Vaasan yliopisto
UNIVERSITY OF VAASA

Juuso Hirvikoski

Firm-level political risk and corporate credit default swap spreads:

Evidence from Europe

School of Accounting and Finance
Master's thesis in Finance
Master's Degree Programme in Finance

Vaasa 2021

UNIVERSITY OF VAASA
School of Accounting and Finance
Author: Juuso Hirvikoski
Title of the Thesis: Firm-level political risk and corporate credit default swap spreads: Evidence from Europe
Degree: Master of Science in Economics and Business Administration
Programme: Master's Degree Programme in Finance
Supervisor: Janne Äijö
Year: 2021 **Pages:** 112

ABSTRACT:

The purpose of this thesis is to examine the relationship between firm-level political risk and European corporate credit default swap spreads. Existing theory models political risk as a mostly systematic type of risk which induces a non-diversifiable effect on asset prices. This notion is challenged by recent studies which find that the incidence of political risk varies considerably across individual firms, suggesting that firm-level political risk is a potentially significant phenomenon. The majority of previous research regarding the influence of political risk on credit default swap spreads has examined the US market using measures which represent aggregate political risk. This thesis provides a new perspective by focusing on the European credit default swap market and utilizing a novel measure of firm-level political risk.

The empirical analysis is conducted using a panel sample which consists of 3374 quarterly observations for 132 firms over the period beginning in the first quarter of 2008 and ending in the second quarter of 2019. The methodological approach is based on a fixed effects panel regression model in which the credit default swap spread is used as the dependent variable and the firm-level political risk measure is used as the main independent variable of interest. Additional firm-specific and market-level control variables are used to isolate the effect of other factors which influence credit default swap spreads. The fixed effects specification will also alleviate the potential omitted variable bias by capturing the effect of unobserved firm characteristics and market-wide trends which vary over time.

The results show that firm-level political risk has a statistically significant positive effect on credit default swap spreads. The significant positive effect is retained when the analysis considers firm-level political risk associated with various political topics, although the evidence is not statistically or economically meaningful enough to assert that the effect is distinctly heterogenous across different political topics. The results also suggest that firm-level political risk has a persistent quality as the effect that it induces in the credit default swap market is realized with a delay. This thesis does not find that firm-level political risk has pronounced interaction effects with the credit default swap spreads of firms which belong to politically sensitive industries. Additional robustness tests confirm that the effect of firm-level political risk is not subsumed when political sentiment and aggregate political risk related to the domestic European market are taken into consideration.

KEYWORDS: Political risk, credit risk, credit default swap, uncertainty

VAASAN YLIOPISTO
Laskentatoimen ja rahoituksen yksikkö

Tekijä:	Juuso Hirvikoski
Tutkielman nimi:	Firm-level political risk and corporate credit default swap spreads: Evidence from Europe
Tutkinto:	Kauppatieteiden maisteri
Oppiaine:	Rahoituksen koulutusohjelma
Ohjaaja:	Janne Äijö
Valmistumisvuosi:	2021 **Sivumäärä:** 112

TIIVISTELMÄ:

Tutkielman tarkoituksena on tarkastella yritystason poliittisen riskin ja eurooppalaisten yritysten luottoriskinvaihtosopimusten hintojen välistä suhdetta. Olemassa oleva teoria kuvaa poliittista riskiä pääosin systemaattisena riskinä, jonka vaikutusta rahoitusvälineiden hintoihin ei ole mahdollista hajauttaa. Viimeaikaisten tutkimusten mukaan poliittisen riskin ilmaantuvuus vaihtelee huomattavasti yksittäisten yritysten välillä viitaten siihen, että yritystason poliittinen riski on mahdollisesti merkittävä ilmiö. Suurin osa aikaisemmista tutkimuksista on tutkinut poliittisen riskin vaikutusta luottoriskinvaihtosopimusten hintoihin Yhdysvaltojen markkinoilla käyttäen aggregaattitason poliittista riskiä kuvaavia mittareita. Tämä tutkielma tarjoaa uuden näkökulman keskittymällä Euroopan luottoriskinvaihtosopimusmarkkinoihin ja hyödyntämällä uutta yritystason poliittista riskiä kuvaavaa mittaria.

Empiirisessä analyysissa käytetty aineisto koostuu 132 yrityksestä ja kattaa yhteensä 3374 kvartaalitason havaintoa aikavälillä, joka alkaa vuoden 2008 ensimmäisestä kvartaalista ja päättyy vuoden 2019 toiseen kvartaaliin. Tutkielman metodologia perustuu kiinteiden vaikutusten paneeliregressiomalliin, jonka selitettävänä muuttujana käytetään luottoriskinvaihtosopimuksen hintaa ja keskeisenä selittävänä muuttujana yritystason poliittisen riskin mittaria. Aineistoon sisältyvät yrityskohtaiset ja markkinatason kontrollimuuttujat eristävät luottoriskinvaihtosopimusten hintoja määrittävien muiden tekijöiden vaikutukset. Regressiomallin kiinteät vaikutukset korjaavat myös mahdollista puuttuvien muuttujien harhaa ottamalla huomioon havaitsemattomien yrityskohtaisten ominaispiirteiden ja ajan myötä muuttuvien markkinatason trendien vaikutukset.

Tutkielman tulokset osoittavat, että yritystason poliittisella riskillä on tilastollisesti merkittävä positiivinen vaikutus luottoriskinvaihtosopimusten hintoihin. Poliittisella riskillä on pitkittynyt vaikutus, joka realisoituu viiveellä luottoriskinvaihtosopimusten markkinoilla. Tulokset näyttävät myös, että tilastollisesti merkittävä positiivinen vaikutus on havaittavissa käytettäessä aihekohtaisia yritystason poliittisen riskin mittareita. Tulosten perusteella ei ole kuitenkaan mahdollista todeta, että erilaisten poliittisten aiheiden vaikutusten välillä olisi huomattavia eroja. Tämän lisäksi poliittisesti herkillä toimialoilla olevien yritysten luottoriskinvaihtosopimusten hinnat eivät reagoi voimakkaammin yritystason poliittiseen riskiin. Täydentävät robustisuustestit osoittavat, että yritystason poliittisen riskin vaikutuksen tilastollinen ja taloudellinen merkitsevyys säilyy ennallaan, kun poliittinen sentimentti ja Euroopan kotimarkkinoita koskeva aggregaattitason poliittinen riski otetaan huomioon.

AVAINSANAT: Poliittinen riski, luottoriski, luottoriskinvaihtosopimus, epävarmuus

Contents

Figures

Tables

1 Introduction

Political events and government policymaking represent a substantial source of risk to firms in the private sector as changes in government policy could have adverse effects on firm profitability. According to Pástor and Veronesi (2012, p. 1219), the entire business environment is shaped by the decisions of politicians who are responsible for setting the government policy stance towards regulations, taxation and laws. Uncertainty is a characteristic trait of politics as enacting policy changes requires extensive and time-consuming negotiations between politicians which renders the policymaking process susceptible to unpredictable outcomes (Pan et al., 2019).

Academic research has examined how uncertainty affects firm behavior and the financial markets. Theoretical literature asserts that uncertainty in general causes firms to be more risk-averse and increases their willingness to delay making investment decisions (Bernanke, 1983). Existing theory posits that uncertainty related to government policymaking is essentially a systematic risk factor which commands a non-diversifiable risk premium on asset prices and amplifies volatility (Pástor & Veronesi, 2013). The theoretical predictions are supported by empirical evidence which confirms that heightened political risk affects the real economy as it is associated with reduced levels of corporate investment (Gulen & Ion, 2016) and influences the financial markets by inducing an equity risk premium and increasing equity volatility (Baker et al., 2016; Brogaard & Detzel, 2015).

The empirical evidence regarding the links between political risk, corporate investment and equity volatility have substantial implications for the relationship between political risk and credit risk. Continued investment is essential for corporate profit development and diminished investment growth signals a reduction in future profitability which will-increase the perceived likelihood of insolvency (Abaidoo & Kwenin, 2013, p. 29; Wisniewski & Lambe, 2015, p. 454). Heightened equity volatility is a significant factor-which increases the probability of default (Merton, 1974). Accordingly, growing political risk is linked to an increased cost of private debt and elevated credit spreads for corporate bonds in the credit markets (Ashraf & Shen, 2019; Kaviani et al., 2020).

Relatively few studies concerning political risk have focused on the market for credit derivatives such as the credit default swap. Credit default swaps enable one party to transfer credit risk associated with an underlying reference entity company to a counterparty for a contractually agreed fixed fee which is referred to as the credit default swap spread (Mengle, 2007, pp. 1–2). It is advantageous to analyze the effect of political risk using credit default swap spreads because they are more informationally efficient and accurate at estimating credit risk compared to the credit spreads of corporate bonds (Blanco et al., 2005).

Prior studies regarding the influence of politics in the financial markets often utilize measures which describe aggregate-level political risk such as national elections or the news-based Economic Policy Uncertainty (EPU) index by Baker et al. (2016) which reflects political risk on the country level. This holds true for most published literature examining the relationship between political risk and credit default swap spreads. For example, Liu and Zhong (2017) report a significant positive association between national election years and credit default swap spreads. Similarly, the studies by Wang et al. (2019) and Wisniewski and Lambe (2015) report a positive relationship between the EPU index and credit default swap spreads.

Firms may exhibit different levels of exposure to government policies and thus react differently to the systematic political risk factor as described by conventional theory (Pástor & Veronesi, 2012, 2013). Studies have shown that firms belonging to industries which are heavily regulated and more dependent on government spending exhibit stronger reactions to heightened aggregate political risk (see e.g., Baker et al., 2016; Kaviani et al., 2020; Wang et al., 2019). However, new evidence suggests that the incidence of political risk can vary by a large margin across firms even within the same industry and aggregate-level measures of political risk are unable to take this variance into consideration, which sets an inherent limitation to analyzing the effect of political risk (Gad et al., 2020).

An alternative to aggregate-level measures is the novel firm-level political risk measure recently developed by Hassan et al. (2019) that is based on textual transcripts of quarterly earnings conference calls. Their firm-level measure quantifies political risk as the share of conversation in a conference call that is devoted to the discussion of risks and uncertainties related to political issues. The authors argue that their measure is a valid proxy for the unique firm-specific exposure to political risk as perceived by conference call participants such as firm management and analysts. Therefore, utilizing the firm-level measure by Hassan et al. (2019) represents a new approach that is potentially alleviated from the limitations posed by aggregate-level measures of political risk and provides an opportunity to analyze whether firm-level political risk affects credit risk as indicated by credit default swap spreads.

1.1 Purpose and contribution

The purpose of this thesis is to examine the effect of firm-level political risk on corporate credit default swap spreads. The nature of the relationship between firm-level political risk and credit default swap spreads is further analyzed by determining whether the effect of is persistent, which political topics are more relevant in explaining credit default swap spreads and whether certain industries are more sensitive to political risk compared to others.

Existing published studies which examine on credit default swaps use either national elections as a source of political risk (Liu & Zhong, 2017) or the EPU index (Wang et al., 2019; Wisniewski & Lambe, 2015) which are both aggregate-level measures. Therefore, these studies are unable to answer whether firm-level political risk has a meaningful relationship with credit default swap spreads. In addition, prior literature focuses almost exclusively on the US market or alternatively features an international sample that is not broken down by country or market. This has left the European credit default swap market relatively untouched. The motivation to conduct this thesis is based on these apparent gaps in academic research.

This thesis contributes to the body of research examining how political factors influence the financial markets. The aim is to provide more insight by using the novel measure by Hassan et al. (2019) to focus on firm-level political risk instead of the conventional measures used in prior studies which document the effects of aggregate political risk. This thesis is also related to the stream of literature devoted to researching the determinants of credit default swap spreads. As noted by Ericsson et al. (2009), the traditional theoretical drivers of credit risk as proposed by the Merton (1974) are insufficient in explaining a notable portion of the variance displayed by corporate credit default swap spreads which has prompted subsequent studies whose findings have identified further determinants. This thesis intends to contribute to this research area by analyzing whether firm-level political risk is a significant determinant of credit default swap spreads.

