		
$DJIA\_gr$	0.06	0.33***	0.55***	-0.01	-0.08	-0.57***	1	
$\Delta stringency\_index$	-0.45***	-0.52***	-0.47***	-0.03	0.6***	0.57***	-0.55***	1

Source: Author's computation

Table 2: Correlation of UK's continuous independent variables

	GDP_gr	$inflation$	$\Delta interest\_rate$	$exchange\_gr$	$\Delta unemployment\_rate$	$\Delta spread$	$FTSE\_gr$	$\Delta stringency\_index$
GDP_gr	1							
$inflation$	0.02	1						
$\Delta interest\_rate$	0.14	-0.45***	1					
$exchange\_gr$	-0.07	0.89***	-0.47***	1				
$\Delta unemployment\_rate$	0.22*	0.00	0.09	-0.00	1			
$\Delta spread$	0.03	0.03	-0.05	0.00	0.02	1		
$FTSE\_gr$	-0.07	-0.15	0.11	-0.25**	-0.05	-0.14	1	
$\Delta stringency\_index$	-0.42***	0.10	-0.17	0.19	0.04	0.57***	-0.28**	1

Source: Author's computation

To be more specific about correlations in tables 1 and 2, we employed Pearson product-moment correlation coefficient. Both historical information and the explanation of this statistics can be found, for example, in Lee Rodgers & Nicewander (1988).

We see that multicollinearity problem should be present in neither countries' regressions as most pairwise correlations are lower than 0.6 in absolute terms. Moreover, for higher correlations in absolute terms, the null hypothesis of insignificance is mostly rejected. Thus, these correlations are statistically present, but their size are not problematic. There is only one pairwise correlation that might cause problems - between UK's $exchange\_gr$ and $inflation$ that is even significant on 99% confidence level. On the other hand, we assume that one of these variables might be dropped during the analysis, so there is no reason to worry for now.

5.3 Summary of employed variables

As already indicated, we base our choice of lags of independent variables on AIC. To be able to do so, we created eight lags of each continuous variable (except from $\Delta stringency\_index$) to have enough to choose from. With respect to $\Delta stringency\_index$, we model this variable only in a static way as it a variable that represents the real economy. Since we work with time series, we also include lag of dependent variable for each country's model as we believe it might also be a significant determinant. Moreover, we also decided that in all our models, there will be at least one independent variable of each type, i.e., there will be at least one variable representing the macroeconomic environment and also one variable representing the financial market.

Lastly, in Appendix 5, we provide the distribution of the employed continuous variables for each country. As such, we chose the following measures: mean, standard deviation, minimum and maximum. We do so for the reader to have a better orientation in the data set. The distribution for both countries can be found in the respective Appendix in tables 17 and 18.

6 Empirical analysis

The following section provides the whole empirical analysis. For both countries, we start with OLS estimation and then employ both 2SLS and GMM procedures. Thereafter, based on the results of the regressions and relevant tests, we conclude which approach is the best for a given country and comment on its results. Moreover, we summarize our contribution and provide policy recommendations. Lastly, we discuss further research opportunities regarding this topic, where we also touch upon the choice of methodology.

It is worth noting that we are only interested in the signs of the relationship between dependent and independent variables and also the significance of particular independent variables. As such, it would make no sense to interpret the ceteris paribus effect explicitly, i.e., if independent variable 1 increases by something, the dependent variable increases by something. The reason for this is the way how all the variables are defined and especially the dependent variable.

6.1 Corporate sector in the US

6.1.1 Estimation

6.1.1.1 Ordinary least squares estimation

With help from AIC, we arrived at the following specification of the model:

$$\begin{aligned}\Delta log\_odd_t = &+ \beta_0 + \beta_1 \Delta log\_odd_{t-1} + \beta_2 GDP\_gr_{t-1} + \beta_3 inflation_{t-3} \\ &+ \beta_4 \Delta interest\_rate_{t-1} + \beta_5 exchange\_rate\_gr_{t-4} \\ &+ \beta_6 \Delta unemployment\_rate_{t-2} + \beta_7 \Delta spread_t \\ &+ \beta_8 DJIA\_gr_{t-1} + \beta_9 fiscal\_1 + \beta_{10} fiscal\_2 \\ &+ \beta_{11} \Delta stringency\_index_t\end{aligned} \tag{6.1}$$

The augmented Dickey-Fuller test rejected the null hypothesis of their non-stationarity on 99% confidence level for all variables. Although the data sample is not very long, based on the augmented Dickey-Fuller test, we rely on asymptotic Gauss-Markov properties.

The model was standardly estimated by OLS, where the result can be seen in Appendix 2 table 10. Even though the results indicate that the model suffers from endogeneity, we firstly dropped $\Delta spread$ as the independent variable because of its extremely low T-statistics. Thus, the new specification is:

$$\begin{aligned}\Delta log\_odd_t = &+ \beta_0 + \beta_1 \Delta log\_odd_{t-1} + \beta_2 GDP\_gr_{t-1} + \beta_3 inflation_{t-3} \\ &+ \beta_4 \Delta interest\_rate_{t-1} + \beta_5 exchange\_rate\_gr_{t-4} \\ &+ \beta_6 \Delta unemployment\_rate_{t-2} + \beta_7 DJIA\_gr_{t-1} \\ &+ \beta_8 fiscal\_1 + \beta_9 fiscal\_2 + \beta_{10} \Delta stringency\_index_t\end{aligned} \tag{6.2}$$

The results of OLS estimation of this specification of the model are summarized in table 3.

Table 3: OLS estimation without $\Delta spread\_ch$

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	0.00193	1.71	0.09385
Δlog_odd_{t-1}	0.49918	4.31	0.00008
GDP_gr_{t-1}	-0.00147	-0.95	0.34546
$inflation_{t-3}$	-0.00162	-1.66	0.10391
$\Delta interest\_rate_{t-1}$	-0.01453	-1.44	0.15657
$exchange\_gr_{t-4}$	-0.00148	-1.55	0.12831
$\Delta unemployment\_rate_{t-2}$	0.00417	5.69	0.00000*
$DJIA\_gr_{t-1}$	-0.00037	-1.03	0.30982
$fiscal\_1$	-0.01875	-2.22	0.03139
$fiscal\_2$	0.03404	3.73	0.00049
$\Delta stringency\_index_t$	0.09397	5.42	0.00000*
Number of observations: 60			
$R^2 = 0.80$			
$Adjusted\_R^2 = 0.76$			

Source: Author's computation

The results in table 3 mostly confirm the direction of the relationship between dependent and independent variables that was expected. Even after working with differenced variables, both R^2 and adjusted R^2 are high (0.80 and 0.76, respectively). All Δlog_odd_{t-1}, $\Delta stringency\_index_t$, $\Delta unemployment\_rate_{t-2}$ are significant at 99% confidence level. In the case of $\Delta unemployment\_rate_{t-2}$, it is a bit surprising as we are dealing with the corporate sector. Thus, the relationship was expected to be less significant. By contrast, as discussed in "Data description", the variable behaved similarly as $\Delta stringency\_index_t$, so this result is not that unexpected. Furthermore, so far, it seems that the inclusion of $\Delta stringency\_index_t$ was appropriate because of its high significance.

On the other hand, low significance of GDP_gr_{t-1} is unexpected because this variable is usually considered as the key determinant of PD. We believe that this is caused by endogeneity that compresses its point estimate towards zero, which results in low T-statistics.

Both dummy variables that should represent the effect of fiscal measures are significant at 99% confidence level, which supports the inclusion of such proxy(ies). With regard to their interpretation, they can be understood in two ways because the coefficient of dummy $fiscal\_1$ is negative, and the coefficient of dummy $fiscal\_2$ is positive. Firstly, it would mean that fiscal measures decreased Δlog_odd (i.e., slowed the growth of PD) during the initial months of the crisis on their own, but later the separate effect of these measures was approximately zero as the coefficients of the dummies almost cancel each other out. This would seem reasonable because during the first months of the crisis, the fiscal measures helped the economy directly in the form of transfers, and it took some time for them to be demonstrated in standard macroeconomic and also financial market variables. Then, based on given arguments, the direct effect of fiscal measures vanished.

On the other hand, it could also indicate that the coefficient for dummy $fiscal\_2$ is biased because GDP_gr_{t-1} passes its bias on this dummy via

their mutual correlation. To deal with the bias, we further employed 2SLS and GMM regressions.

6.1.1.2 Two stage least squares estimation

We assumed that only GDP_gr_{t-1} is endogenous, and as its instruments, we used UK's GDP_gr_t, $\Delta interest\_rate_t$, and $\Delta unemployment\_rate_t$. The choice of the first is clear. The choice of the remaining two was a bit arbitrary as we hoped that the variables would further improve the regression. The results of the 2SLS regression are summarized in table 4.

Table 4: 2SLS without $\Delta spread\_ch$

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	0.00209	1.63	0.10895
Δlog_odd_{t-1}	0.49230	4.24	0.00000*
GDP_gr_{t-1}	-0.00209	-0.83	0.41268
$inflation_{t-3}$	-0.00148	-1.52	0.13444
$\Delta interest\_rate_{t-1}$	-0.01420	-1.43	0.15983
$exchange\_gr_{t-4}$	-0.00146	-1.51	0.13638
$\Delta unemployment\_rate_{t-2}$	0.00415	5.84	0.00000*
$DJIA\_gr_{t-1}$	-0.00040	-1.05	0.29784
$fiscal\_1$	-0.02019	-1.92	0.06093
$fiscal\_2$	0.03641	2.63	0.11033
$\Delta stringency\_index_t$	0.09431	5.64	0.00000*
Weak instruments test p-value: 0.00098			
Hausman test p-value:0.82579			
Sargan test p-value: 0.56914			

Source: Author's computation

By using these instruments for GDP_gr_{t-1} with 2SLS regression with robust errors, we did not obtain the expected results as far as GDP_gr_{t-1} is concerned. The point estimate of this variable remained more or less the same, and T-statistics further decreased (due to the increase in standard error), which is natural in IV regressions, especially with robust errors. Nevertheless, this phenomenon can be minimized by the quality of instruments. We

safely rejected the null hypothesis of the Weak instruments test. Hence we minimized the decrease in T-statistics as much as possible. Taking this into account, there are two possible scenarios. Firstly, instruments are fine, and the variable is insignificant due to high robust errors in 2SLS regression, which should be resolved by applying GMM regression on the same underlying model. Secondly, the instruments are endogenous, which should not hold as the Sargan test did not have enough evidence to reject the null hypothesis. On the other hand, as already mentioned, the Sargan test is not valid under heteroskedasticity and serial correlation. This will be overcome by applying the Hansen J-Test after the GMM estimation.