1.2 Research hypotheses

The first research hypothesis is derived from both theoretical predictions and empirical evidence regarding the effect of political risk in the financial markets and by extension the credit risk of individual firms. According to conventional theory, political risk increases equity volatility (Pástor & Veronesi, 2013). Equity volatility is a key theoretical driver of credit risk and it is empirically proven to be significant determinant of credit default swap spreads (Ericsson et al., 2009; Merton, 1974).

Political risk is associated with declining corporate investment and future deteriorations in aggregate economic conditions (Baker et al., 2016; Gulen & Ion, 2016). This has implications for credit default swap spreads as they are influenced by macroeconomic uncertainty (Baum & Wan, 2010). Accordingly, prior literature has documented that aggregate political risk has a positive relationship with credit default swap spreads (see e.g., Liu & Zhong, 2017; Wang et al., 2019; Wisniewski & Lambe, 2015). Taken together, this thesis expects that firm-level political risk has positive effect on corporate credit default swap spreads.

The first research hypothesis is defined as:

H_1: Firm-level political risk has a positive effect on corporate credit default swap spreads.

Following the confirmation of the first hypothesis, three additional research hypotheses are formed to further examine the relationship between firm-level political risk and credit default swap spreads from different perspectives.

The second research hypothesis examines if the effect induced by firm-level political risk is persistent. The results of several studies which analyze the influence of political risk on asset prices and firm-level outcomes are suggestive of a long-lasting component. For example, Gulen and Ion (2016) found that a shock to aggregate political risk proxied by the EPU index exerts a negative effect on corporate investment which is realized with a delay over the course of five quarters following the initial shock. Nodari (2014) reported that a categorical EPU index which measures uncertainty towards financial regulation policy has a persistent positive effect on the credit spreads of corporate bonds.

Although Wang et al. (2019) found that an increase in the EPU index is immediately reflected in credit default swap spreads, they noted that it takes up to six quarters after the initial positive shock for the effect to completely diminish. Pan et al. (2019) used the firm-level political risk measure by Hassan et al. (2019) and documented a persistent negative effect on long-term corporate debt and leverage ratios which lasts for up to six quarters. Prior research has not yet examined how persistent the influence of firm-level political risk is in the credit default swap market, which forms the basis for the second research hypothesis.

The second research hypothesis is defined as:

H_2: Firm-level political risk has a persistent effect on corporate credit default swap spreads.

The third research hypothesis aims to answer whether credit default swap spreads have varying reactions to the different topic-specific variants of the firm-level political risk measure used in this thesis. Baker et al. (2016) found that categorical versions of the EPU index are linked to increased equity volatility and diminishing employment growth, Gulen and Ion (2016) reported a similar negative association with corporate investment and Yu et al. (2017) stated that the categorical EPU versions exert heterogenous effects on equity betas across different industries. The categorical EPU versions are also found to exhibit a positive relationship with credit default swap spreads as documented by Wang et al. (2019).

Hassan et al. (2019) found that an increase in the topic-specific variant of their firm-level political risk measure has a significant positive relationship on future corporate lobbying expenses associated with that particular topic. The effect of the topic-specific firm-level political risk measure on long-term corporate debt and leverage ratios is shown to vary considerably across different topics by Pan et al. (2019). It is therefore of high interest to examine whether the credit default swap market exhibits heterogenous reactions towards different political topics as well.

The third research hypothesis is defined as:

H_3: Topic-specific firm-level political risk measures have heterogenous effects on corporate credit default swap spreads.

The fourth research hypothesis is inspired by evidence from previous research noting that the effect of political risk is heterogenous across different industries. For example, Baker et al. (2016) argued that the financial, defense and healthcare industries are more sensitive to politics and reported that aggregate political risk has a stronger positive effect on the equity volatility of firms in those industries. Likewise, Kaviani et al. (2020) stated that the EPU index has a stronger effect on the credit spreads of corporate bonds issued by firms which are heavily regulated and more reliant on government spending.

According to the results obtained by Wang et al. (2019), the credit default swap spreads of firms in politically sensitive industries react more strongly to aggregate political risk. Considering these results, this thesis is motived to examine whether policy-sensitive industries display similar reactions towards firm-level political risk. The expectation is that firm-level political risk has a stronger effect on the credit default swap spreads of firms which belong to politically sensitive industries.

The fourth research hypothesis is defined as:

H_4: The effect of firm-level political risk on corporate credit default swap spreads is pronounced for firms in politically sensitive industries.

1.3 Structure of the Thesis

This thesis consists of seven chapters. The first chapter introduces the topic of the thesis and defines the research hypotheses. The second chapter provides a theoretical framework by introducing the fundamentals of credit risk and credit default swaps. In addition, the concept of political risk is introduced and key theories describing the asset-pricing implications of political risk are reviewed in the second chapter. The third chapter contains a literature review of relevant studies regarding the effect of political risk in the financial markets. The data and variables utilized in this thesis are described in the fourth chapter and the methodology used to conduct the empirical portion of the thesis is reviewed in the fifth chapter. The sixth chapter presents and interprets the empirical results. The seventh chapter presents the final conclusions based on the empirical findings as well as suggestions for future research ideas.

2 Theoretical framework

The purpose of this chapter is to introduce the concepts of credit risk, credit default swaps and political risk. The chapter begins by first describing the concept of credit risk and main theoretical methods for measuring credit risk. The subsequent section introduces the fundamentals of credit default swaps and examines factors which affect the pricing credit default swap spreads. Finally, the concept of political risk and key theories describing the asset-pricing implications of political risk are reviewed.

2.1 Credit risk

Credit can be defined as a transaction in which a creditor grants an asset to a debtor who agrees to pay the value of the asset back to the creditor at some future point in time as well as possible compensatory fees such as interest payments (Chacko et al., 2016, p. 10). Debt securities such as corporate bonds issued by firms represent a fundamental type of credit as the issuer of a bond is obligated to repay the initial principal sum to bond investors on a prespecified maturity date in addition to typically paying a periodic fee referred to as a coupon payment (Chacko et al., 2016, p. 12).

Credit assets are exposed to credit risk, which is defined by Crouhy et al. (2014, p. 27) as the risk of a financial loss caused by the debtor failing to perform their contractual obligations such as conducting coupon payments or paying back the entire principal sum of a bond. Credit risk is synonymous with default risk, which is a refers to uncertainty whether a debtor will default on their contractually obligated payments (Schönbucher, 2003, p. 1).

In addition to uncertainty regarding the probability of a default and the exact timing when a default will occur, a key component of credit risk is recovery risk which is defined by Schönbucher (2003, p. 1) as uncertainty regarding the severity of financial losses incurred in the event of a default. Creditors can recover some of their initial investment after a default because they have a contractual claim on the debtor's remaining assets (Benzschawel, 2012, p. 19). The uncertain quantity in recovery risk is the extent how much of the value of a credit asset can be recovered after a default, which is measured by the recovery rate (Scönbucher, 2003, p. 1).

The magnitude of credit risk is expressed by the expected loss that a credit asset incurs in the event of a default which is calculated as:

$$Expected\ loss = Probability\ of\ default * (\ 1 - Recovery\ rate\ ), \tag{1}$$

where the first component is the probability of default which is defined as the statistical probability of a debtor defaulting during a fixed time horizon and the second component is loss given default (Benschzawel, 2012, p. 20). The percentage of the initial principal investment that can be recovered following a default event is determined by the recovery rate and the remaining nonrecoverable portion of the principal is defined as the loss given default (Benzschawel, 2012, p. 19).

Most investors conduct their assessments of credit risk by utilizing public credit ratings, which are forward-looking assessments of the probability of default and loss given default associated with bonds issued by a debtor (Dattatreya et al., 2012, pp. 25–26). Companies referred to as credit rating agencies conduct credit analysis and issue their official assessment of credit risk in the form of a public credit rating (Fabozzi et al., 2012, p. 277). Credit ratings can be broadly segmented into the investment-grade, high yield and distressed class according to the credit risk of the issuing firm (Benzschawel, 2012, p. 15). Investment-grade bonds have minimal default risk, high-yield bonds feature an increased risk of default but pay a larger coupon in compensation and bonds in the distressed class are either close to a default or have already defaulted (Benzschawel, 2012, p. 15).

Table 1 presents the credit rating scales used by S&P Global Ratings and Moody's Investor Service which are the two largest credit rating agencies in operation (Benzschawel, 2012, p. 14).

Table 1. Credit rating scales used by Moody's Investor Service and S&P Global Ratings (adapted from Benzschawel, 2012, p. 14).

Class	*Moody's*	*S&P*	*Description*
Investment-grade	Aaa	AAA	Highest quality
	Aa1	AA+	High quality
	Aa2	AA	
	Aa3	AA-	
	A1	A+	Strong payment capacity
	A2	A	
	A3	A-	
	Baa1	BBB+	Adequate payment capacity
	Baa2	BBB	
	Baa3	BBB-	
High-yield	Ba1	BB+	Likely to pay; some risk
	Ba2	BB	
	Ba3	BB-	
	B1	B+	High-risk obligations
	B2	B	
	B3	B-	
	Caa	CCC+	Current vulnerability to default
		CCC	
		CCC-	
Distressed	Caa	CC	Bankruptcy; default; other problems
	C	C	
	D	D	

2.2 Credit spreads

The theoretical price of a bond can be calculated as the present value of the expected cash flows, which are the principal paid back at the time of maturity and the periodic coupon payments (Hull, 2015, p. 82). The yield of a bond is the discount rate that must be applied to all cash flows so that the present value of the bond equals the market price (Hull, 2015, p. 82).

Investors in the credit markets quote the prices of corporate bonds and compare their relative level of credit risk by examining the credit spread, which refers to the difference between the yield of a risky defaultable corporate bond and the yield of a risk-free government bond of a similar maturity (Chacko et al., 2016, pp. 22–25). Government bonds are virtually free of default risk as government bonds are fully backed by the credit of the issuing country and sovereign defaults are rare events (Fabozzi & Mann, 2012, p. 277). The credit spread represents additional compensation over the yield of a risk-free gov-ernment bond that is demanded by investors for holding an asset that is exposed to credit risk (Elton et al., 2001, p. 247).

The expected loss associated with a corporate bond is incorporated in the credit spread which leads to the conclusion that credit spreads are theoretically determined by the probability of default and loss given default (Elton et al., 2001, p. 247). However, Elton et al. (2001) note that that the expected loss or default component alone is not enough to explain the level of the credit spread. Elton et al. propose that taxes are a second factor influencing credit spreads which arises due to interest on corporate bonds being taxed whereas interest on government bonds is not taxable. In addition, they argue that bond prices are influenced by the same systematic risks that affect other assets in the financial market and suggest that credit spreads incorporate a risk premium that compensates for being exposed to non-diversifiable market risk.

Credit spreads are also influenced by factors related to the liquidity of corporate bonds. Longstaff et al. (2005) claim that the non-default component of in credit spreads can be explained by liquidity risk which is not part of the market premium component observed by Elton et al. (2001). Longstaff et al. (2005) posit that the market for government bonds is highly liquid and bond investors demand an additional premium for holding less liquid corporate bonds. Consequently, their study finds that proxies that measure the liquidity of a specific bond issue such as average bid-ask spread and factors that affect market-wide liquidity are positively linked to credit spreads.

2.3 Modelling credit risk

The valuation of financial assets exposed to credit risk is conducted using credit risk pricing models. The two predominant theoretical frameworks used to model credit risk consist of the structural approach in which the probability of default is estimated from firm fundamentals and the reduced form approach which models defaults as random events which are determined by an exogenous statistical process (Ericsson et al., 2009, p. 110).

2.3.1 Structural models

Structural models utilize financial statement and equity market information and estimate the probability of default for a firm by assessing the structure of its assets and liabilities (Benzschawel, 2012, p. 79). The structural approach is based on the notion that a default occurs when the market value of the firm's assets falls below a specified threshold which is determined as the value of the obligations that the firm owes to its creditors in the form of outstanding debt and equity (Chacko et al., 2016, p. 67).

Chacko et al. (2016, pp. 70–71, 78) explain that the structural approach is built on the assumption that equity and corporate liabilities are equivalent to contingent claims on the firm's assets. They elaborate that this assumption stems from the observation that bondholders have the right to receive assets from the issuer company as debt payments but are not obligated to do so. In a similar manner, they describe that equity is a claim on the firm's assets but shareholders have no obligation to act on the claim as they can sell their shares at will.