Furthermore, coefficients of all other variables also remained more or less the same with only lower T-statistics where the reason is the same as in the case of GDP_gr_{t-1}. As a result, the Hausman test did not have enough evidence to reject the null hypothesis. Despite the results of the last test, based on which we should stick to OLS estimates, we further employ GMM estimation to confirm the results of the key hypotheses and to see whether the instruments are fine.

The GMM estimation is employed on the same underlying model as in the case of 2SLS regression with the same assumptions about endogeneity and usage of instruments. We wish to obtain higher T-statistics.

6.1.1.3 Generalized method of moments estimation

The results of GMM estimation can be found in table 5. First of all, we further did not apply the Hausman test to test the significance of the difference between coefficients of OLS and GMM estimates as we rather rely on economic logic behind the results from the GMM estimation. On the other hand, we interpret the Hansen J-Test because it obtains different results than the Sargan test in the 2SLS regression due to heteroskedasticity and serial correlation assumptions. The test rejects the null hypothesis very strongly, even on 99% confidence level. This means that all our instruments

are invalid. As a reaction to this, we tried different combinations of instruments with the hope not to reject this test for them. The results can be seen in Appendix 4. Unfortunately, the test rejected the null hypothesis on 99% confidence level in all cases, which indicates that UK's macroeconomic, and financial market variables are, in fact, correlated with the US's error term. Therefore, in the interpretation of the GMM regression, we stick to the specification in table 5 despite the bias in many coefficients.

Table 5: GMM without $\Delta spread\_ch$

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	0.00202	1.25	0.21293
Δlog_odd_{t-1}	0.47646	1.28	0.19987*
GDP_gr_{t-1}	-0.00824	-1.61	0.10695
$inflation_{t-3}$	0.00085	0.65	0.51388
$\Delta interest\_rate_{t-1}$	0.00579	0.82	0.41202
$exchange\_gr_{t-4}$	0.00101	1.02	0.30779
$\Delta unemployment\_rate_{t-2}$	0.02518	2.12	0.03376
$DJIA\_gr_{t-1}$	0.00009	0.21	0.83401
$fiscal\_1$	-0.03843	-1.91	0.05644
$fiscal\_2$	0.06531	2.10	0.03591
$\Delta stringency\_index_t$	0.09749	2.41	0.015927
J-Test p-value: 0.00533			

Source: Author's computation

With regard to the results, we see that many independent variables are newly biased when compared to the results from OLS. For example, the coefficients for all $inflation_{t-3}$, $\Delta interest\_rate_{t-1}$, $exchange\_gr_{t-4}$, $DJIA\_gr_{t-1}$ are now of opposite sign from what they previously were. On the other hand, key variables of our hypotheses have almost identical point estimates regardless of whether we estimate by OLS, 2SLS, GMM (with any possible instruments). Taking this into account, we believe that even these technically unreliable results allow us to draw important conclusions.

The aforementioned phenomenon is very surprising and certainly good for our hypotheses because even after we induced (further) bias into the re-

gression, all $fiscal\_1$, $fiscal\_2$, $\Delta stringency\_index_t$ are significant at 90% confidence level ($fiscal\_2$ even on 95% and $\Delta stringency\_index_t$ even on 99%) with the same sign in all three regressions (OLS, 2SLS, GMM), which makes the results of these variables very robust to model misspecification. By the word (further) in the previous sentence, we mean that we do not know certainly, whether the bias was already present in the OLS regression. However, we know for sure that the choice of the instruments in GMM estimation induced even more bias into the model.

Reader might be confused by looking at the results in Appendix 4 and reading here that these particular variables are significant in GMM estimation. In Appendix 4, we only show our attempts to see whether some UK's macroeconomic variable are exogenous. While doing those regressions, we did not care much about the relevance of those instruments, i.e., weak instrument issue. Therefore, even though the results of some of those regressions would indicate the insignificance of these variables, we do not take them seriously and do not rely on them. In the context of GMM results, we commented only on the results in table 5.

6.1.2 Summary of the results

6.1.2.1 General summary

Since the Hansen J-test had enough evidence to reject the null hypothesis, the results from both 2SLS and GMM regressions are not reliable. Furthermore, the fact that 2SLS and GMM estimates are different can be attributed to the size of the sample (Hansen, 1982). Taking the aforementioned into consideration, we stick to OLS results despite the (potential) bias in the estimates.

We have found that all Δlog_odd_{t-1}, $\Delta unemployment\_rate_{t-2}$, $fiscal\_1$, $fiscal\_2$, and $\Delta stringency\_index_t$ are significant determinants of corporate Δlog_odd_t on more than 99% confidence level. The signs of their coefficients are in line with what was expected and also with the aforementioned liter-

ature. With respect to other independent variables, the signs of their coefficients are again as expected, but their T-statistics are too low to make any inference. We attribute this to the high number of regressors. On the other hand, we decided to keep them all in the regression not to cause any (further) bias in the results as they are not that insignificant. The most surprising is low T-statistics for GDP_gr_{t-1}, which is even lower than T-statistics of other insignificant variables, which is strange. A variable representing GDP is generally considered as the key regressor in PD modeling as we indicated in the section "Data description". We believe that this variable is biased, which we unsuccessfully tried to eliminate.

6.1.2.2 Hypothesis 1

Based on the results and liable to the choice of estimation procedures, we have found enough evidence to reject the null hypothesis that fiscal measures were not significant determinants of change of corporate aggregate probability of default in the US.

As far as the interpretation is concerned, the results confirm that the effect of fiscal measures on their own was not long-lasting as the coefficients then cancel each other out. Furthermore, the conclusion regarding this hypothesis is very robust as the relationship between $fiscal\_1$, $fiscal\_2$, and Δlog_odd_{t-1} remained more or less the same regardless of the bias we induced.

6.1.2.3 Hypothesis 3

Based on the results and liable to the choice of estimation procedures, we have found enough evidence to reject the null hypothesis that growth of stringency index was not a significant determinant of change of corporate aggregate probability of default in the US.

Moreover, as with the Hypothesis 1, the conclusion regarding this hypothesis is very robust as the relationship between $\Delta stringency\_index_t$ and Δlog_odd_{t-1} was almost the same regardless of the bias induced.

6.1.2.4 Robustness checks

To be sure that our results are valid, we also did robustness checks to confirm that the relationship between the dependent variable and independent variables is not coincidental. Since we chose a different methodology than previous researchers, we propose the following robustness checks that we believe is the most suitable with respect to the data set. The test is as follows: From the data set, we used only those observations prior to 2020 to avoid shocks in all independent variables caused by the COVID-19 crisis. This also means that we dropped all $fiscal\_1$, $fiscal\_2$, $\Delta stringency\_index_t$ from our model in equation 6.2. We then estimated this adjusted model by OLS. The purpose was to see whether point estimates and standard errors of the remaining variables remained more or less the same as in table 3. The results of this test can be seen in Appendix 3 in table 12. Apart from GDP_gr_{t-1} and $\Delta unemployment\_rate_{t-2}$, the sign of the relationship between independent variables and the dependent variable is more or less the same. With respect to T-statistics of each variable, they are a bit lower, which is reasonable due to lower variance in the shorter data set. The fact that the coefficient of GDP_gr_{t-1} is of the opposite sign corroborates the idea of the endogeneity of this variable that we tried to remedy. On the other hand, we do not know why the coefficient for $\Delta unemployment\_rate_{t-2}$ is now of opposite sign. We suspect that the reason might be the noise in the data that we could not account for due to the length of the set. Despite this only setback, we consider our results from the regressions to be valid.

6.2 Corporate sector in the UK

6.2.1 Estimation

6.2.1.1 Ordinary least squares estimation

Based on the AIC, we arrived at this specification of the model:

$$\begin{aligned}\Delta log\_odd_t = &+ \beta_0 + \beta_1 \Delta log\_odd_{t-1} + \beta_2 GDP\_gr_{t-1} + \beta_3 inflation_{t-7} \\ &+ \beta_4 \Delta interest\_rate_{t-7} + \beta_5 exchange\_rate\_gr_{t-7} \\ &+ \beta_6 \Delta unemployment\_rate_t + \beta_7 \Delta spread_{t-5} \\ &+ \beta_8 FTSE\_gr_{t-5} + \beta_9 fiscal + \beta_{10} \Delta stringency\_index_t\end{aligned} \tag{6.3}$$

We also tested all variables by the augmented Dickey-Fuller test, where the null hypothesis was rejected on 99% confidence level. Thus we again rely on asymptotic Gauss-Markov properties.

The model was estimated by OLS, where the results can be found in Appendix 2 in table 11. We followed a similar procedure as in the case of the US. Therefore, we firstly decided to drop some variables based on robust F-Test before dealing with endogeneity. The dropped independent variables are: Δlog_odd_{t-1}, $exchange\_rate\_gr_{t-7}$, $\Delta unemployment\_rate_t$, $\Delta spread_{t-5}$. We decided to drop so many variables because the F-Test allowed us, i.e., it did not have enough evidence to reject the null hypothesis on joint insignificance of all these variables for the regression and also because each of their robust standard errors was much lower than in the case of any variable in the regression for the US.

Moreover, dropping $exchange\_rate\_gr_{t-7}$ from regression is good to avoid potential multicollinearity. We assume so because $exchange\_rate$ and $inflation$ are strongly correlated on 99% confidence level. This phenomenon was shown in section "Data description" in table 2. Although the correlation of 0.89 is not that high, we still believe that dropping $exchange\_rate\_gr_{t-7}$ from the model is only beneficial.

The new specification of the model is following:

$$\Delta log\_odd_t = + \beta_0 + \beta_1 GDP\_gr_{t-1} + \beta_2 inflation_{t-7} + \beta_3 \Delta interest\_rate_{t-7} + \beta_4 FTSE\_gr_{t-5} + \beta_5 fiscal + \beta_6 \Delta stringency\_index_t \tag{6.4}$$

The results of the OLS regression of this model are in table 6:

Table 6: OLS estimation with dropped variables

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	0.13306	8.97	0.00000*
GDP_gr_{t-1}	-0.00002	-4.83	0.00000*
$inflation_{t-7}$	-0.00223	-1.17	0.24861
$\Delta interest\_rate_{t-7}$	0.02619	2.32	0.02427
$FTSE\_gr_{t-5}$	0.00011	0.55	0.58144
$fiscal\_1$	-0.00013	-0.05	0.95681
$\Delta stringency\_index_t$	0.03903	6.27	0.00000*
Number of observations: 60			
$R^2 = 0.52$			
$Adjusted\_R^2 = 0.47$			

Source: Author's computation

Firstly, even after dropping so many independent variables, including the lag of the dependent variable, both R^2 and $Adjusted\_R^2$ are still quite high with values 0.52 and 0.47, respectively. Secondly, the biggest difference from the US estimation is that, based on OLS regression, GDP_gr_{t-1} is a significant determinant of Δlog_odd_t on more than 99% confidence level with the expected sign of the relationship. The coefficient for $inflation_{t-7}$ has also the expected sign, but admittedly, we expected that it would be more significant after dropping so many independent variables from the regression. Because of that, we do not expect $inflation_{t-7}$ to be biased as its significance rose, but simply not enough to become significant.