Given the previously mentioned observations, creditors essentially have an option on the assets of the company and the structural approach allows to model the probability of default for corporate liabilities by taking advantage of option-pricing models. Accordingly, the original structural model introduced by Merton (1974) was built upon the Black and Scholes (1973) option pricing formula. Next, the fundamentals of the classical structural model as represented by the Merton (1974) model are reviewed.

Backshall et al. (2012, pp. 1026–1027) present the classical structural model scenario where the capital structure of a firm consists of equity and a zero-coupon bond with a principal value of *K* that the firm is contractually obligated to pay to back to bondholders at the time of maturity *T*. They describe that in the classical scenario, failing to perform the required payment results in bondholders taking ownership of the firm's assets which will have a market value of *V(T)* at the exact time of maturity.

According to Backshall et al. (2012, pp. 1027–1028), if the firm's market value is equal or higher than the face value of the bond at the time of maturity, the bondholders will receive *K* and shareholders receive the residual asset value *V(T) – K.* They state that if the firm's asset value is less than the face value of the bond, the bondholders will take over the firm's assets and incur a loss amounting to *K - V(T)* whereas shareholders are left with a claim to the firm's equity which is has zero value. Consequently, Backshall et al. note that the payoff for shareholders owning firm equity corresponds to holding a European call option that is written on the firm's assets with a strike price of *K* and maturity of *T.*

The Merton (1974) model assumes that the market value of a firm changes continuously over time according to stochastic process defined as:

$$dV = (\alpha V - \gamma)dt + \sigma V dz, \tag{2}$$

where

V = firm value

α = expected rate of return

γ = interest and dividend payments

σ = standard deviation

dz = the standard Wiener process (Choudhry & Lizzio, 2015, p. 164).

The Merton (1974) model presents that by modeling equity as a call option, the value and volatility of equity can be linked to the value and volatility of firm assets. Accordingly, the value and volatility of the firm's assets can be solved with equity market information (Benzschawel, 2012, p. 81).

The equations for equity value and equity volatility are presented as:

$$V_E = V_A N\left(\delta_T + \sigma_A \sqrt{T}\right) - e^{rT} K N(\delta_T), \tag{3}$$

$$\sigma_e = \frac{V_A}{V_E} N\left(\delta_T + \sigma_A \sqrt{T}\right) \sigma_A, \tag{4}$$

where

V_E = the value of equity

V_A = the value of assets

σ_A = asset volatility

σ_e = equity volatility

T = the maturity date

r = the risk-free interest rate

K = the value of debt

$N(.)$ = the cumulative normal probability density function

δ_T = the distance-to-default measure (Benschzawel, 2012, p. 81).

Benzschawel (2012, p. 81) defines the distance-to-default measure featured in the preceding equations as the distance between the mean of the firm's asset value distribution and the value of debt. The distance-to-default measure is the key component in the structural model which reflects the default probability of a firm.

The distance-to-default measure can be calculated with the following equation (Benschzawel, 2012, p. 81):

$$\delta_T = \frac{log\left(\frac{V_A}{K}\right) + \left(r - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}}. \quad (5)$$

Equation 5 for the distance-to-default measure shows that the probability of default in structural models is determined by the volatility of the firm's assets, the risk-free interest rate and the level of financial leverage as depicted in the numerator by the value of assets V_A divided by the value of debt K.

The classical structural approach as featured in the original Merton (1974) model is arguably unrealistic as it allows the value of the firm to decline to virtually zero prior to maturity without any consequences because the default is triggered only when firm value is below the value of debt at the time of maturity (Backshall et al., 2012, pp. 1028–1029). Subsequent modifications of the structural approach include so-called first-passage time models such as the model introduced Black and Cox (1976) in which a default can occur at any time prior to maturity when firm value falls below a predetermined default barrier value (Backshall et al., 2012, p. 1029).

2.3.2 Reduced-form models

According to Chacko et al. (2016, pp. 134–135, 142), reduced-form models do not describe a fundamental mechanism behind defaults, nor do they determine default probabilities from balance sheet information. Instead, Chacko et al. state that the reduced form approach treats defaults as abrupt events which occur seemingly at random following an external signal. They elaborate that the default process featured in reduced form models is completely exogenously determined as the signal which indicates that a default has occurred is the output of a statistical process.

The statistical process used by reduced-form models is called the Poisson process, which describes the probability distribution of random events during a specific time period (Chacko et al., 2016, p. 135). The sole parameter in the Poisson process is the default intensity, which determines how often a specific event will occur (Chacko et al., 2016, p. 136). Duffie and Singleton (2003, p. 60) explain that the default intensity in the Poisson process varies with an underlying state variable referred to as the driver, which represents information by which default intensity is updated over time. They state that market prices of financial assets, credit ratings and prevailing macroeconomic conditions are used as state variables in reduced form models.

The model introduced by Jarrow and Turnbull (1995) is one of the first reduced-form models. The Jarrow-Turnbull model is constructed using a defaultable risky zero-coupon bond and a risk-free zero-coupon bond and features the main assumptions that default intensity and the constant recovery rate are exogenously assigned and independent from each other (van Deventer et al., 2013, pp. 360–362).

The Jarrow-Turnbull model is presented as:

$$(t,T) = \left[e^{-\lambda\mu(T-t)} + \left(1 - e^{-\lambda\mu(T-t)}\right)\delta\right] P(t,T), \tag{6}$$

where

$v(t,T)$ = the price of a risky zero-coupon bond

$P(t,T)$ = the price of a risk-free zero-coupon bond

t = current time

T = the time at maturity

λ = default intensity as determined by the Poisson process

μ = the underlying state variable that drives the Poisson process (a positive constant smaller than 1)

δ = the constant recovery rate (van Deventer et al., 2013, p. 360).

The model can be better understood by highlighting the two main terms inside the brackets in Equation 6 which describe expected outcomes. Van Deventer et al. (2013, p. 360) define the first term $e^{-\lambda\mu(T-t)}$ as the risk-neutral probability that the zero-coupon bond does not default between time t and the maturity date T. They define the second term $1 - e^{-\lambda\mu(T-t)}$ as the risk-neutral probability of default for the risky zero-coupon bond between time t and the maturity date T.

Van Deventer et al. (2013, p. 361) conclude that the price of a risky zero-coupon bond in the Jarrow-Turnbull model is determined by two components, the first of which component is equal to the risk-neutral present value of the risky bond that can be recovered after a default as determined by the recovery rate. The authors state that the second component is equal to the risk-neutral present value of the risk-free zero-coupon bond in case of no default. Therefore, the value of a defaultable risky bond can be explained as the difference between the value of a risk-free bond and the loss given default (Choudhry & Lizzio, 2015, p. 171).

2.4 Credit default swaps

A derivative is a financial instrument whose value depends on the value of an underlying variable such as the value of an asset that is traded in the financial markets (Hull, 2015, p. 1). A specific type of a derivative is the credit derivative which is a contract involving a payoff that is dependent on the credit risk of one or more underlying entities (Hull, 2015, p. 571). Credit derivatives are negotiated directly between market participants and traded privately in the over-the-counter (OTC) markets instead of public exchanges (Hull, 2015, p. 571).

The most common type of credit derivative is the credit default swap, which is essentially an agreement to transfer credit risk exposure between the two parties entering the credit default swap contract who are referred to as the protection buyer and the protection seller, respectively (Mengle, 2007, p. 1). The protection buyer pays a periodic fee to the protection seller who in exchange offers credit risk protection on a notional amount of debt issued by a reference entity, which can be an individual company or a sovereign country (Mengle, 2007, p. 1). The protection seller is obligated to compensate the protection buyer when circumstances for a specific credit event are met (Mengle, 2007, p. 2).

Schönbucher (2007, pp. 15–16) describes that the credit event is a predetermined event indicating that the reference entity has defaulted, which triggers a payoff to the protection buyer that is intended to be equal to the financial loss incurred following a default. Schönbucher also notes that the credit default swap contract usually identifies specific bonds issued by the reference entity which are referred to as reference assets or obligations. The notional amount of debt that the credit default swap contract is written on equals the face value or the initial principal of the reference assets (Schönbucher, 2007, p. 16).

The credit default swap contract bears resemblance to traditional insurance in the sense that the protection buyer is essentially purchasing insurance against default and the notional amount of reference entity debt can be thought of as the extent of insurance coverage (Bonfim, 2015, p. 68). However, Ciby (2013, p. 327) states that credit default swaps are unlike traditional insurance considering that protection buyers can enter in a so-called naked credit default swap position in which they do not own any of the reference assets that the credit default swap insures against default.

2.4.1 The credit default swap market

The earliest use of credit default swaps is attributed to the investment bank JPMorgan Chase & Co which first utilized the instrument in 1994 as a tool to hedge their credit risk exposure (Augustin et al., 2016, p. 176). Only four years later in 1998 the credit default swap market was estimated to be worth approximately 180 billion USD (Acharya et al., 2009, p. 253). The International Swaps and Derivatives Association (ISDA) introduced a standardized contract for OTC market credit default swaps in 1998 which led to explosive growth in the size of the market (Hull, 2015, p. 574). To provide an example, the notional amount outstanding in the credit default swap market was 6 trillion USD in 2004 which had ballooned to 61 trillion USD by the end of 2007 (Stulz, 2010, p. 78).

The proliferation of credit default swaps has been identified as one the main culprits behind the US subprime crisis from 2007 to 2008 which led to the onset of the Global Financial Crisis in late 2008 and the subsequent sovereign debt crisis in the Eurozone from 2010 to 2011 (Augustin et al., 2016, p. 177). The credit default swap market has diminished in size at a steady rate following the crisis periods although the modern credit default swap market is still notably large with a notional amount outstanding amounting to 7,5 trillion USD at the end of December 2019 (Bank for International Settlements, 2020).

According to Callen et al. (2009, p. 1365), the three largest participants in the credit default swap market are major commercial banks, insurance companies and hedge funds. Callen et al. elaborate that commercial banks utilize credit default swaps to as a tool to transfer credit risk from their loan portfolios without changing their balance sheet structure, insurance companies sell credit default swaps to obtain exposure to a type of risk that is uncorrelated with their main line of business and hedge funds trade credit default swaps as part of speculative trading strategies.

The credit default swap market includes single-name contracts which provide protection against the default of only one reference entity and multi-name contracts such as basket and portfolio credit default swaps which involve payoffs that are dependent on credit events encountered by multiple reference entities (Bonfim, 2015, pp. 6–7). A basket credit default swap offers credit risk protection on a group of reference entities and the payoff is triggered when a single reference entity in the group or alternatively the n^{th} reference entity in a sequence sets off a credit event (Chacko et al., 2016, p. 160). According to Bonfim (2015, pp. 108–109), portfolio credit default swaps concern a larger pool of reference entities and differ from basket contracts in that they provide compensation against default-related losses up to a predetermined total sum that is not paid off entirely following a single credit event. Bonfim elaborates that a credit event by a reference entity included in the portfolio credit default swap results in a payment to the protection buyer and the contract terminates when the predetermined total sum is completely paid out.

A notable multi-name product is the credit default swap index, which offers credit protection on an entire index of constituent reference entities and the notional amount is allocated equally between each reference entity (Mengle, 2007, p. 3). Notable credit default swap indices include the iTraxx Europe index and the CDX North America index which represent corporate credit default swaps written on European and U.S. firms, respectively (Stulz, 2010, p. 75). The iTraxx Europe and CDX North America indices both constitute of 125 investment-grade reference entity companies (Hull, 2015, p. 579).

2.4.2 The mechanics of credit default swaps

In a typical single-name credit default swap contract, the protection buyer agrees to pay the protection seller a periodical fixed payment that is quoted as basis points on a notional amount of debt issued by the underlying reference entity (Crouhy et al., 2014, p. 437). The periodical payment or premium is called the credit default swap spread and it represents compensation demanded by the protection seller for assuming the credit risk associated with debt issued by a given reference entity (Hull, 2015, p. 573).

Crouhy et al. (2014, p. 438) state that the occurrence of a credit event will trigger a default payment from the protection seller to the protection buyer that will be equal to the notional amount of debt deducted by a predetermined recovery value. They continue to explain that the recovery value is commonly defined as the post-default market price of an underlying deliverable reference asset as specified in the credit default swap contract. The structure of a single-name credit default swap contract is illustrated in Figure 1.

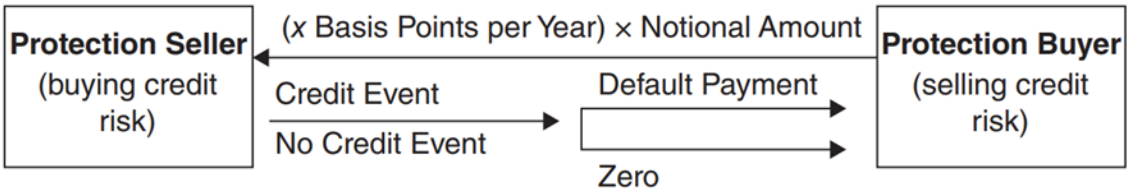

Figure 1. Structure of a single-name credit default swap contract (Crouhy et al., 2014, p. 438).

The method for conducting default payment is determined by a specific settlement procedure which typically involves delivering reference assets to the protection seller (Schönbucher, 2007, p. 15). A physical settlement requires that the protection buyer must deliver reference assets to the protection seller to receive the default payment (Bonfim, 2015, p. 68). In a cash settlement scenario, the protection buyer is not obligated to deliver any reference assets and the default payment conducted by the protection seller is equal to the difference between the notional face value and the recoverable post-default market value of the reference asset (Bonfim, 2015, p. 69). When the default payment is a fixed sum that is prespecified in the contractual terms, the contract is called a digital credit default swap (Chacko et al., 2016, p. 158).

It is imperative that the both the protection seller and the protection buyer are in agreement of what constitutes as a legitimate credit event. For this purpose, the credit default swap contract terms often specify a set of standardized credit events which are officially defined by ISDA (Bonfirm, 2015, p. 302). The eight main credit events as defined by ISDA include bankruptcy, obligation acceleration, obligation default, failure to pay, repudiation, moratorium, restructuring and government intervention (Chen et al., 2013, p. 528).

Chen et al. (2013, p. 528) describe that failure to pay occurs when the reference entity fails to perform contractually due payments and bankruptcy refers to the scenario in which the reference entity becomes insolvent. They state that obligation acceleration ensues when a reference asset becomes due earlier than what was previously estimated whereas obligation default is a broader credit event that can be triggered when the reference asset has even the potential of being declared due and becoming payable prematurely. Chen et al. continue to explain that repudiation and moratorium both refer to a scenario in which the reference entity rejects the legitimacy of its obligations. Restructuring refers to arrangements which result in any kind of adjustments to the obligations of a reference entity (Chen et al., 2013, p. 528). Government intervention is a relatively new credit event introduced by ISDA in 2014 which is triggered when government action leads to certain changes in the obligations of a reference entity (Bonfim, 2015, p. 302).

2.4.3 The pricing of credit default swap spreads

The pricing of credit default swaps involves valuing the two distinctive payment streams of the contract which are known as the protection leg and the premium leg. The protection leg refers to the default payment conducted by the protection seller whereas the premium leg refers to the periodic premium payment carried out by the protection buyer (Chacko et al., 2016, pp. 1, 169). The reduced form approach is preferred by real-word practitioners in the pricing of credit default swaps whereas the structural approach is more suited towards fundamental credit risk management such as predicting default probabilities (Chen et al., 2013, p. 533).

An example of the reduced-form approach to pricing credit default swaps is the model introduced by Hull and White (2000). Their model incorporates risk-neutral default probabilities and expected recovery rates which are estimated from empirical market data. They assume that risk-neutral default probabilities, recovery rates and risk-free interest rates are independent from each other. In addition, their model assumes that the protection seller is entitled to unpaid accrued premium payments and the protection buyer is entitled to unpaid interest accrued on the deliverable reference asset up until the occurrence of a credit event.

Hull and White (2000) assert that valuing the protection leg requires that the expected payoff for the protection buyer must defined first. They define the expected payoff as the default payment, which is typically the notional amount L minus the post-default market value of the deliverable reference asset as determined by the recovery rate R as well as accrued interest on the reference asset $A(t)$.

The expected default payment can be then expressed as (Hull & White, 2000):

$$L - RL[1 + A(t)] = L[1 - R - A(t)]. \tag{7}$$

The present value of the protection leg is thus the risk-neutral probability of the expected payoff for the protection buyer. The equation for calculating the present value of the protection leg is defined as:

$$\int_0^T [1 - \hat{R} - A(t)\hat{R}]q(t)v(t)dt, \tag{8}$$

where

$\widehat{R}$ = the risk-neutral expected recovery rate of the reference asset

$A(t)$ = accrued interest on the reference asset at time t

$v(t)$ = the present value of \$1 received at time t

T = the time to maturity of the credit default swap contract

$q(t)$ = the risk-neutral probability of default at time t (Hull & White, 2000).

Similarly, the present value of the premium leg is the risk-neutral probability of the expected payoffs for the protection seller. The present value of the premium leg can be calculated with the equation defined as:

$$\int_0^T q(t)[u(t) + e(t)]dt + w\pi u(T), \tag{9}$$

where

w = total premium payments per year by the protection buyer

$u(t)$ = the present value of the premium payments between zero and time t

$u(T)$ = the present value of the premium payments between zero and maturity T

$e(t)$ = the present value of the accrued premium payment at time t

π = the risk-neutral probability of a default not occurring at time t calculated as $1 - q(t)$ (Hull & White, 2000).

The expected payoff components in Equation 9 can be interpreted in the following manner. In their model, Hull and White (2000) assume that the premium payments continue until a credit event occurs or the credit default swap expires at time of maturity T. If the contract expires without a credit event occurring, their model predicts that the expected payoff for the premium leg will be $w[u(T)]$ which denotes the present value of all premium payments conducted during the lifespan of the contract. If a credit event occurs at time t, they state that the expected payoff will be $w[u(t) + e(t)]$ which is the present value of the premium payments conducted thus far plus any unpaid accrued premium payments.

The fair pricing of a credit default swap requires that the total value of the premium payments conducted by the protection buyer is equal to the value of the default payment conducted by the protection seller (Chacko et al., 2016, p. 173). In other words, the present value of both the protection leg and the premium leg should be equal.

The Hull-White model asserts that by combining Equation 8 and Equation 9, the credit default swap spread can be then calculated as the value of s which makes the following expression equal to zero (Hull & White, 2000):

$$s = \frac{\int_0^T [1 - \hat{R} - A(t)\hat{R}] q(t)v(t)dt}{\int_0^T q(t)[u(t) + e(t)]dt + \pi u(T)}. \tag{10}$$

2.4.4 The determinants of credit default swap spreads

Prior literature has suggested various factors which determine both the level of credit default swap spreads and their variation. Hull et al. (2004) assert that on a fundamental level, credit default swaps spreads have an inverse relationship with the credit quality of the underlying reference entity and by extension the credit rating of the reference entity. They point towards significant empirical evidence indicating that credit default swap spreads anticipate future credit rating downgrades well in advance of their announcement. Therefore, credit default swaps spreads provide a potentially more informative continuous measure of credit risk compared to discretely issued credit ratings.

Blanco et al. (2005) claim that a theoretical non-arbitrage relationship should exist between credit default swaps spreads and the credit spreads of corporate bonds. They argue that the spreads of both instruments should be equal if they have the same maturity and relate to the same reference entity considering that both spreads should be derived from the same level of credit risk attributed to the underlying entity. Contrary to the expected relationship, they state that credit default swaps are more efficient in reflecting actual credit risk compared to corporate bonds and credit default swap spreads are less affected by non-default factors compared to credit spreads. This result is corroborated by Longstaff et al. (2005) who claim that credit default swap spreads are unaffected by the taxation issues related to the underlying bonds which affect credit spreads.

The main theoretical factors influencing default probabilities as proposed by the Merton (1974) structural model are strongly linked to credit default swap spreads and their variation. The study by Ericsson et al. (2009) reports that financial leverage, equity volatility and the risk-free interest rate together explain approximately 60% of the variation in credit default swap spread levels as well as 23% of the variation in spread changes. Even so, the authors note that a notable portion of the variance is left unexplained by the structural credit risk factors.

Extant literature regarding credit default swap spread determinants suggests additional firm-specific factors that are based on financial statements and equity market information. For example, Callen et al. (2009) find that accounting measures related to earnings which represent firm profitability are inversely related to credit default swap spreads. Bai and Wu (2016) report that accounting ratios that proxy for investment activity have a similar inverse and significant relationship with spreads which is in line with the notion that more profitable firms with better growth opportunities are less prone to default. Das et al. (2009) state that regression models comprised of accounting-based variables such as firm size, profitability, efficiency and solvency ratios can explain nearly two-thirds of the variation in credit default swap spread levels credit default swap spreads. They find that models with variables drawn from the equity market such as equity return and equity volatility have equally comparable explanatory power.

Wang et al. (2013) assert that factors which extend beyond firm-specific characteristics such as premiums for systematic market risk are priced in credit default swap spreads. Accordingly, Galil et al. (2014) argue that market-wide factors should be used in conjunction with firm-specific determinants explain most of the variation in credit default swap spreads. They also claim that the maintain that market-wide determinants with significant explanatory power include equity market index returns, implied market volatility and the term structure of the yield curve as well as more traditional macroeconomic indicators such as industrial output growth.

General economic uncertainty is also reflected in credit default swap spreads as Baum and Wan (2010) state that variables which proxy for fluctuations in macroeconomic conditions are more strongly related to spreads than structural credit risk factors. More specifically, they show that uncertainty measured as the conditional variance of the gross domestic product growth rate, the industrial production index and returns of the S&P 500 Composite index represent significant determinants. Pereira et al. (2018) extend the scope of the research which has mainly focused on the US market by confirming that structural model variables, accounting-based and equity market variables as well as common market-wide factors exhibit significant explanatory power in the European and UK credit default swap markets as well.

Resembling the credit spreads of corporate bonds, liquidity has been identified as a significant determinant of credit default swap spreads. Corò et al. (2013) report a significant relationship between various firm-specific and industry-level liquidity measures and credit default swap spreads. They affirm that heightened illiquidity in the credit default swap market causes spreads to increase. They also note that role of liquidity is especially prominent during periods of distress in the financial markets considering that the relative explanatory power of liquidity measures overpowered traditionally significant firm-specific determinants of credit risk during the Global Financial Crisis.

Corò et al. (2013) argue that the assumption that credit default swap spreads are an accurate measure of pure credit risk does not hold when there is a high level of uncertainty in the financial markets because a significant liquidity risk premium could be incorporated in spreads. Other studies support the notion that recessionary periods should be accounted for when examining the determinants of credit default swap spreads. For instance, Galil et al. (2014) state that the explanatory power of credit default swap spread determinants was altered during the most critical phase of the Global Financial Crisis and the credit default swap market has undergone substantial structural changes following the crisis. Similarly, Pereira et al. (2018) assert that the explanatory power of determinants that proxy for macroeconomic conditions has grown stronger following the crisis.

2.5 Political risk and uncertainty

Political risk refers to the possibility that firm cash flows are negatively affected by government actions or deficiencies in key institutions belonging to the executive, legislative or judicial branches of the government (Bekaert et al., 2014, p. 473). Political risk can be considered in the form of political uncertainty, which refers to uncertainty faced by investors and firms regarding possible changes to government policies in the future and their impact on firm profitability (Pástor & Veronesi, 2013).

Regarding the difference between risk and uncertainty, Crouhy et al. (2014) assert that "variability that can be quantified in terms of probabilities is best thought of as risk while variability that cannot be quantified at all is best thought of simply as uncertainty" (p. 11). However, uncertainty is fluid concept that has been portrayed in academic research by a wide range of proxy measures (Bloom, 2014, pp. 153–154). Given their broad and arguably ambiguous definitions, the terms political risk and political uncertainty have been used interchangeably in prior literature to describe the same underlying phenomenon. Accordingly, this thesis uses the term political risk as a general term which covers both the political risk and political uncertainty concepts.

Rugman and Collinson (2009, p. 391) divide political risks into two categories based on their perceived scope. Their first category is macro-level political risk, which has a broad impact on the economy at large. They state that the second category is micro-level political risk, which refers to localized risk affecting specific industry sectors or individual companies. Rugman and Collinson further detail that micro-level risk typically arises from the government enacting changes to regulations, taxes and laws which target a specific industry or business activity.