On the other hand, what stroke us immediately were the coefficients for both $\Delta interest\_rate_{t-7}$ and $FTSE\_gr_{t-5}$. As far as $\Delta interest\_rate_{t-7}$ is concerned, the variable is significant, but the sign of the variable is opposite

to what we expected and also to what we obtained in the case of the US. This might be either attributed to the fact that we employed later lag of this variable in the regression than in the case of the US (for the US, we used first lag) and coefficients is all right or to the fact that that the variable is endogenous and the coefficient should be of opposite sign. Fortunately, the latter can be checked. Although $FTSE\_gr_{t-5}$ is not significant and could be dropped, we decided to keep the variable in the model due to two reasons. Firstly, we simply wanted a variable representing the financial market in the regression. Secondly, we believe that the variable is biased. We assumed that the bias both changed its sign of the coefficient and compressed it closer towards zero.

As far as the variables important for the hypotheses are concerned, the signs of the relationships are as we expected. On one hand, $\Delta stringency\_index_t$ is statistically significant (even on 99% confidence level). On the other hand, dummy $fiscal$ is not significant at all. It might be that the potential bias in both $\Delta interest\_rate_{t-7}$ and $FTSE\_gr_{t-5}$ compressed the coefficient of dummy $fiscal$ towards zero by their mutual correlation. This would then be the explanation for such a low T-statistics of this dummy.

6.2.1.2 Two stage least squares estimation

As already said, we suspect $\Delta interest\_rate_{t-7}$ and $FTSE\_gr_{t-5}$ to be both endogenous. As instruments, we chose the US's $\Delta interest\_rate_t$, $DJIA\_gr_t$, $exchange\_rate\_gr_t$, $\Delta unemployment\_rate_t$. The choice of first two instruments is clear. On the other hand, the choice of the latter two was arbitrary as we hoped that their implementation would further improve 2SLS regression. Having too many instruments can be problematic. Wooldridge (2016) mentions it might induce multicollinearity. Despite that, we assumed that four instruments for two endogenous variables are not that much and proceeded with the regression. The results of 2SLS estimation are summarized in table 7.

Firstly, the sign of the coefficient for $\Delta interest\_rate_{t-7}$ became negative as we expected. The variable is not significant even at 90% confidence level, which is not that surprising because of robust errors in 2SLS regression. Low T-statistics can be further attributed to imperfect instruments as we did not manage to reject the null hypothesis of the Weak instrument test for this variable (even on 90% confidence level).

Table 7: 2SLS estimation with dropped variables

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	0.24461	1.97	0.05347
GDP_gr_{t-1}	-0.00005	-1.95	0.05663
$inflation_{t-7}$	-0.01407	-1.41	0.16397
$\Delta interest\_rate_{t-7}$	-0.07332	-1.01	0.31628
$FTSE\_gr_{t-5}$	0.00181	0.89	0.37479
$fiscal\_1$	-0.01685	-1.07	0.29034
$\Delta stringency\_index_t$	0.01812	1.25	0.21562
Number of observations: 60			
Weak instruments for $\Delta interest\_rate_{t-7}$ P-value: 0.20161			
Weak instruments for $FTSE\_gr_{t-5}$ P-value: 0.13081			
Hausman test P-value: 0.05843			
Sargan test P-value: 0.44896			

Source: Author's computation

About $FTSE\_gr_{t-5}$, its coefficient is now less compressed toward zero, but the sign is still positive. We identify three possible reasons for this. Firstly, the sign should really be positive, but this is the least probable scenario. Secondly, the instruments are exogenous but are not good as we did not manage to reject the null hypothesis of the respective test for this variable. This would mean that the instruments did not have enough power to change the sign of the relationship. On the other hand, the P-value of this test is much lower than in the case of $\Delta interest\_rate_{t-7}$, where the inclusion of the instruments changed the coefficient as expected. Lastly, the instruments are endogenous. We rather support the second argument as the Sargan test did not have enough evidence to reject the null hypothesis. On the other hand, the Hausman test had enough evidence to reject its null hypothesis on 90%

confidence level, which is mostly caused by the change of the coefficient of $\Delta interest\_rate_{t-7}$ in 2SLS regression from OLS regression.

With regard to $\Delta stringency\_index_t$, its coefficient remained more or less the same, but its error increased substantially, which caused this variable to be insignificant after 2SLS regression. Despite that, we had believed that the variable would be more significant in GMM estimation because of its higher efficiency.

Last but not least, the coefficient for dummy $fiscal$ is now higher in absolute value with also smaller error, which makes the T-statistics far bigger, although still not significant enough to make any statistical conclusions. We expect the variable to be at least marginally significant in GMM estimation.

6.2.1.3 Generalized method of moments estimation

Just as in the case of the US, we estimated the same specification of the model, which we estimated by 2SLS estimation, also by GMM estimation. The assumptions regarding the instruments were also the same. The results can be found in table 8.

As expected, all the coefficients for the variables remained more or less the same as in the case of 2SLS. The major difference is that T-statistics of all variables are now higher in absolute terms. This also means that the variable $FTSE\_gr_{t-5}$ that we suspect to be endogenous is now significant even at 99% confidence level. We contribute this to endogeneity that we could not eliminate by IVs as we did in the case of $\Delta interest\_rate$. What changed significantly both from OLS and 2SLS regressions is that $inflation_{t-7}$ is now significant at 99% confidence level, so as is $interest\_rate_{t-7}$ on 90% confidence level.

With regard to key variables of our hypotheses, dummy $fiscal$ is now significant at 99% confidence level, which is good for the Hypothesis 2. On the other hand, the variable $\Delta stringency\_index_t$ remains still insignificant as in

the case of 2SLS regression even on 90% confidence level. This would not be a problem had not we have to prefer instrumental variable regressions results because of the rejecting of the null hypothesis of the Hausman test. Moreover, we believe that the results of this test are valid because instrumental variable regressions results are a lot different from the OLS ones in a logical way.

Table 8: GMM estimation with dropped variables

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	0.24525	4.59	0.00000*
GDP_gr_{t-1}	-0.00005	-4.46	0.00000*
$inflation_{t-7}$	-0.01425	-2.10	0.03593
$\Delta interest\_rate_{t-7}$	-0.07329	-1.71	0.08815
$FTSE\_gr_{t-5}$	0.00155	1.97	0.00484
$fiscal$	-0.01897	-2.63	0.00845
$\Delta stringency\_index_t$	0.01168	1.03	0.3022
Number of observations: 60			
J-test P-value: 0.44689			

Source: Author's computation

6.2.2 Summary of the results

6.2.2.1 General summary

Based on the results of the Hausman test that we consider to be reasonable, we need to stick to the results of instrumental variable regressions. As such, we report the results from GMM estimation due to their efficiency.

We have found that all GDP_gr_{t-1}, $inflation_{t-7}$, $FTSE_{t-5}$, and $fiscal$ are all significant on 99% confidence level. Apart from $FTSE_{t-5}$, all of the aforementioned variables have the expected sign of the coefficient. With respect to $FTSE_{t-5}$, we contribute its positive estimate to the bias we could not control for. Moreover, $interest\_rate_{t-7}$ has become significant (on 90% confidence level) after GMM estimation that eliminated the endogeneity problems with this variable.

6.2.2.2 Hypothesis 2

Based on the results and liable to the choice of estimation procedures, we have found enough evidence to reject the null hypothesis that fiscal measures were not significant determinants of change of corporate aggregate probability of default in the UK.

As for the interpretation, there is no need to do so as in the case of the US since the dummy structure here is way simpler and obvious.

6.2.2.3 Hypothesis 4

Based on the results and liable to the choice of estimation procedures, we did not found enough evidence to reject the null hypothesis that growth of stringency index was not a significant determinant of change of corporate aggregate probability of default in the UK.

This can be attributed to the construction of this variable, as we mentioned in the "Data description" section. Maybe, we "penalized" the variable too much, which made it insignificant. On the other hand, the variable was constructed the same way also for the US regressions where it was significant, so this should theoretically not be the problem. One might argue that had we found exogenous instruments for the US's model, the growth of stringency index would have become insignificant in the same way as for the UK. We do not think this is the case because of two reasons. Firstly, we do not know for sure that the bias is present in the US's OLS regression. Secondly, even if the bias is present, it is not huge because most of the variables had estimates and T-statistics that were expected. Thus, the instrumental variable regression of any type would not have too much to change.

On the other hand, we can also attribute this insignificance to the "messier" behavior of the UK's variables than the US's ones. This phenomenon can be directly seen in Appendix 1.

6.2.2.4 Robustness checks

As in the case of the US, we also did robustness checks to confirm that the results we found are not coincidental. The procedure was the same one we proposed in the US's section. Therefore, we dropped from equation 6.4 variables $fiscal$ and $\Delta stringency\_index_t$, used only the data prior to 2020, and estimated the adjusted model. The results can be found in Appendix C in table 13. When comparing these results with the results from table 6, we see that the coefficients of all variables are roughly the same, so as are, the T-statistics except for the one for GDP_gr_{t-1}. We attribute this to the fact that prior to 2020, GDP_gr_{t-1} was almost constant, which results in lower variance for this variable in the data set prior 2020. Thus, such a difference is reasonable. Based on the given arguments, we consider our underlying model to be robust.

6.3 Contribution and recommendations

To summarize the findings of the thesis, we present here our contribution that is fourfold. We start by interpreting Hypotheses 1 and 2, then continue with explaining their contribution, and finish by providing policy recommendations stemming from them. After this, the same procedure is repeated with Hypotheses 3 and 4.

Firstly, we rejected Hypotheses 1 ('Fiscal measures were not significant determinants of change of corporate aggregate probability of default in the US'). This rejection implies that fiscal measures "artificially" decreased corporate aggregate probability of default in the US.

Secondly, Hypothesis 2 ('Fiscal measures were not significant determinants of change of corporate aggregate probability of default in the UK') was rejected too. This result can be interpreted in the same way as in the case of the US, i.e., fiscal measures "artificially" decreased corporate aggregate probability of default in the UK.