In theory, escalating political risk reduces future cash flows and raises discount rates (Brogaard & Detzel, 2015, p. 4). Macro-level political risk that is more systematic in nature and less diversifiable should increase the rates according to which future cash flows are discounted to their present value whereas micro-level political risk that is idiosyncratic and diversifiable should directly decrease expected cash flows (Bekaert & Hodrick, 2011, pp. 484, 487).

The earliest studies examining the effect of uncertainty in general relied on real options theory which describes one channel through which the effect political risk propagates to real economic activity. Real options theory views that a firm-level investment decision is a type of option that can be exercised at will (Bloom, 2014, p. 163). A classic example of real options theory is provided by Bernanke (1983) who presents a theoretical model of investment behavior under uncertainty. In the model, firms are value-maximizing agents who will decide to invest only when the expected return of an investment is higher than the cost of delaying investment. The model assumes that expected returns are conditional on all information available to firms and investment is to a large extent irreversible.

The model introduced by Bernanke (1983) posits that uncertainty regarding future outcomes reduces the value of expected returns and discourages firms from making highly irreversible investment decisions. According to the model, the possibility of bad news which could negatively affect the expected value of investment will incentivize firms to wait and see until uncertainty is resolved. Therefore, Bernanke concludes that heightened uncertainty increases the option value of delaying investment and decreases the option value of committing to an investment.

The core assumption presented by real options theory is supported by empirical research which has found that heightened uncertainty related to politics has adverse consequences for economic outcomes. For example, political risk has been shown to exert a negative effect on corporate investment levels which can be persistent (Gulen & Ion, 2016). The negative influence of political risk also impedes other investment-like activity such as hiring which results in decreasing employment growth (Baker et al., 2016; Hassan et al., 2019). The suspension of regular investment and hiring activities by individual firms can lead to reductions in aggregate economic output (Gambetti et al., 2019, p. 373). Elevated levels of political risk can potentially signal future recessionary periods as noted by Baker et al. (2016) who found that aggregate political risk shocks are linked to significant deteriorations in indicators that are traditionally used to measure macroeconomic conditions such as industrial output and gross domestic product growth.

The general equilibrium model of government policy choice originally introduced by Pástor and Veronesi (2012) and further extended by Pástor and Veronesi (2013) provides a theoretical framework describing how political risk affects asset prices. Pástor and Veronesi (2013) consider that all firms in an economy are owned by investors who derive their wealth from firm profitability. Their model assumes that the expected profitability of each firm is influenced by the policy currently set by the government. They describe that the government chooses to set policy which maximizes aggregate firm profitability and is compelled to change to a new policy if the prevailing policy is perceived to have a sufficiently adverse effect on profitability. Pástor and Veronesi state the government's choice of new policy is constrained by political costs, which refer to the amount of political capital that the government is required to expend or alternatively stands to gain by implementing a specific policy.

According to Pástor and Veronesi (2013), investors do not know the full impact of the prevailing policy on aggregate firm profitability, nor the true level of political costs associated with the different new policies considered by the government. Therefore, investors are uncertain whether the government will decide to implement a policy change and what is the new policy that the government will choose to adopt. Their model posits that uncertainty regarding the government's policy choice is essentially non-diversifiable due to the assumption that government policy influences the profitability of all firms. Pástor and Veronesi state that investors demand a risk premium to compensate for their exposure to non-diversifiable uncertainty.

The risk premium described by the Pástor and Veronesi (2013) model consists of capital shocks, impact shocks and political shocks. They describe that the capital shock component represents non-political shocks, such as fluctuations in economic conditions, which have an impact on aggregate firm profitability. The uncertainty regarding the impact of prevailing government policy on aggregate firm profitability is represented in their model as the impact shock component which is updated as investors observe realized aggregate firm profitability. Pástor and Veronesi state that the political shock component represents uncertainty regarding the political costs associated with different government policy choices. They note that the political shock component changes as investors learn of political costs from the continuous flow of external information such as political news.

Pástor and Veronesi (2013) proclaim that political shocks represent the main theoretical channel through which new information about political issues can influence asset prices. Their model also predicts that political risk increases the volatility and correlation of asset prices. They explain that volatility is increased due to the political shock component amplifying the effect of external information. As a result, they posit that the correlation of asset prices increases as well due to the assumption that political risk is non-diversifiable and political news will affect the profitability of all firms.

Political risk is countercyclical in the sense that it is elevated during periods of weak economic conditions such as recessions and reduced during expansionary periods (Brogaard & Detzel, 2015, p. 9). Pástor and Veronesi (2013) state that the government is more likely to replace the prevailing policy during weak economic conditions when aggregate firm profitability is deteriorating. They explain that the impact shock component of the risk premium shrinks as the negative impact of the current policy on aggregate firm profitability is realized and investors become more certain that a policy change will occur. Consequently, their model predicts that the political shock component is pronounced during recessions and therefore overall political risk will be elevated as well.

Although political risk is to a large extent undiversifiable as all firms are affected by uncertainty regarding government policy, Pástor and Veronesi (2012) argue that the effect of government policies may vary across firms. They simulate this possibility by modifying their theoretical model to include a government beta which reflects industry-specific exposure to government policy. Their extended theoretical model predicts that the effect of political risk is pronounced for firms in industries which are more exposed to government policies as measured by a higher government beta.

3 Literature review

This thesis builds upon the findings of academic literature examining the asset-pricing implications of political risk, which has been researched extensively in the financial markets using various asset classes and proxy measures. This chapter begins by first reviewing previous literature concerning the effect of political risk in the equity market. Relevant studies regarding the relationship between political risk and the cost of private debt and corporate bonds in the credit markets are then presented. The last section examines research which specifically focuses on the effect of political risk in credit default swap market.

3.1 The effect of political risk in the equity market

Academic literature has examined how the political system affects the financial markets by utilizing national elections as a source of political risk. The earlier studies include Niederhoffer et al. (1970) who examined daily returns of the Dow Jones Industrial Average equity market index during 18 different U.S. presidential elections from 1900 to 1968. They found that the index reacts to presidential elections and tends to exhibit higher returns in the weeks preceding and following the actual election date. Riley and Luksetich (1980) also investigated the behavior of the Dow Jones Industrial Average index during 20 different U.S. presidential election periods from 1900 to 1975. Their results indicated that market index returns are lower on average during the month leading up to the election date and higher returns are observed only afterwards for a short period, which differs partially from Niederhoffer et al. (1970).

International evidence is presented by Pantzalis et al. (2000) who analyzed abnormal returns during presidential and parliamentary elections using equity market index data of 33 countries from 1974 to 1995. Their findings showed that positive abnormal returns are significantly higher during the two-week period before the election date. The study noted that the market reaction is stronger when investors face greater uncertainty regarding the outcome of the election resulting from the election being called early or the incumbent political party losing. Moreover, the authors found that the market is more sensitive to elections following periods of weak economic conditions.

Subsequent studies have highlighted the relationship between political risk and equity volatility. Bialkowski et al. (2008) examined how equity market volatility behaves during parliamentary and presidential election periods in 27 countries. They found that market volatility is significantly higher directly after the election date and begins to decline with a delay after 15 days past the event. The authors attributed this lag to the final election results becoming public knowledge several days past the event date. The authors also reported that market volatility is further increased following close elections and when the outcome of the election leads to a change in the political affiliation of the incumbent party.

Elections are characterized by continuously evolving public opinion regarding the eventual outcome and thus the level of election-induced uncertainty varies leading up to the actual voting day. This aspect is considered by Li and Born (2006) who examined how changes in uncertainty related to US presidential elections influence the equity market from 1964 to 2000 in the US. Their methodology featured a continuous measure of election uncertainty derived from public opinion poll results which reflects expected probabilities of winning for both the incumbent candidate and the challenger. They found that the continuously evolving market perception of political risk has a significant positive relationship with equity prices and volatility. Li and Born noted that the election process generates higher levels of political risk when the outcome is more uncertain. To be more specific, their results indicated that equity volatility is higher when the election features a greater degree of uncertainty caused by neither candidate being a clear favorite to win.

The conclusions of Li and Born (2006) are corroborated in the European market by Smales (2017) who investigated how uncertainty regarding the outcome of the Brexit referendum influences implied volatility indices in the UK and Germany. The study utilized Brexit opinion poll data to construct a time-varying measure of referendum uncertainty defined as the proportion of the Leave-vote in relation to the proportion of the Remain-vote. The findings of the study suggest a significant positive relationship between higher levels of political risk as indicated by increased uncertainty regarding the eventual outcome of the referendum and implied market volatility in both countries. Resembling the results of prior election-based studies, Smales reported that Brexit-related voter uncertainty has a pronounced effect on implied volatility in the UK market especially when opinion polls indicate less certainty regarding the eventual outcome of the referendum.

The seminal study by Baker et al. (2016) introduced the Economic Policy Uncertainty (EPU) index, which a news-based measure of aggregate political risk. The EPU index is constructed by searching through newspaper articles that include key terms related to the economy, government policy and uncertainty. In comparison to political events with fixed dates such as elections, the EPU index has the advantage of being a continuous measure. In addition, it captures perceived risk due uncertainty related to government economic policy on a broader scope and not just political risk induced by electoral uncertainty. Baker et al. (2016) initially found that heightened levels of the EPU index display a significant positive association with both realized and implied equity volatility.

Pástor and Veronesi (2013) analyzed the relationship between the EPU index and the US equity market from 1985 to 2010 to determine whether the assumptions posed by their general equilibrium model hold in practice. They reported that elevated levels of aggregate political risk as proxied by EPU intensify both realized and implied equity volatility while increasing the correlation of asset prices in the equity market. Furthermore, they confirmed that the positive effect that EPU exerts on equity volatility is stronger during in weak economic conditions.

Regarding the risk premium induced by political risk, Brogaard and Detzel (2015) examined the relationship between US equity market returns and the EPU index and obtained presented evidence of negative relationship between equity returns and aggregate political risk the short term. Over a longer two to three-month horizon, they found that the EPU can forecast a positive risk premium in log excess equity returns. In line with the theoretical predictions, they stated that the risk premium is more substantial during economic downturns and robust enough to exist during normal economic conditions as well. The authors concluded that the EPU index commands a significant risk premium that is distinct from the risk premium induced by general economic uncertainty.

The studies reviewed so far have mostly examined how political risk influences the equity market on the general level. However, prior research has also found that certain industries and firms are more exposed to political risk as theoretically predicted by Pástor and Veronesi (2012). For example, Boutchkova et al. (2012) analyzed how aggregate political risk influences industry-level equity volatility in fifty countries from 1990 to 2006. Their methodology used national elections and a political risk index provided by the International Country Risk Guide to proxy for country-specific aggregate political risk. They differentiated between the effect of global political risk emanating from trading partner countries and domestic political risk. The results of the study showed that both types of political risk are positively linked to equity volatility but the strength of the effect is dependent on industry characteristics.

Boutchkova et al. (2012) noted that a notable contributor to industry-level differences is international trade exposure, which they quantify as the proportion of export sales out of total industry sales. They explained that global political risk has a more substantial effect on export-oriented industries as their dependency on international trade amplifies their sensitivity to political risk emanating from foreign countries. The authors also proposed that political risk weakens the governmental institutions which enforce contracts between businesses and increases uncertainty regarding future labor regulations. The study documented that the equity volatility of industries which are more exposed to contract enforcement risk due to their reliance on subcontractors and third-party transactions as well as labor-intensive industries exhibit substantially stronger reactions to both domestic and global political risk.

Baker et al. (2016) proposed that firms which operate in industries that obtain a larger share of their revenues from government contracts are more exposed to uncertainty related to the government's spending policies. Their study utilized a variable that reflects the intensity of industry-level exposure to government purchasing to measure sensitivity to political risk. They ran panel regressions with implied equity volatility as the dependent variable and observed that firms in policy-sensitive industries have significant positive interactions effects with the EPU index. In addition, the authors found that categorical EPU indices relating to national security, health care and financial regulation exhibit significant interactions with dummy variables denoting defense, health care and financial firms, respectively. Their findings showed that political risk has greater influence over firms which are dependent on government purchasing and under heavier regulatory oversight.

A more deliberate approach towards analyzing industry heterogeneity was taken by Yu et al. (2017) who specifically examined how aggregate political risk measured by EPU affects long-term industry betas in the US from 1994 to 2015. The study grouped firms based on their Global Industry Classification Standard (GICS) industry classification and determine beta as the correlation between aggregated equity returns of each industry and the S&P 500 market index. The findings of the study indicated that differences between industries as the betas of the Information Technology, Financials and Materials industries are more sensitive to EPU whereas the Consumer Staples, Energy and Utilities are the least affected. In addition, the results suggested that the Financials and Health Care industries are less influenced by EPU during crisis periods. The authors also examined heterogeneity towards different topics by using the categorical variants of the EPU index. They found that the influence of the Fiscal Policy and Government Spending categories are weaker during stable economic conditions. The Tax, Health Care and National Security categories retained substantial and significant explanatory power across their entire sample.

In one of the relatively few studies regarding industry-level heterogeneity towards aggregate political risk in the European markets, Hill et al. (2019) examined the differing exposure amongst British firms to domestic political risk induced by the Brexit referendum. The study analyzed the relationship between firms' equity prices and changes in the probability of the Leave-vote winning calculated from odds placed by professional bookmakers. In addition, the equity market reaction to the eventual referendum result was investigated in the study using a standard event study framework. Industry-level analysis revealed that firm belonging to the financial, consumer goods and consumer services industries are the most sensitive to political risk induced by the Brexit referendum whereas the basic materials and healthcare industries are amongst the least affected. In addition, the authors reported that British firms which are more diversified internationally are less exposed to domestic political risk related to Brexit.

The only study which examines the effect of firm-level political risk in the equity market is conducted by Hassan et al. (2019). The methodology differs from the prior literature presented thus far as it used their own firm-level measure of political risk instead of proxies for aggregate political risk such as the EPU index and elections. Hassan et al. found that their firm-level political risk measure has a statistically significant positive effect on both implied and realized equity volatility which is robust to controlling for time and industry sector fixed effects. They claimed that the influence of political risk is more unevenly distributed across firms than what is expected according to the assumptions presented in previous literature.

According to Hassan et al. (2019), controlling the variation of firm-level political risk over time with time fixed effects captures only 1% of the total variation, which indicates that the firm-level political risk measure varies across firms more than it varies over time following a common trend. Overall, the authors argued that their results contrast the presumption of conventional theory as presented by Pástor and Veronesi (2013) which asserts that political risk is mainly a systematic and non-diversifiable risk factor.

3.2 The effect of political risk in the credit market

In addition to having a notable effect on the cost of equity and equity volatility, previous literature suggests that heightened political risk increases the cost of debt. For example, Ashraf and Shen (2019) examined how political uncertainty proxied by the EPU index affects the average interest rates on syndicated corporate loans as well as loans extended to small firms and households utilizing bank-level data from 17 countries spanning from 1998 to 2012. The results implied that the EPU index has a significant positive impact on the interest rates on all types of loans even after controlling for bank-specific and market-level credit risk factors. Moreover, the findings suggested that banks become more hesitant to extend new credit when facing intensified political risk as EPU has a negative relationship with bank loan growth rates. The authors stated that their results are mainly driven by the increase in default probabilities on the borrower side induced by heightened political risk, which leads to banks charging higher interest rates to compensate for their exposure to elevated credit risk.

The rising cost of debt provoked by political risk influences firm-level decisions regarding the use of debt in capital structures as noted by Pan et al. (2019). Their study is related to this thesis as it utilized the firm-level political risk measure by Hassan et al. (2019) to examine how the use of long-term debt and leverage ratios is affected by political risk using a sample of 3779 US firms covering the period from 2001 to 2016. Pan et al. found that the firm-level political risk measure has a significant negative effect on long-term debt and leverage ratios, which the authors propose is caused by firms being averse to using debt when borrowing costs are higher due to increased political risk.

Pan et al. (2019) also investigated firm-level characteristics which could exacerbate the effect of firm-level political risk. Inspired by real options theory, the authors built an industry-level measure of investment irreversibility that is derived from the redeployability of assets in each industry. In addition, they used credit ratings to examine how sensitivity to political risk is affected by the financial condition of a firm. They obtained results indicating that the effect of firm-level political risk is amplified for firms facing dire financial conditions as indicated by low credit ratings as well as for firms with more irreversible investments. Their findings are in line with the predictions of real options theory as well as with Ashraf and Shen (2019) who proclaimed that increased cost of debt is mainly the result of higher credit risk on the borrower side during periods of elevated aggregate political risk.

Studies examining the corporate bond market exhibit similar results. For example, Nodari (2014) analyzed how political risk related to the uncertainty of financial regulation policy affects aggregate credit spreads in the U.S. measured as the difference between the credit spreads of Moody's Baa-rated and Aaa-rated benchmark corporate bonds from 1985 to 2012. The study measured political risk with the Financial Regulation Policy Uncertainty index, which is a categorical version of the EPU index by Baker et al. (2016). The results obtained using a linear vector autoregression model showed that a political risk shock has a persistent positive effect on aggregate credit spreads that is robust to controlling for general economic uncertainty and aggregate political risk. Moreover, the authors confirmed that effect is stronger during economic downturns as predicted by the Pástor and Veronesi (2013) model.

Waisman et al. (2015) substantiated the earlier findings by Nodari (2014) and examined the credit spreads of individual corporate bonds in the US from 1980 to 2012 to determine their reaction towards changes in aggregate political risk proxied by presidential election years and the EPU index. According to their findings, credit spreads are higher in general during presidential election years and especially during election associated with greater levels of political risk caused by closer winning margins eliciting considerably higher credit spreads. Similarly, they reported that the EPU index is found to have a significant positive relationship with credit spreads. The authors also performed subsample analysis by dividing their sample into periods of low and high aggregate political risk based on the level of the EPU index and found that credit spreads are significantly increased only in the latter subsample.

Further evidence regarding the relationship between the EPU index and credit spreads is provided by Kaviani et al. (2020) who examined the US corporate bond market from 2002 to 2015. Their study analyzed monthly changes in credit spreads to account for autocorrelation. They found a significant positive relationship between the EPU index and credit spreads which is line with prior studies. The authors also focused on examining firm-level characteristics and reported that the effect of aggregate political risk is intensified for firms which are subject to a greater number of regulations and more dependent on government contracts which resembles the earlier findings by Baker et al. (2016). Kaviani et al. reported that higher effective tax rates, increased political activity as measured by lobbying expenses as well as dependency on external financing are additional firm-level factors which amplify the effect of aggregate political risk.

3.3 The effect of political risk in the credit default swap market

A handful of recent studies are dedicated to analyzing the relationship between political risk and credit default swap spreads. Wisniewski and Lambe (2015) examined how corporate credit default swaps spreads are affected by aggregate political risk from 2006 to 2014. Their study considered the European and US credit default swap markets on the aggregate level by using the iTraxx Europe and CDX North America Investment Grade credit default swap indices instead of individual credit default swap contracts. In addition, the study used the European and US EPU indices as proxies for aggregate political risk. The authors used vector autoregressions (VAR) to model the interactions between the credit default swap and EPU indices. Their results show that EPU indices

Granger cause the credit default swap indices in Europe and the US, which implies that EPU can be used to forecast credit default swap spreads.

Wisniewski and Lambe (2015) conducted further analysis using impulse response functions and confirmed that a positive shock to the EPU index is associated with heightened credit default swap spread levels. Interestingly, they found that credit default swap spreads are more sensitive to aggregate political risk in Europe compared to the US. Their results implied that US credit default swap market has a delayed response to changes in the EPU index whereas the response in Europe is more immediate. Using variance decomposition analysis, the authors found that changes in the European EPU index contribute almost 25% of the forecasted variance in the European iTraxx index. In comparison, changes in the US EPU index contribute to only 8% of the forecasted variance in the US CDX index.

A more recent study by Liu and Zhong (2017) documented how aggregate political risk induced by national elections influence corporate credit default swap spreads in 30 different countries from 2003 to 2012. According to their results, aggregate political risk is positively related to credit risk as credit default swap spread levels increase during a two-year period prior to an election year, reach their peak levels on the actual election year and then decline during the post-election years. The results also showed that national elections evoke a stronger reaction in firms located in countries which suffer from greater levels of political instability and legal systems which feature weaker investor protections.

In a finding that is relevant for this thesis, Liu and Zhong (2017) presented evidence of a heterogenous response to aggregate political risk at the firm-level. They divided total equity volatility into a systematic component according to its sensitivity to the volatility of the MSCI World Index and an idiosyncratic component and propose that firms which exhibit more idiosyncratic volatility are more susceptible to political risk. Their results affirmed that credit default swap spreads are mostly impacted by political risk through the idiosyncratic volatility channel. Moreover, the authors stated firms that which are internationally diversified as measured by the number of foreign subsidiaries are more resistant to the effects of domestic aggregate political risk associated with national elections in their home country.

Wang et al. (2019) provided further empirical evidence by examining the relationship between US corporate credit default swap spreads and the EPU index from 2001 to 2016. Their study scrutinized individual credit default swap contracts in contrast to Wisniewski and Lambe (2015) who examined the relationship between credit default swap indices and EPU. In line with previous literature, Wang et al. (2019) reported that an increase in the EPU index is linked to rising credit default swap spreads. More detailed analysis in their study revealed that all subcomponents of the EPU are significant positive drivers of credit default swap spreads, with the newspaper and government fiscal policy uncertainty components having the greatest explanatory power over spread changes. The authors also classified firms in the finance and defense industries as policy-sensitive and demonstrated that they exhibit a significant positive interaction with the EPU index. The result implies that policy-sensitive firms react more strongly to changes in the EPU index and supports the existence of firm-level heterogeneity towards the influence of aggregate political risk.

The study by Gad et al. (2020) is related to this thesis as it examined how the firm-level political risk measure developed by Hassan et al. (2019) is related to the price of syndicated corporate loans, bonds credit spreads and credit default swap spreads in the US from 2002 to 2016. Their findings show that firm-level political risk has a positive relationship with credit risk as indicated by rising loan costs, credit spreads and credit default swap spreads. They noted that positive effect on credit default swap spreads remains statistically significant after controlling for year, sector as well as firm fixed effects.

Gad et al. (2020) also utilized credit default swap spread data to examine whether the influence of firm-specific political shocks is transmitted via special lending relationships between the providers of corporate loans and their respective borrowers. They reported that heightened firm-level political risk for a lending firm serving as the lead arranger in a corporate loan syndicate group results in a statistically significant increase in the borrowing firm's credit default swap spreads. In summary, their study found compelling evidence that political risk exposure specific to individual firms is priced by investors in the credit default swap market.

4 Data

This thesis analyzes the effect of firm-level political risk on corporate credit default swap spreads. The purpose of this chapter is to present the data utilized in the empirical portion of the study. The chapter begins by describing the collection and construction process for the sample data. The individual variables and the reasoning for their inclusion are reviewed. The latter portion of this chapter discusses characteristics of the sample data and presents the descriptive statistics for the variables as well as their correlation coefficients.

4.1 Construction of the sample

The construction of the sample dataset begins by acquiring corporate credit default swap spread data for all European firms available from Refinitiv Datastream. The credit default swap data in Datastream begins on 31.12.2007, which sets a hard boundary for the beginning of the time period examined in this thesis.

The initial data collection phase excludes firms which are not constituents of major European stock market indices. This filtering step is taken to ensure that the sample is limited to only include firms which have sufficiently actively traded and liquid credit default swaps due to their established market presence. The market indices used in this filtering phase are ATX for Austria, BEL20 for Belgium, CAC 40 for France, DAX30 for Germany, ISEQ 20 for Ireland, FTSE MIB for Italy, AEX for the Netherlands, PSI 20 for Portugal, IBEX 35 for Spain, SMI for Switzerland and FTSE100 for the United Kingdom. The initial data collection phase yields credit default swap data for a total of 182 European firms.

The standard convention of previous research regarding the determinants of credit default swap spreads is to exclude financial firms such as banks from the analysis. The reasoning is that the specialized business models of financial firms differ significantly from non-financials considering that banks have higher leverage ratios and are subject to more stringent regulatory requirements which affect their asset-liability structures (Pereira et al., 2018, p. 190). However, financial firms are not excluded from the sample in this thesis as their inclusion is important for studying the research hypothesis whether the effect of firm-level political risk differs by industry.