The inclusion of fiscal proxies contributes to the existing literature regarding both probability of default modeling and credit risk as a whole because, by the time of the submission of this thesis, we could not find any empirical research that would deal with the same phenomenon.

Based on the results of Hypotheses 1 and 2, we recommend that credit risk managers incorporate proxies representing fiscal measures in the estimation of TTC-PD that serve as an input for calculating regulatory capital in the US's and the UK's banks. We do so because BCBS (2006) for this purpose requires that time series of probability of default need to be at least five years long. This should cover both ups and downs of the economy. Thus, if banks include in their time series the period of the COVID-19 crisis without accounting for this, the estimates of aggregate probability of default will be lower, which will result in lower capital requirements for the upcoming periods. This would leave banks more vulnerable to potential crises.

Thirdly, we rejected Hypothesis 3 ('Growth of stringency index was not a significant determinant of change of corporate aggregate probability of default in the US'). This result indicates that proxy representing crisis or any possible chaos in the world's economy is worth having in such models for the case of the US.

Lastly, we did not have enough evidence to reject Hypothesis 4 ('Growth of stringency index was not a significant determinant of change of corporate aggregate probability of default in the UK'). Statistically, we cannot give any recommendations based on the result of the Hypothesis. On the other hand, as already discussed in previous sections, we might "penalized" the variable too much with respect to its variance.

We are not the first to employ such a proxy for a crisis in probability of default modeling. Zsigraiová (2014) did it before us. What differentiates us from her is the choice of proxy. She employed a dummy variable, whereas we used an index that was specifically created during the COVID-19 crisis. There is no doubt that Zsigraiová (2014) did not have such an index available because the crisis in her sample was of a different structure (Global Financial crisis of 2007-2009). Nevertheless, it does not belittle our contribution.

Based on the result of Hypothesis 3, we assume that a proxy that represents any event, which causes chaos in the economy and on the markets in general, could be potentially a good input for stress testing in the US. In other words, banks could test what pandemics, wars, or potentially crises of other forms cause to probability of default and subsequently to regulatory capital by employing such a special variable. Although we did not have enough evidence to reject Hypothesis 4, we still think that these recommendations can also be considered in the UK due to the aforementioned "penalty" in terms of variance of growth of stringency index.

To demonstrate our contribution graphically, we provide here table 9 to compare ourselves with a few other researchers. The aim is to show what different types of independent variables have been used by them and by us.

Table 9: Comparison of the employed variables in previous studies

Author(s)	Methodology	Frequency of data	Period	Independent variabales			
				Macroeconomic	Financial market	Crisis proxy	Fiscal measures
Virolainen (2004)	SUR	Quarterly	1986-2003	✓	x	x	x
Fiori *et al.* (2009)	SUR	Quarterly	1991-2008	✓	✓	x	x
Agrawal & Maheshwari (2014)	LOGIT/MDA	Monthly	2001-2012	✓	✓	x	x
Jakubik & Schmieder (2008)	OLFM	Quarterly	1994/1998-2006	✓	x	x	x
Zsigraiová (2014)	OLFM	Monthly	2002-2013	✓	x	✓	x
Antonsson (2018)	OLS	Monthly	2008-2015	✓	x	x	x
This thesis	OLS/2SLS/GMM	Monthly	2015-2020	✓	✓	✓	✓

Source: Author's computation

6.4 Further research opportunities

In this subsection, we propose recommendations for further research regarding this topic. Moreover, we also discuss the choice of the methodology and reasons why other approaches were not feasible.

First of all, we recommend longer data set because 60 observations is not much to rely on asymptotic properties. If one has such an opportunity, then more independent variables could be included. Most of them would be probably insignificant because it is likely that the mutual correlation between variables would increase with a higher number of regressors. On the other hand, one might still find a new significant variable that we unintentionally omitted. Furthermore, if someone wants to follow us in the analysis, we recommend trying different instruments for the US's endogenous variable(s) because the chosen UK's macroeconomic and financial market variables were not suitable due to the Hansen J-test results.

A careful reader might ask the following question: Why did we choose this methodological approach and not the others? There are a few reasons for this.

With respect to VAR, we do not consider this method suitable because it is an example of multivariate time series regression. As such, also independent variables become dependent variables during the estimation of the given system, which is in our case not always suitable because of the chosen proxies for COVID-19 and fiscal measures, i.e., it would make no sense to assume that GDP_gr is determinant of $\Delta stringency\_index$. Although there are ways how to solve this, we did not try them because the outcome would be uncertain due to the length of the data set and a high number of regressors.

As far as SUR estimation is concerned, it is not feasible due to our data structure. Both Virolainen (2004) and Fiori *et al.* (2009), who applied this method, had industry-specific data, which is not our case. This made it impossible for us to follow them.

As for OLF model, it is not suitable because of the following reason. Greene (2012) says that OLF model is standardly estimated by the Maximum Likelihood Estimator. To be able to do so, he stresses that variables need to be independent and identically distributed. By looking at the correlation matrices for both countries, we know that this condition is not satisfied. On the other hand, Zsigraiová (2014) had the same problem. She solved it but at the expense of the number of predictors, which we did not want to.

Lastly, to follow the approach of Agrawal & Maheshwari (2014) was not possible too because our data set differs from their significantly. Firstly, they analyze on an individual level, i.e., their dependent variable is not aggregated. Secondly and lastly, they do not work with actual PD but its proxy.

Based on the given arguments, we assume that the "simple" approach we chose is the best one when the length of the data set and the purpose of the analysis are taken into account. Moreover, the appropriateness of our choice is supported by Antonsson (2018), who approached the analysis similarly by using OLS. On the other hand, she did not take into account the possible non-linear relationship between the dependent variable and independent variables, which we did. When compared to her, we also tried to improve the OLS estimation by both 2SLS and GMM regressions.

7 Conclusion

The thesis dealt with corporate credit risk management during the COVID-19 crisis. As a proxy of corporate credit risk, we employed corporate aggregate probability of default (PD) provided by Credit Benchmark. To measure the impact of the crisis on corporate aggregate PD, we used variables representing macroeconomic and financial market environments. Furthermore, as proxies for the COVID-19 shock and governments' fiscal measures, we employed COVID-19 stringency index, proposed by Hale *et al.* (2020), and dummy variable(s), respectively. Our data set consisted of 60 monthly observations. All continuous variables were at least differenced due to stationarity concerns and interpretation. The analysis was based on OLS, 2SLS, and GMM estimations. The reasons for the choice of the latter two were endogeneity concerns and greater efficiency, respectively.

As for the US, we stuck to OLS estimates due to the rejection of the Hansen J-test for GMM. Variables representing the lag of the dependent variable and unemployment rate are both significant determinants of change in corporate aggregate PD with a positive relationship. The significance of the lag is not unexpected, but the significance of the latter one might be surprising as we analyzed corporate PD. However, we argued that it is logical based on descriptive statistics. Furthermore, we rejected Hypotheses 1 ('Fiscal measures were not significant determinants of change of corporate aggregate PD in the US') and Hypothesis 3 ('Growth of stringency index was not a significant determinant of change of corporate aggregate PD in the US'). The coefficient of the variable representing GDP was negative, which is in line with all Virolainen (2004), Fiori *et al.* (2009), Zsigraiová (2014), and Antonsson (2018). What surprised us was its insignificance since the results of the aforementioned researchers indicate the opposite. Thus, we considered this variable to be biased, which was supported by the results of the robustness checks. Lastly, the remaining independent variables were insignificant too, but we contributed this to a high number of predictors.

Concerning the UK, we stuck with GMM estimates due to the results of the Hausman test, which preferred instrumental variable regressions over OLS regression, and the Hansen J-Test, which did not reject the null hypothesis. Unlike the US, we ended up with far less regressors, which we justified by not rejecting the F-Test and extremely low T-statistics of each omitted predictor. We found that variables representing GDP and inflation are both significant determinants of change of corporate aggregate PD with a negative relationship. For GDP, this is in line with Virolainen (2004), Fiori *et al.* (2009), Zsigraiová (2014), and Antonsson (2018), whereas for inflation with Jakubik *et al.* (2007), Zsigraiová (2014) and Agrawal & Maheshwari (2014). A variable representing stock market index is significant too but with positive coefficient, which was not expected and is not supported by Hamerle *et al.* (2011) and Agrawal & Maheshwari (2014). Moreover, we rejected Hypothesis 2 ('Fiscal measures were not significant determinants of change of corporate aggregate PD in the UK'). On the contrary, we did not have enough evidence to reject Hypothesis 4 ('Growth of stringency index was not a significant determinant of change of corporate aggregate PD in the US').

The results of the hypotheses allow us to present our contribution and recommendations. Firstly, the rejection of Hypotheses 1 and 2 indicates that fiscal measures "artificially" decreased corporate aggregate PD in the US and the UK. Thus, we recommend that respective bank credit risk managers incorporate proxies representing fiscal measures in their estimation of through-the-cycle PD that serve as an input for the calculation of regulatory capital.

Secondly, the rejection of the Hypothesis 2 implies that proxy representing crisis or any possible chaos in the world's economy is worth having in these US models. Taking this into account, we assume that such proxy might be a good input for stress testing in the US. Although we did not manage to reject Hypothesis 4, we think that this recommendation can also apply to the UK because we might defined change of stringency index too strictly in terms of variance.