The next data collection phase involves obtaining the data required for the main independent variable of interest and control variables. Data for the firm-level political risk measure developed by Hassan et al. (2019) is obtained from their website. At the time of data collection process, the firm-level political risk dataset consists of 11 617 publicly listed firms and features quarterly observations from the first quarter of 2002 to the second quarter of 2019 which sets a natural boundary for the end of the sample period examined in this thesis. Historical equity prices, financial statements, equity indices and the EURO STOXX 50 Implied Volatility Index are acquired from Datastream. The 3-month EURIBOR interest rate as well as sovereign bond yields are obtained from the European Central Bank's Statistical Data Warehouse. Finally, the different Economic Policy Uncertainty indices is obtained from the website operated by Baker et al. (2016).

The datasets obtained from different sources are then combined. The firm-level political risk dataset does not identify firms by their stock ticker code or their Datastream code. As such, firms in the political risk dataset are matched manually to correct firms in the Datastream dataset. The matching firm-quarter combinations are then merged with the country-level and market-level data. Notably, 50 firms are dropped from the initial European credit default swap spread dataset due to completely missing firm-level political risk data. Listwise deletion is utilized to drop all observations with missing variables. The final full sample consists of 132 firms and 3374 firm-quarter observations in total and spans the period from the first quarter of 2008 to the second quarter of 2019.

It must be noted that different country-level standards regarding financial statement reporting frequency poses a challenge in terms of the data. Firms from most European countries generally practice quarterly reporting. In contrast, French and British firms typically report their financial statements and arrange earnings conference calls on a semiannual basis. Semiannual reporters have financial statement data available only for the second and fourth quarter each year. Earnings conference calls are usually held during the month following the end of a fiscal quarter, which means that semiannual reporters have firm-level political risk values for the first and third quarter. Consequently, they have missing financial statement values for every quarter with non-missing firm-level political risk values. Deleting all observations with missing quarterly values would eliminate almost every French and British firm from the sample, which in turn could severely impair the statistical power of the full sample.

Missing financial statement observations for semiannual reporting French and British firms are filled in by applying the imputation method of carrying forward the last observed value. More specifically, missing quarterly observations at time *t* are imputed by replacing them with value of the preceding observation at time *t-1*. The precedent for this approach of using imputation to fill in missing data can be found in previous relevant studies such as Ericsson et al. (2009) and Galil et al. (2014) who used linear interpolation to fill in missing accounting variables as well as Annaert et al. (2013) who replaced missing credit default swap spread data by carrying forward the last observed value.

The format of the final sample can be described as panel data, which consists of observations in a time series for a cross-section of individual entities. The variables in a panel data have a double subscript in which *i* identifies panel entities and *t* identifies points in the time series (Baltagi, 2005, p. 11). Accordingly, the sample data used in this thesis is transformed into a panel data format where individual firms and quarters are identified as the panel entities and time series. The resulting panel data is unbalanced due to some panel entities such as semiannually reporting firms having fewer quarterly observations for the firm-level political risk measure compared to other firms.

4.2 Variables

4.2.1 Credit default swap spread

The dependent variable used in this thesis is the credit default swap spread. The original credit default swap spread data consists of quarterly mid-spreads of five-year European corporate credit default swap contracts. Five-year constant maturity credit default swaps are chosen as they represent most of all trading in the credit default swap market and their spreads are the least affected by issues caused by illiquidity (Pereira et al., 2018, p. 190).

Studies regarding the determinants of credit default swap spreads have found that the natural logarithm of credit default swap spreads provide a better fit in regressions compared to the original non-transformed values (Aunon-Neurin et al., 2002, p. 30). Accordingly, the natural logarithm transformation of the credit default swap spread values is utilized in this thesis. The variable is denoted as *ln(CDS)*.

4.2.2 Firm-level political risk

The firm-level political risk measure developed by Hassan et al. (2019) is the main independent variable of interest used in this thesis. The measure is based on the language used in quarterly earnings conference calls in firm management and analyst participating in the call discuss issues pertaining to the firm's ongoing activities and profitability. Hassan et al. (2019) analyze textual transcripts of the earnings calls to measure the share of discussion which is devoted to risks and uncertainties associated with political issues. The resulting quantified measure can be interpreted to proxy for the level of exposure to political risk that is specific to individual firms as perceived by firm management and other stakeholders.

The methodology utilized by Hassan et al. (2019) involves comparing the language patterns exhibited in call transcripts with those found in specific example texts referred to as training libraries, which represent typical language associated with political and non-political topics. They utilize political science and financial accounting textbooks as political and non-political training libraries, respectively. They decompose training libraries into all adjacent two-word combinations, referred to as bigrams, which are used to identify political and non-political discussion in a call transcript. The authors then identify discussion associated with political risk in the text by the presence of bigrams which are accompanied by words that are synonymous with risk and uncertainty. This methodology is used to construct measures for *overall firm-level political risk* and *topic-specific firm-level political risk*.

Overall firm-level political risk is defined by Hassan et al. (2019) as the total level of political risk exposure as determined by the language used in an earnings conference call. They construct the measure by first determining the total number of political and non-political bigrams found in a call transcript. The authors then count the number of political bigrams that appear in close proximity to words synonymous with risk and uncertainty and divide their number by the total number of bigrams in the transcript. Hassan et al. state that resulting measure is reflects the overall share of discussion in a conference call which concerns risk related to political issues.

The equation for calculating the overall firm-level political risk measure is presented as:

$$PRisk_{it} = \frac{\sum_{b}^{B_{it}} \left(1[b \in \mathbb{P} \setminus \mathbb{N}] \times 1[|b - r| < 10] \times \frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}} \right)}{B_{it}}, \tag{11}$$

where

b = a single political bigram

B = the total number of political bigrams

r = the position of a word that is a synonym for risk and uncertainty

$\mathbb{P}$ = the political training library

$\mathbb{N}$ = the non-political training library (Hassan et al., 2019).

According to Hassan et al. (2019), the first term of the equation $1[b \in \mathbb{P} \backslash \mathbb{N}]$ indicates bigrams associated with political topics but not non-political topics and the second term $1[|b - r| < 10]$ indicates whether bigrams are within the space of 10 words from a synonym for risk and uncertainty. They point out that each bigram is weighted by the third term which measures how representative the bigram is of political language. Hassan et al. elaborate that the numerator $f_{b,\mathbb{P}}$ in the third term reflects the frequency of bigram *b* in the political training library and the denominator $B_{\mathbb{P}}$ is the total number of bigrams in the political training library.

Topic-specific firm-level political risk is an additional measure which is specified by Hassan et al. (2019) to reflect firm-level political risk associated with a specific political topic. They construct the topic-specific political risk measures using similar methodology as the overall measure with the main distinction that each topic-specific measure uses a different training library which features language that is typical in the discussion of a specific topic. Hassan et al. present eight variants of the topic-specific measure: Economic policy & Budget, Environment, Trade, Institutions & Political process, Healthcare, Security & Defense, Technology & Infrastructure and Tax.

The political risk variables are transformed to a natural logarithm form so that the variables are closer to normal distribution. The transformation is conducted to render the values of their individual observations more comparable in scale which improves their fit in a linear regression model and reduces the prominence of outliers. The overall firm-level political risk variable and topic-specific firm-level political risk variables are denoted as *ln(PRisk)* and *ln(PRiskTopic)*, respectively.

4.2.3 Control variables

The control variables used in this thesis aim to separate the effect of various firm-level and market-level factors which could influence credit default swap spreads. The selection of independent control variables is based on the collective findings of academic research concerning the effect of political risk and the determinants of credit default swap spreads. Further details regarding each of the control variables along with the reasoning for their inclusion are described in this section.

The firm-level control variables are *Equity volatility*, *Leverage*, *Return on assets*, *Firm size* and the *Market to Book ratio*.

Equity volatility is calculated as the standard deviation of daily log equity returns from the past 250 days and converted to an annualized form following the methodology of Galil et al. (2014) and Pereira et al. (2018). The value of the variable represents annualized equity volatility on the last day of each quarter. Equity volatility is one of the components in the structural model of credit risk by Merton (1974) and is expected to have a positive sign. The variable is denoted as *EquityVol*.

Leverage is calculated from quarterly financial statements as the book value of total debt divided by the book value of total assets. According to the structural model of credit risk, increased leverage lowers the value of assets in relation to the value of debt which will consequently increase the probability of default (Merton, 1974). Leverage is expected to have a positive sign. The variable is denoted as *Leverage*.

Return on assets is calculated from quarterly financial statements as net income divided by total assets. Return on assets is used as a proxy for firm profitability. Return on assets is expected to have a negative sign considering that increased profitability reduces the probability of default, which is in turn reflected as decreasing credit default swap spreads (Callen et al., 2009, p. 1368). The variable is denoted as *ROA*.

Firm size is calculated from quarterly financial statements as the natural logarithm of the book value of total assets in a similar manner as Pereira et al. (2018). The logarithm transformation is undertaken to make the scale of different firm sizes comparable. According to Chan and Chen (1991), small firms are on average riskier than large firms and have worse access to external financing which could reasonably exacerbate credit risk issues. In accordance, firm size is expected to have a negative sign. The variable is denoted as *ln(Size).*

Market to Book is a ratio calculated from quarterly financial statements as market capitalization divided by the book value of equity. The market to book ratio measures the growth opportunities for each firm. The expected sign is negative as growth firms with higher market to book ratios have typically less credit risk due to expected future asset growth (Wang et al., 2013, p. 3736). The natural logarithm transformation is undertaken to normalize the value distribution of the variable, which is strongly skewed in its original form. The variable is denoted as *ln(MTB).*

The market-level control variables are *Market return*, *Implied market volatility*, *Risk-free interest rate*, *Yield spread* and *Recession.*

Market return is calculated as the equity market index return during the past 12 months following Pereira et al. (2018). Equity indices for each firm are chosen based on the indices used in the first filtering step during the sample construction process. The return of the equity index over the past year is used to proxy for the overall business conditions as reflected by the financial markets. It is expected to have a negative sign as higher returns signal better market conditions, which reduces the probability of default and therefore leads to lower credit default swap spreads (Pereira et al., 2018, p. 192). The variable is denoted as *MarketRet*.

Implied market volatility is represented by the EURO STOXX 50 Implied Volatility Index (VSTOXX) following Pereira et al. (2018). Market volatility is expected to have a positive sign as it signals the level the of uncertainty in the financial markets and should fundamentally have a similar relationship with credit default swap spreads as equity volatility (Galil et al., 2014, p. 273). The logarithm transformation is undertaken to normalize the distribution of the raw index values. The variable is denoted as *ln(MarketVol).*

Risk-free interest rate is measured as the 3-month EURIBOR interest rate following Pereira et al. (2018). The variable is measured on a quarterly frequency as the average of daily closing prices throughout every quarter. The risk-free interest rate is a component of the Merton (1974) structural model in which a higher interest rate indicates that a default is less likely. In addition, a positive relationship exists between higher interest rates and aggregate economic growth, which leads to a decreased probability of default on the firm level (Annaert et al., 2013, p. 450). The risk-free interest rate is expected to have a negative sign. The variable is denoted as *RiskFree*.

Yield spread is measured as difference between the yields of a 10-year maturity sovereign bond and a 2-year maturity sovereign bond belonging to the home country of each firm following Ericsson et al. (2009). The yield spread serves as a forward-looking measure that proxies for expected future economic conditions. An increase in the yield spread signals both improving economic conditions as well as rising interest rates (Annaert et al., 2013, p. 451). Therefore, it is expected to have a negative sign. The variable is denoted as *Spread*.

Recession is a dummy variable which denotes recession periods. The recession dummy is included following the example of Pan et al. (2018) who utilize it as a market-level control variable. Previous literature displays that behavior of credit default swap markets is altered by economic downturns, which warrants that they should be controlled for (eg. Galil et al., 2014; Pereira et al., 2018). In addition, the general equilibrium model by Pástor and Veronesi (2013) poses the theoretical assumption that political risk has a stronger impact on asset prices during economic downturns. The recession dummy is expected to have a positive sign as poor economic conditions increase the probability of default. The variable is denoted as *Recession*.

Recession periods are determined according to the chronology of business cycles provided by the Euro Area Business Cycle Network. The chronology assigns the beginning date of a recession period as the quarter following a peak in the Euro area business cycle and the ending date as the quarter in which there is a through (Euro Area Business Cycle Network, n.d. a). The first peak in the Euro area business cycle occurs in the first quarter of 2008 and is followed by a through in the second quarter of 2009. The business cycle exhibits a second peak in the third quarter of 2011 and a subsequent through in the first quarter of 2013 (Euro Area Business Cycle Network, n.d. b).