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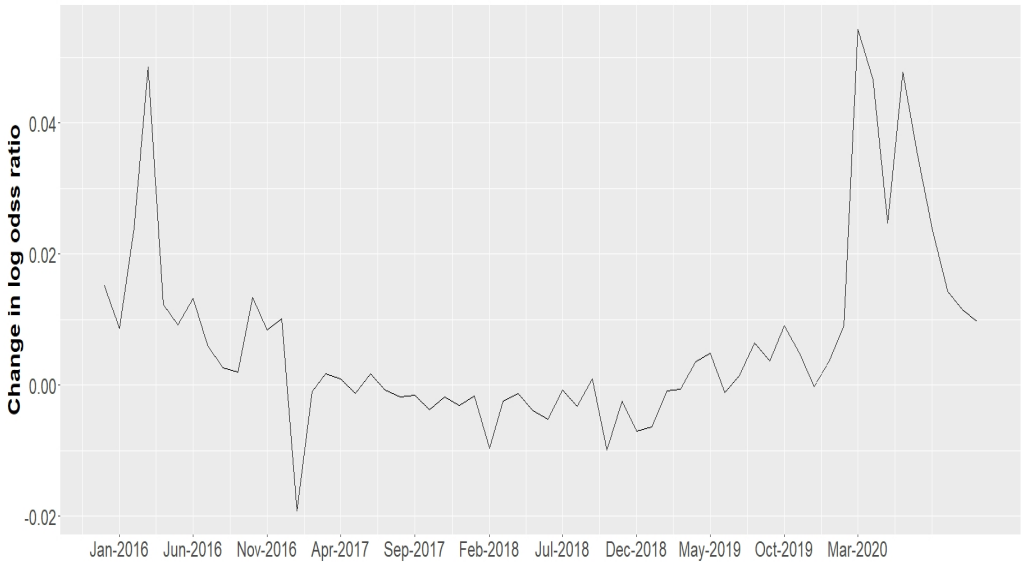
A Appendix 1

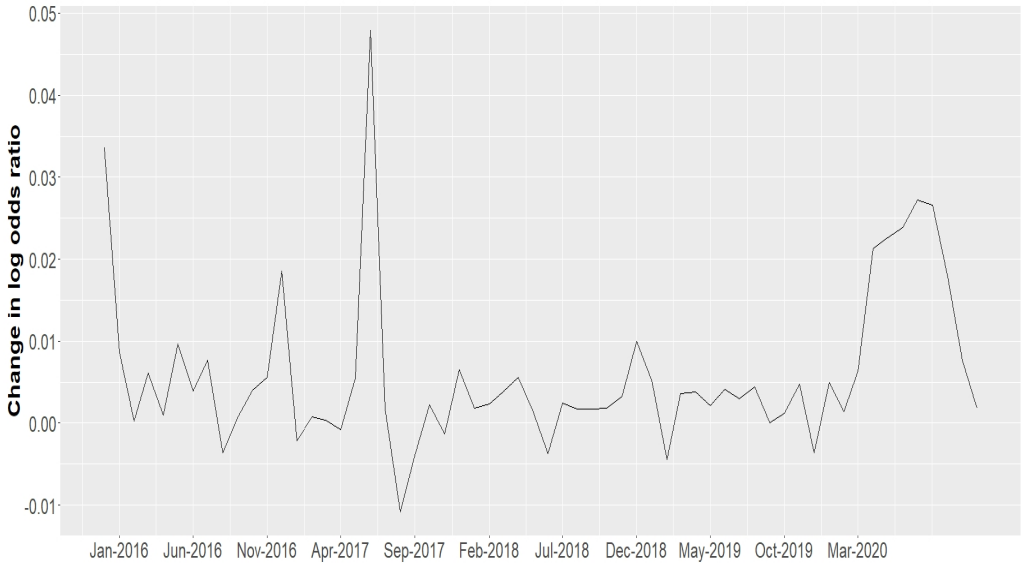
A.1 Change in log odds ratio

Figure 6: Change in log odds ratio US



Source: Author's computation

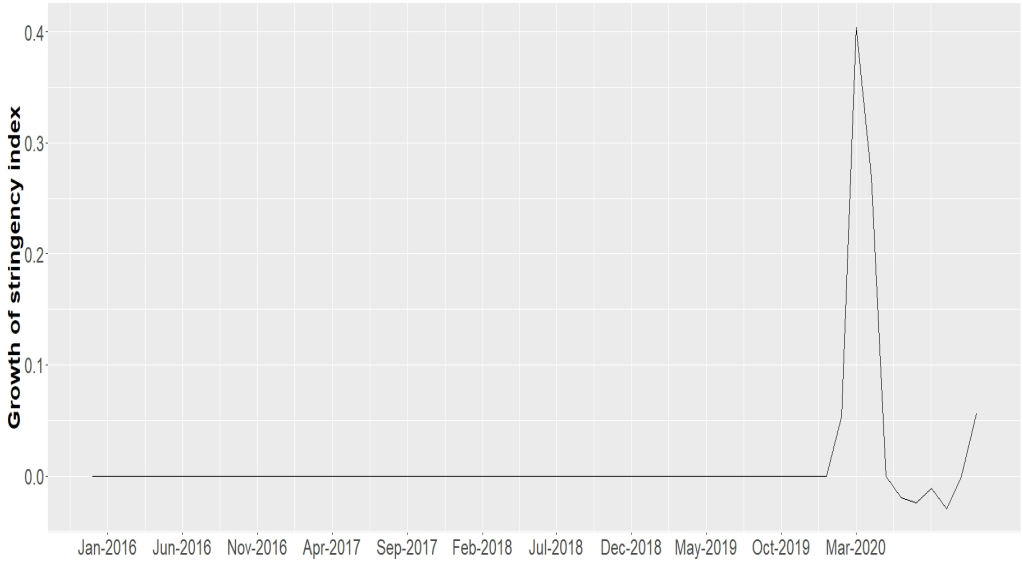
Figure 7: Change in log odds ratio UK



Source: Author's computation

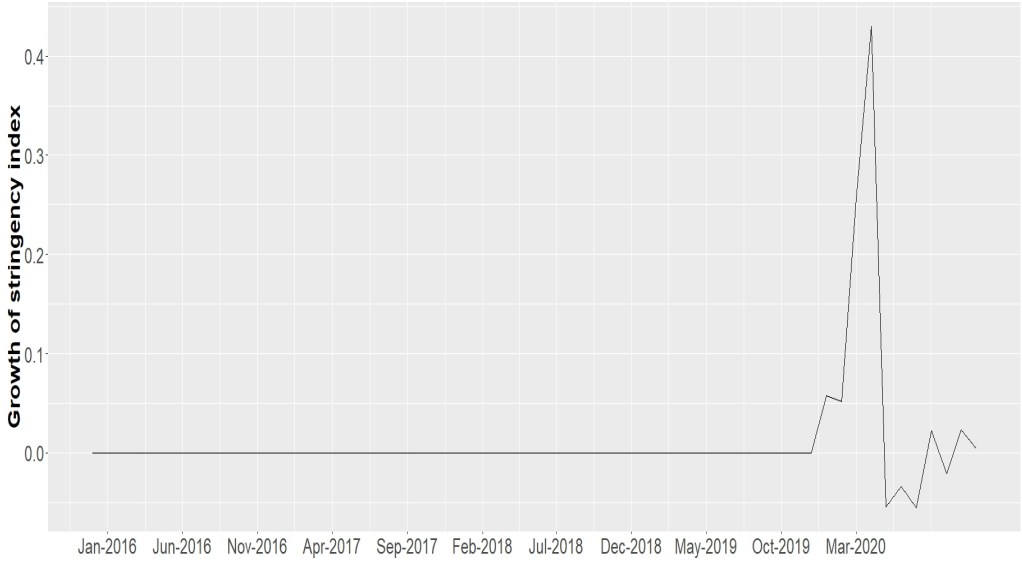
A.2 Change in COVID-19 stringency index

Figure 8: Change in st. index US



Source: Author's computation

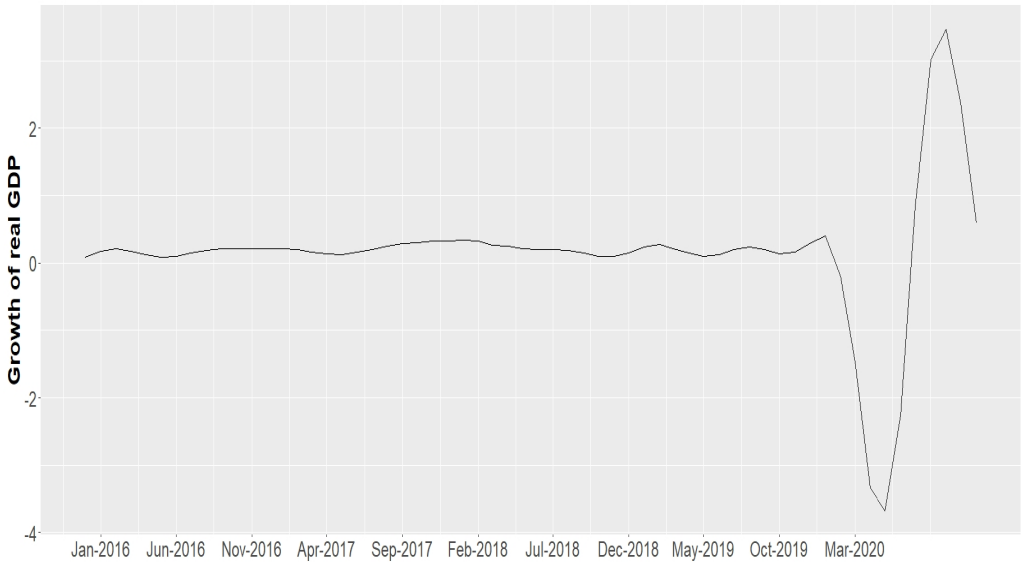
Figure 9: Change in st. index UK



Source: Author's computation

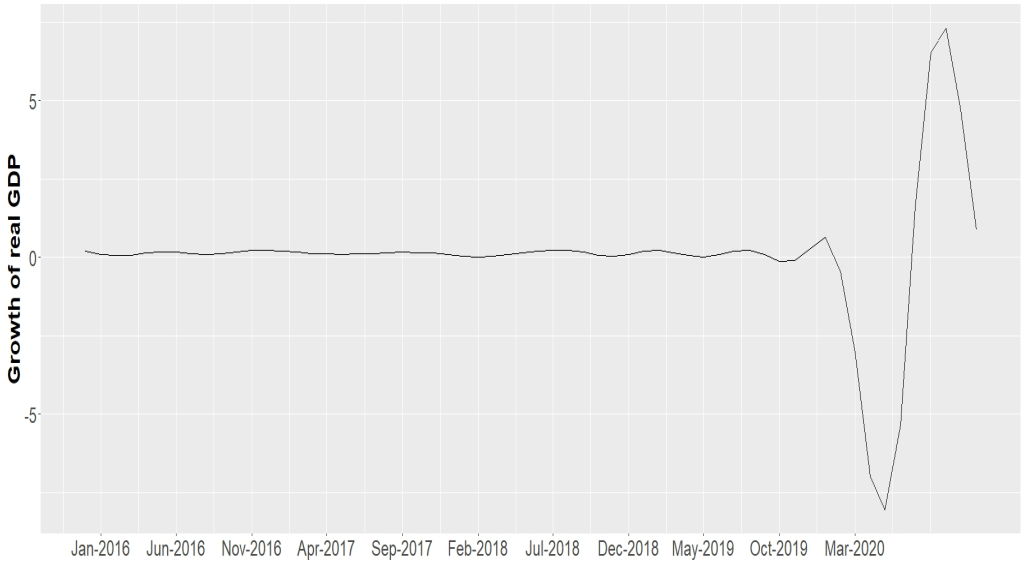
A.3 Growth of real gross domestic product

Figure 10: GDP growth US



Source: Author's computation

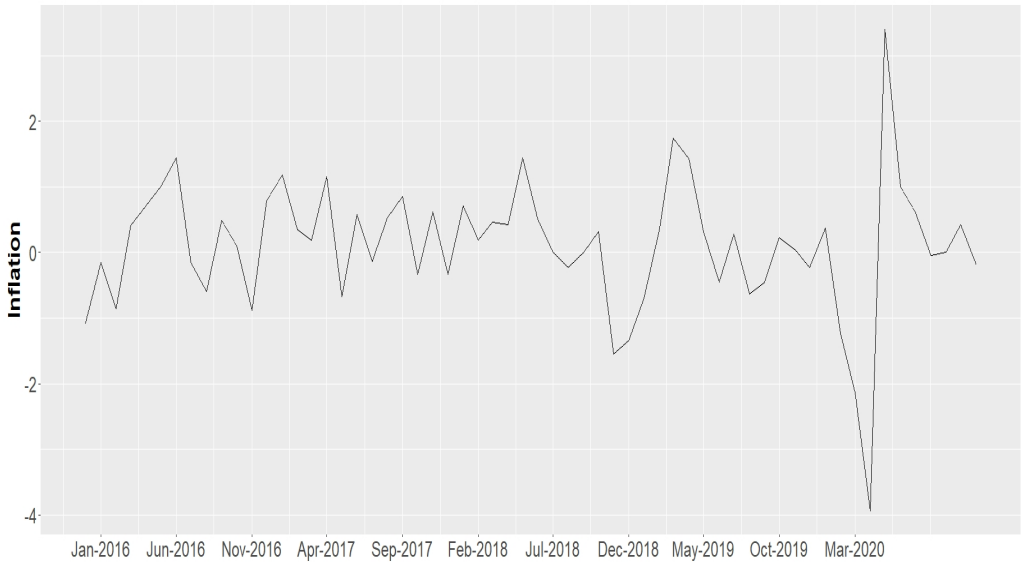
Figure 11: GDP growth UK



Source: Author's computation

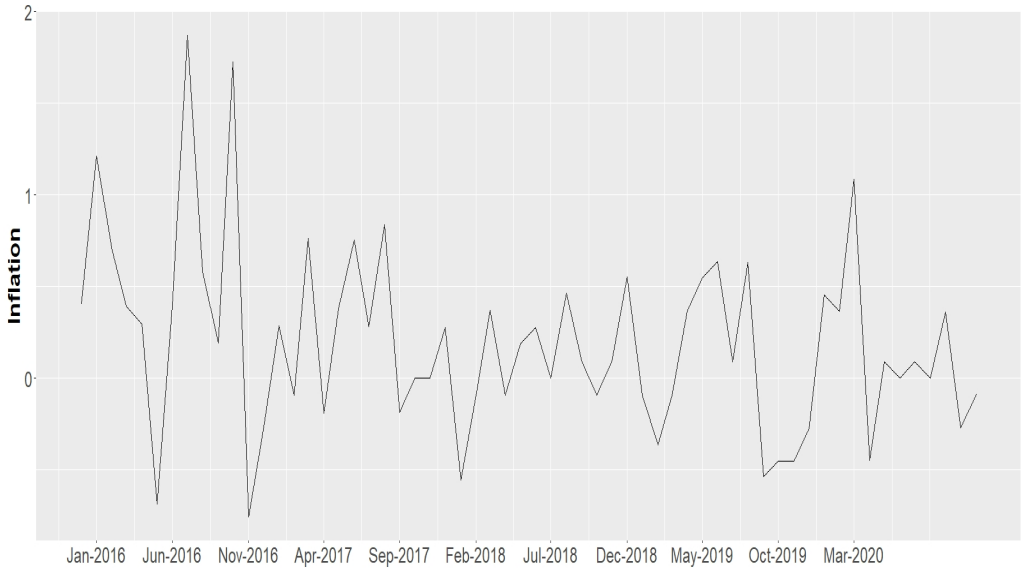
A.4 Inflation

Figure 12: Inflation US



Source: Author's computation

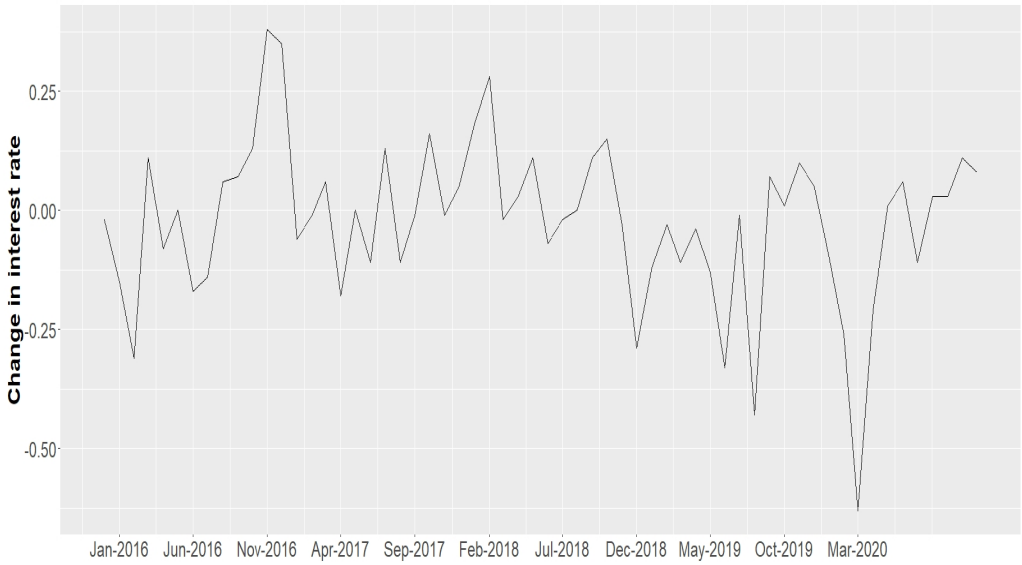
Figure 13: Inflation UK



Source: Author's computation

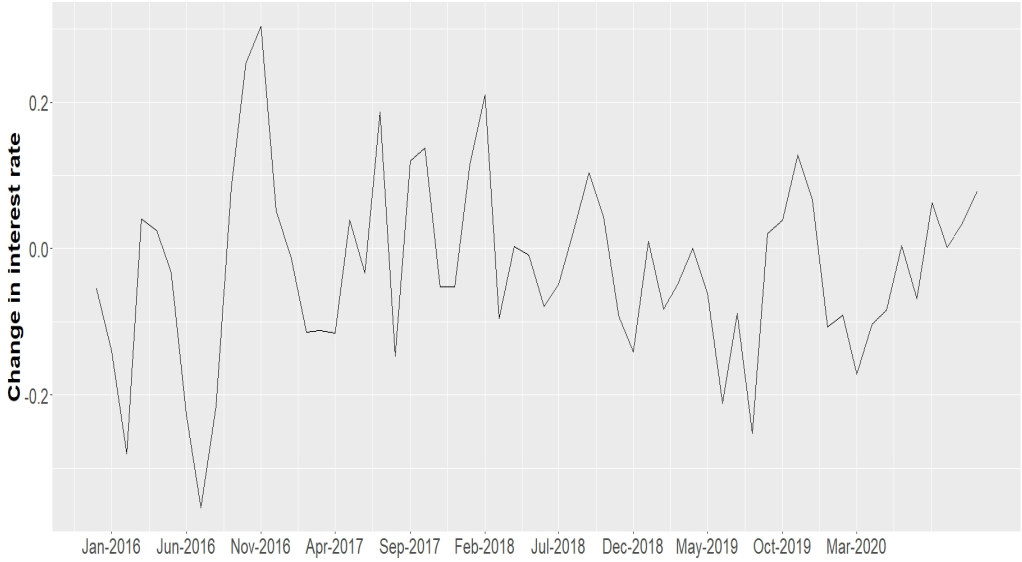
A.5 Change in interest rate

Figure 14: Change in interest rate US



Source: Author's computation

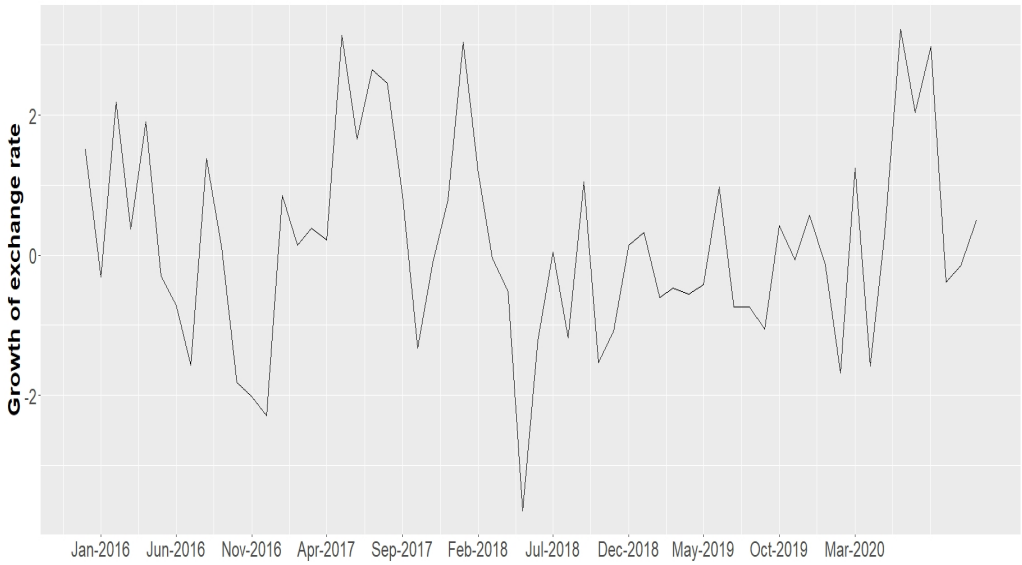
Figure 15: Change in interest rate UK



Source: Author's computation

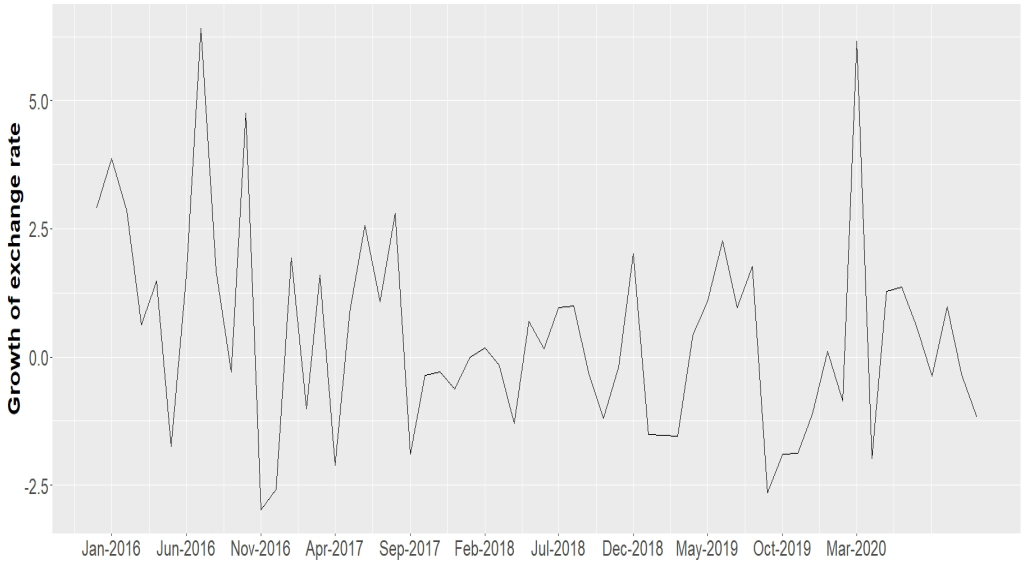
A.6 Change in exchange rate

Figure 16: Change in exchange rate US



Source: Author's computation

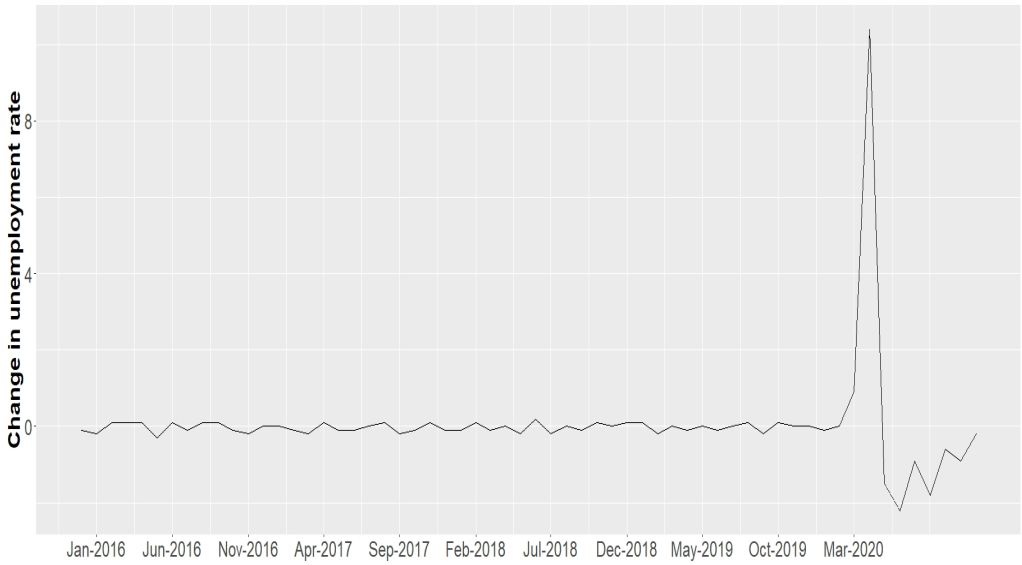
Figure 17: Change in exchange rate UK



Source: Author's computation

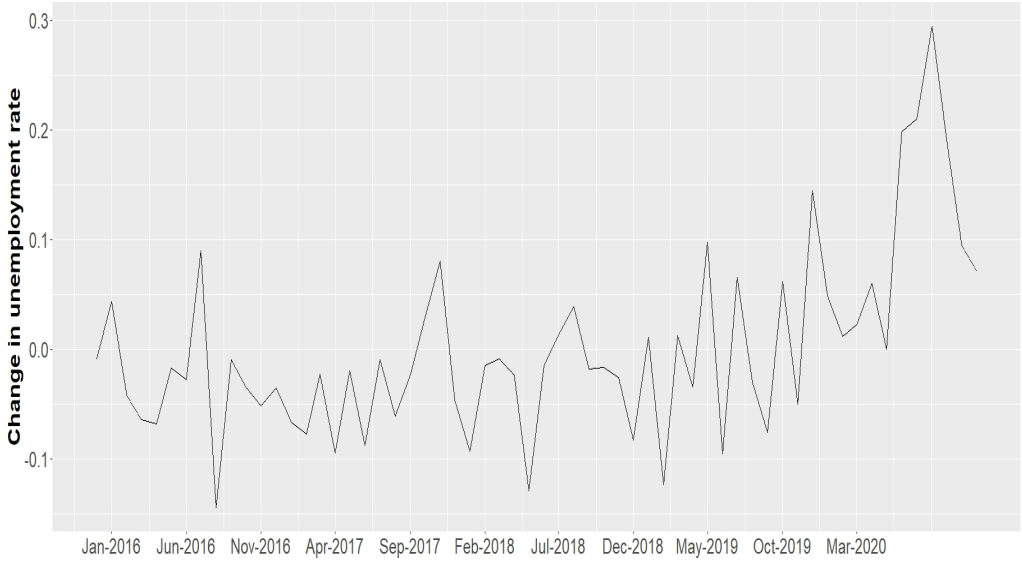
A.7 Change in unemployment rate

Figure 18: Change in unemployment rate US



Source: Author's computation

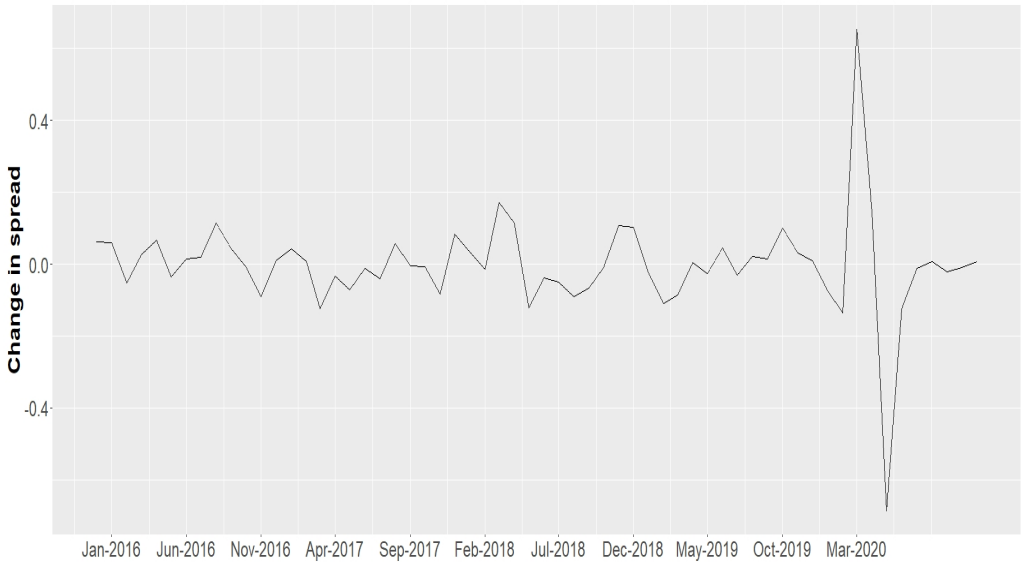
Figure 19: Change in unemployment rate UK



Source: Author's computation

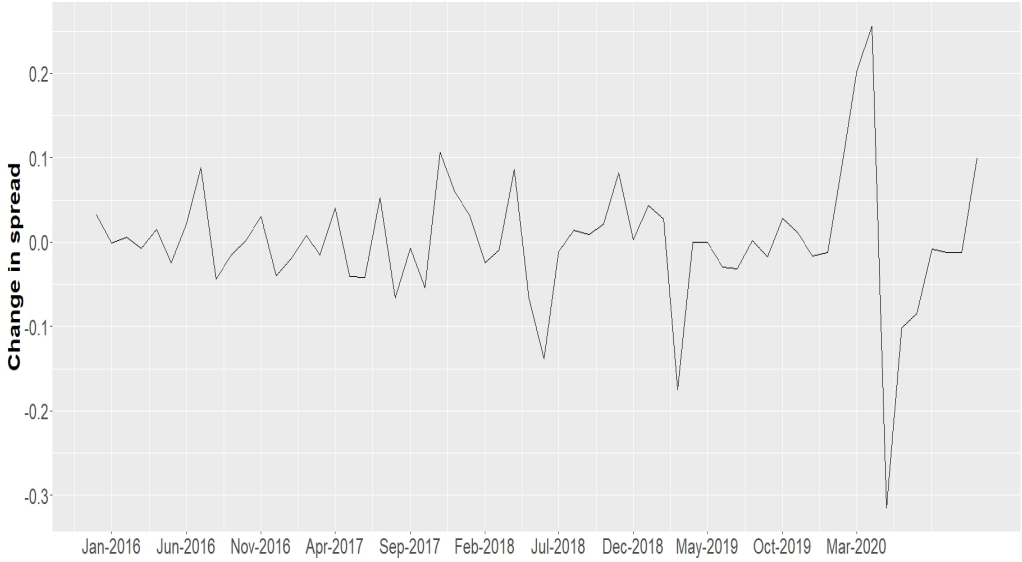
A.8 Change in spread

Figure 20: Change in spread US



Source: Author's computation

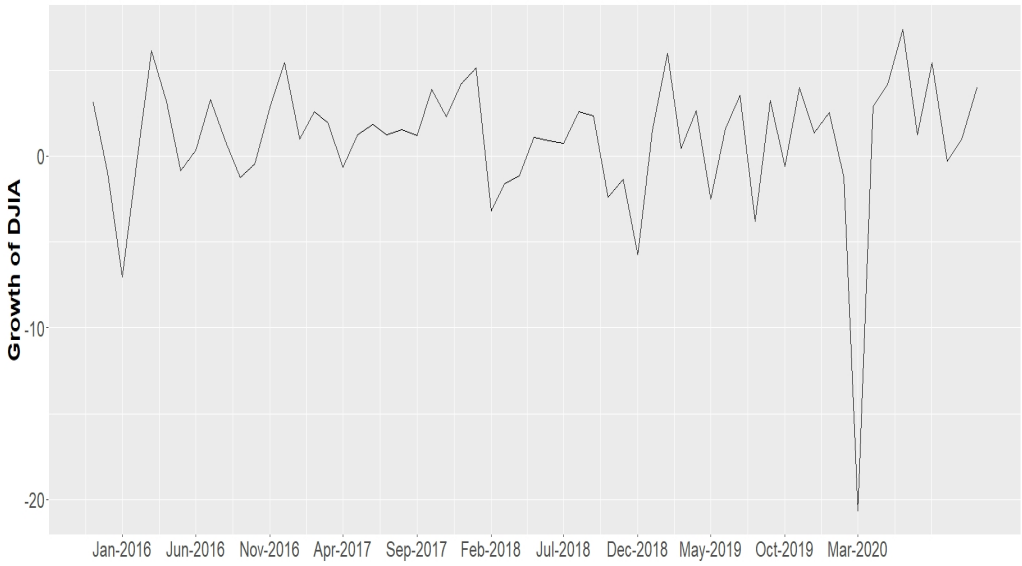
Figure 21: Change in spread UK



Source: Author's computation

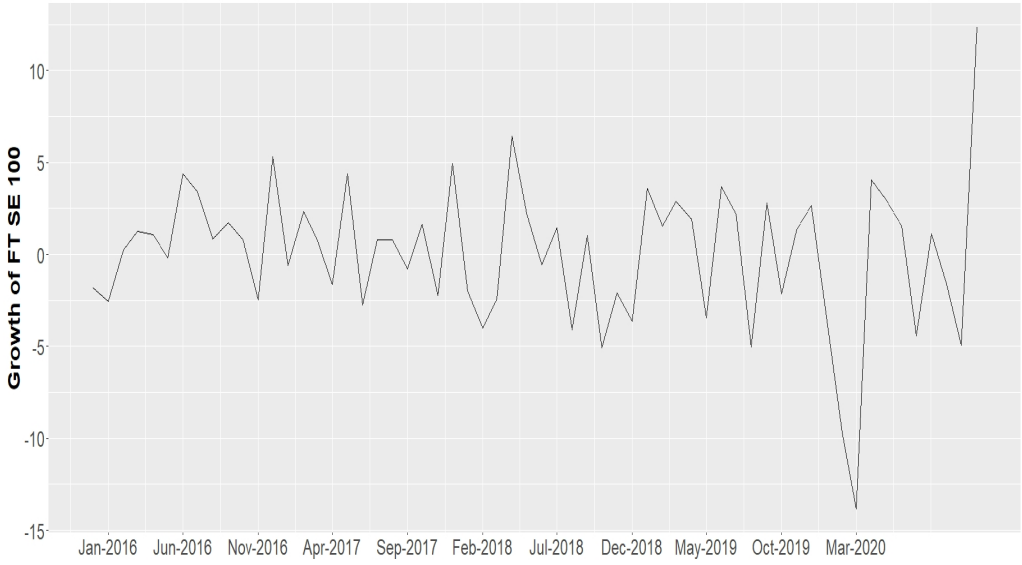
A.9 Growth of stock market index

Figure 22: DJIA growth rate



Source: Author's computation

Figure 23: FT SE 100 growth rate



Source: Author's computation

B Appendix 2

Table 10: OLS estimation with $\Delta spread\_ch$ - US

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	0.00196	1.7	0.09558
Δlog_odd_{t-1}	0.50598	4.5	0.00005
GDP_gr_{t-1}	-0.00152	-0.94	0.35442
$inflation_{t-3}$	-0.00159	-1.56	0.12593
$\Delta interest\_rate_{t-1}$	-0.01404	-1.35	0.18443
$exchange\_gr_{t-4}$	-0.00147	-1.50	0.14094
$\Delta unemployment\_rate_{t-2}$	0.00435	4.19	0.00012
$\Delta spread_t$	-0.00336	-0.28	0.77981
$DJIA\_gr_{t-1}$	-0.00041	-0.97	0.33934
$fiscal\_1$	-0.02108	-1.70	0.09581
$fiscal\_2$	0.03658	2.52	0.01513
$\Delta stringency\_index_t$	0.09951	3.87	0.00033
Number of observations: 60			
$R^2 = 0.80$			
$Adjusted\_R^2 = 0.75$			

Source: Author's computation

Table 11: OLS estimation with all variables - UK

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	0.11482	4.85	0.00001
Δlog_odd_{t-1}	0.12919	0.98	0.33359
GDP_gr_{t-1}	-0.00002	-4.83	0.00001
$inflation_{t-7}$	-0.00147	-0.40	0.69153
$\Delta interest\_rate_{t-7}$	0.02264	1.69	0.09794
$exchange\_gr_{t-7}$	-0.00011	-0.14	0.89096
$\Delta unemployment\_rate_t$	0.00222	0.11	0.91166
$\Delta spread_{t-5}$	0.00049	0.05	0.95992
$FTSE\_gr_{t-5}$	0.00011	0.36	0.71952
$fiscal\_1$	-0.00114	-0.28	0.78053
$\Delta stringency\_index_t$	0.03780	5.69	0.00000*
Number of observations: 60			
$R^2 = 0.54$			
$Adjusted\_R^2 = 0.45$			

Source: Author's computation

C Appendix 3

Table 12: OLS for robustness checks - US

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	-0.00246	-0.65	0.51784
Δlog_odd_{t-1}	0.58682	4.04	0.00023
GDP_gr_{t-1}	0.02111	1.09	0.28000
$inflation_{t-3}$	-0.00162	-1.81	0.07794
$\Delta interest\_rate_{t-1}$	-0.01360	-1.45	0.15560
$exchange\_gr_{t-4}$	-0.00147	-1.62	0.11238
$\Delta unemployment\_rate_{t-2}$	-0.00240	-0.25	0.80167
$DJIA\_gr_{t-1}$	-0.00091	-1.98	0.05435
Number of observations: 49			
$R^2 = 0.54$			
$Adjusted\_R^2 = 0.47$			

Source: Author's computation

Table 13: OLS for robustness checks - UK

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	0.12710	1.99	0.05332
GDP_gr_{t-1}	-0.00002	-1.91	0.06265
$inflation_{t-7}$	-0.00288	-1.2	0.22563
$\Delta interest\_rate_{t-7}$	0.02853	3.2	0.00258
$FTSE\_gr_{t-5}$	0.00029	0.72	0.47549
Number of observations: 49			
$R^2 = 0.33$			
$Adjusted\_R^2 = 0.26$			

Source: Author's computation

D Appendix 4

Table 14: GMM with $\Delta UK\_interest\_rate\_ch$ and $UK\_unemployment\_rate\_ch$ as instruments

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	0.00618	2.31	0.02082
Δlog_odd_{t-1}	0.3636	0.64	0.52202
GDP_gr_{t-1}	-0.0203	-2.07	0.03808
$inflation_{t-3}$	0.00300	1.53	0.12540
$\Delta interest\_rate_{t-1}$	-0.00354	-0.36	0.71966
$exchange\_gr_{t-4}$	0.00041	0.27	0.79074
$\Delta unemployment\_rate_{t-2}$	0.00467	2.06	0.03901
$DJIA\_gr_{t-1}$	-0.00146	-3.15	0.00162
$fiscal\_1$	-0.07036	-2.54	0.01110
$fiscal\_2$	0.11327	3.33	0.00087
$\Delta stringency\_index_t$	0.10389	4.54	0.00000*
J-Test P-value: 0.00149			

Source: Author's computation

Table 15: GMM with ΔUK_GDP_gr and $\Delta UK\_unemployment\_rate\_ch$ as instruments

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	0.00579	2.22	0.02622
Δlog_odd_{t-1}	0.48057	1.51	0.13003
GDP_gr_{t-1}	-0.00693	-1.10	0.27158
$inflation_{t-3}$	-0.00105	-0.55	0.57973
$\Delta interest\_rate_{t-1}$	-0.01290	-0.93	0.35199
$exchange\_gr_{t-4}$	-0.00103	-0.98	0.32823
$\Delta unemployment\_rate_{t-2}$	0.03234	1.36	0.17284
$DJIA\_gr_{t-1}$	-0.00178	-2.38	0.01727
$fiscal\_1$	-0.03564	-2.43	0.01470
$fiscal\_2$	0.06871	2.59	0.00959
$\Delta stringency\_index_t$	0.10055	3.59	0.00033
J-Test P-value: 0.00002			

Source: Author's computation

Table 16: GMM with ΔUK_GDP_gr and $\Delta UK\_interest\_rate\_ch$ as instruments

Dependent variable: Δlog_odd			
Variable	Estimate	T-stat.	P-value
intercept	0.00321	0.8918	0.37251
Δlog_odd_{t-1}	0.45456	1.13	0.25900
GDP_gr_{t-1}	-0.01665	-1.28	0.20029
$inflation_{t-3}$	0.11662	0.96	0.33374
$\Delta interest\_rate_{t-1}$	0.00664	0.86	0.38773
$exchange\_gr_{t-4}$	0.00089	0.62	0.52958
$\Delta unemployment\_rate_{t-2}$	0.02122	1.64	0.10169
$DJIA\_gr_{t-1}$	-0.00019	0.23	0.81642
$fiscal\_1$	-0.04602	-0.99	0.32318
$fiscal\_2$	0.0876	1.36	0.17464
$\Delta stringency\_index_t$	0.10306	3.89	0.00010
J-Test P-value: 0.02511			

Source: Author's computation

E Appendix 5

Table 17: Distribution of US's variables

Variable	Mean	Standard deviation	Minimum	Maximum
Δlog_odd	0.007	0.015	-0.019	0.054
GDP_gr	0.156	1.013	-3.670	3.467
$inflation$	0.106	1.022	-3.932	3.402
$\Delta interest\_rate$	-0.023	0.171	-0.630	0.380
$exchange\_gr$	0.173	1.145	-3.642	3.224
$\Delta unemployment\_rate$	0.027	1.438	-2.200	10.400
$\Delta spread$	-0.002	0.141	-0.685	0.653
$DJIA\_gr$	0.914	3.964	-20.625	7.380
$\Delta stringency\_index$	0.012	0.063	-0.029	0.404

Source: Author's computation

Table 18: Distribution of UK's variables

Variable	Mean	Standard deviation	Minimum	Maximum
Δlog_odd	0.006	0.010	-0.011	0.048
GDP_gr	0.058	2.155	-8.044	7.298
$inflation$	0.200	0.515	-0.754	1.870
$\Delta interest\_rate$	-0.027	0.126	-0.354	0.304
$exchange\_gr$	0.417	1.997	-2.9741	6.412
$\Delta unemployment\_rate$	0.001	0.085	-0.144	0.294
$\Delta spread$	0.001	0.079	-0.314	0.256
$FTSE\_gr$	0.054	3.936	-13.807	12.352
$\Delta stringency\_index$	0.011	0.066	-0.055	0.430

Source: Author's computation