In conclusion, there are two recession periods in total. The first period ranges from the second quarter of 2008 to the second quarter of 2009 and the second period from the fourth quarter of 2011 to the first quarter of 2013. The first recession period is assumed to represent the most acute phase at the onset of the Global Financial Crisis while the second recession period is assumed to be representative of the subsequent European Sovereign Debt Crisis.

4.2.4 Political sentiment

In addition to the political risk measures, this thesis includes a sentiment measure to test the robustness of the empirical results. According to Hassan et al. (2019), any measure of risk faces a major challenge in that changes in the value of a risk measure are likely to be correlated with news which affect its conditional mean or the expected value, namely good or bad news. They posit that high values of overall firm-level political risk may be accompanied by good or bad sentiment regarding political events, in other words variation in the conditional mean of political risk. Hassan et al. argue that failing to consider this variation and the possibly different influence of positive and negative sentiment could introduce bias to the results.

Hassan et al. (2019) state that the political sentiment measure indicates the conditional mean of the political risk measure and describes whether the expected outcome of political risk is positive or negative. They construct the measure by calculating the number of political bigrams in a conference call transcript which are accompanied by words that are used describe positive or negative outcomes such as the words good and difficult. They further explain that the political sentiment measure takes on a more negative value if the discussion of political risk features a greater number of negative words and a more positive value in response to a larger share of positive words.

Political sentiment is calculated using as a modified version of Equation 11 presented as:

$$PSentiment_{it} = \sum_{b}^{B_{it}} \left(1[b \in \mathbb{P} \backslash \mathbb{N}] \times \frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}} \times \sum_{c=b-10}^{b+10} S(c) \right), \tag{12}$$

where

c = a single bigram

$S(c)$ = a function which takes on a value of 1 if bigram *c* is associated with positive sentiment, a value of -1 if bigram *c* is associated with negative sentiment and a value of 0 if bigram *c* is not related to any type of sentiment (Hassan et al., 2019).

Unlike the firm-level political risk measures, the political sentiment variable cannot be transformed into a natural logarithm form as it can take on negative values. However, the variable is approximately normally distributed to begin with and thus fit to be used in the original form. The variable is denoted as *PSentiment*.

4.2.5 Aggregate political risk

This thesis includes additional independent variables that proxy for aggregate political risk which are used in subsequent robustness tests. These additional variables consist of the US-based Economic Policy Uncertainty index, the European Economic Policy

Uncertainty index developed by Baker et al. (2016) and the Global Economic Policy Uncertainty index developed by Davis (2016).

Economic Policy Uncertainty index is a news-based index measure which is designed by Baker et al. (2016) to reflect uncertainty related to government economic policy in the US. They construct the measure by analyzing 10 leading newspapers in the United States and counting the number of articles which contain terms associated with the economy, uncertainty and government policy. The authors then scale the number of articles that fulfil the criteria to the total number of articles and average across all newspapers monthly. The resulting index value represents the proportional share of newspaper articles discussing economic policy uncertainty in each month.

European Economic Policy Uncertainty index is a measure which represents European-wide economic policy uncertainty by combining the country-level EPU indices for France, Germany, Italy, Spain, and the United Kingdom (Economic Policy Uncertainty, n.d. a). The country-level indices are built by Baker et al. (2016) using similar methodology as the utilized in the original EPU index and each of them analyzes two major newspapers in their respective country. The European-wide EPU index is averaged equally from 10 newspapers in total.

Global Economic Policy Uncertainty index is a measure which represents economic policy uncertainty on a global level by combining 21 country-level EPU indices built by Baker et al. (2016) and Davis (2016). The composition includes country-level indices for Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom and the United States (Economic Policy Uncertainty, n.d. b). The Global EPU index is formed by weighing the monthly value of each country-level EPU index by the gross domestic product of their respective country and averaging all the GDP-weighted indices together (Davis, 2016).

The original monthly EPU indices are transformed to a quarterly frequency determined as the arithmetic average of the monthly values throughout each quarter. In addition, the quarterly value is transformed into a natural logarithm format following Gulen and Ion (2016). The US EPU, European EPU and Global EPU variables are denoted as *ln(USEPU)*, *ln(EUEPU)* and *ln(GEPU)*, respectively.

4.3 Sample characteristics

The full sample utilized in this thesis includes 132 firms and consists of 3374 firm-quarter observations in total. The full list of firms included in the sample can be found in Appendix 1. Table 2 displays the composition of the sample grouped by industry. Industry groups are determined according to the Industry Classification Benchmark (ICB) classification for each firm which is obtained from Datastream.

Table 2. Sample composition and key variable characteristics by ICB industry.

ICB Industry	*Firms*	*Obs*	*Mean ln(CDS)*	*Mean ln(PRisk)*
Basic Materials	9	259	4.32	4.18
Consumer Discretionary	30	700	4.60	4.57
Consumer Staples	12	235	4.45	4.10
Energy	4	159	4.35	4.59
Financials	29	781	4.59	5.43
Health Care	9	323	3.89	4.67
Industrials	19	416	4.44	4.66
Telecommunications	7	197	4.41	4.17
Utilities	13	304	4.55	4.95

The ICB industry groups represented in the sample are Basic Materials, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Telecommunications and Utilities. The Consumer Discretionary and Financials industries stand out as the largest industry groups in the sample and consist of 30 and 29 firms, respectively. The industry groups with the least firms are Energy with 4 firms and Telecommunications with 7 firms. The limited availability of credit default swap spread and political risk data for European firms can be seen in large differences in sample sizes between each industry group.

Table 2 also displays the mean level of the credit default swap spread and the overall firm level political risk measure by industry. The values for the two key variables are presented in natural logarithm form. Financial firms have the highest values for the overall firm-level political risk on average whereas for other industries the mean levels are relatively similar. The mean levels of credit default swap spreads are distributed uniformly across industries, apart from health care firms which have smaller mean spreads.

Figure 2 displays the development of credit default swap spread and overall firm-level political risk throughout the sample period from the first quarter of 2008 to the second quarter of 2019. The variables are displayed in the natural logarithm form and measured as the mean value across all firms in the sample in each quarter. It is evident that credit default swap spreads spiked extremely high in 2008 which reflects the onset Global Financial Crisis as well as a second elevated period from 2011 to 2013 during the European Sovereign Debt Crisis. The aggregated credit default swap spreads of the sample exhibit a distinct downward trend beginning in early 2013 which last up until the end of the sample period, indicating that credit risk is significantly lower in the post-crisis period.

The development of firm-level political risk mirrors the movements in credit default swap spreads relatively well throughout the recession periods and up until early 2013. However, after the first quarter of 2013 it does not feature a similar downward trend as credit default swap spreads but instead continues at roughly the same level for the rest of the sample period. There is a small period of heightened overall firm-level political risk from 2015 to early 2017 during which credit default swap spreads seem to increase accordingly.

The spike in political risk that is perceived across multiple firms could be related to the run-up and eventual fallout of Brexit, which refers to the decision by the United Kingdom to withdraw from the European Union following a referendum vote that took place in the second quarter of 2016.

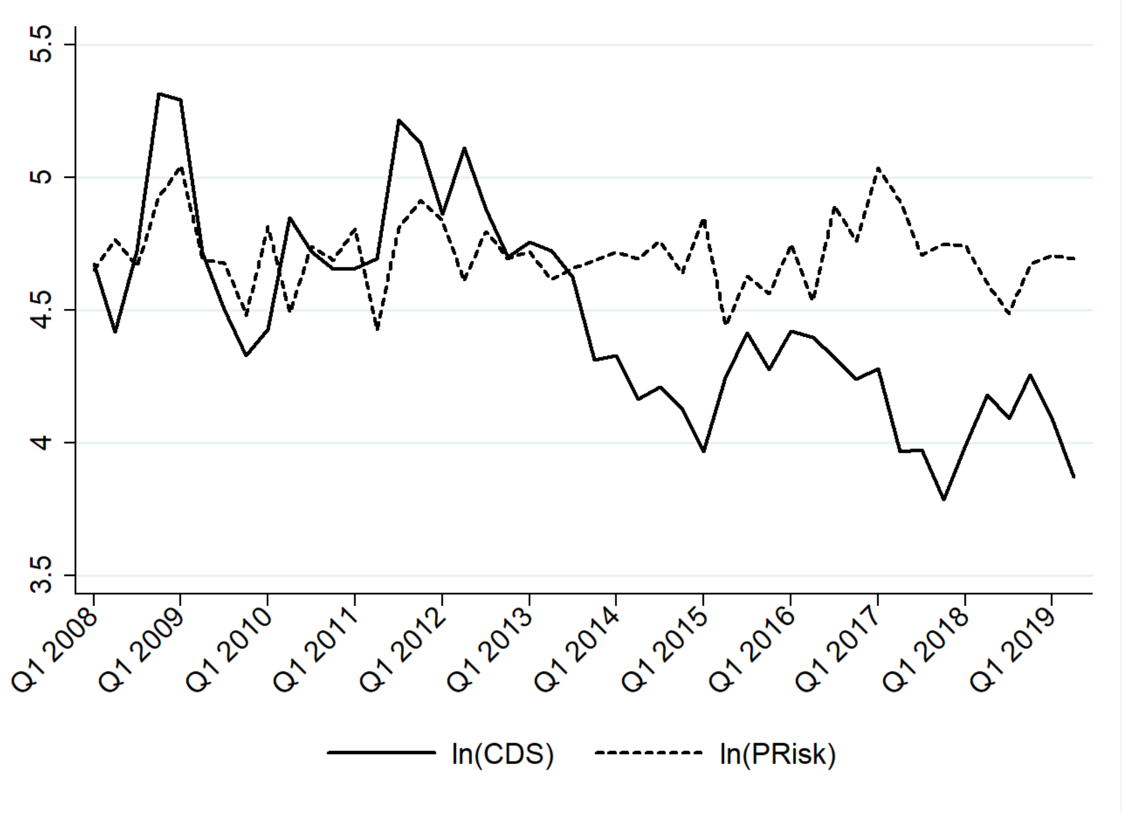

Figure 2. Development of the mean credit default swap spread and mean overall firm-level political risk over time.

4.4 Descriptive statistics

Table 3 presents the descriptive statistics for all the variables used in this thesis. The descriptive statistics are calculated based on the full sample consisting of 3374 firm-quarter observations for each variable from the first quarter of 2008 to the second quarter of 2019.

Skewness and kurtosis are important concepts to consider in the interpretation of descriptive statistics. Skewness measures how symmetrical the distribution of values is compared to a normal distribution and describes whether the values tend to be more frequently positive or negative (Hair et al., 2014, p. 33). The presence of excessive peaks or alternatively abnormal flatness in the distribution compared to a normal distribution is measured with kurtosis (Hair et al., 2014, p. 34).

Table 3. Descriptive statistics for the full sample.

Variable	*Mean*	*St.dev*	*Min*	*Max*	*Skewness*	*Kurtosis*	*J-B*
ln(CDS)	4.45	0.66	3.09	6.40	0.48	3.13	119.71*
ln(PRisk)	4.74	1.10	0.93	6.92	-0.47	2.99	115.24*
ln(PRiskEconomic)	8.17	1.08	3.14	10.43	-0.44	3.34	112.03*
ln(PRiskTrade)	7.66	1.23	1.58	10.32	-0.58	3.91	224.99*
ln(PRiskEnvironment)	8.08	1.14	1.54	10.54	-0.43	3.51	119.83*
ln(PRiskInstitutions)	7.61	1.12	0.48	10.08	-0.51	4.06	205.33*
ln(PRiskHealth)	7.94	1.10	3.41	10.36	-0.45	3.32	116.93*
ln(PRiskSecurity)	8.11	1.08	2.05	10.58	-0.42	3.55	118.42*
ln(PRiskTax)	8.07	1.16	2.10	10.48	-0.56	3.85	208.04*
ln(PRiskTechnology)	7.69	1.15	1.16	10.08	-0.58	3.88	218.27*
EquityVol	0.29	0.13	0.14	0.85	1.94	7.84	1335.7*
Leverage	0.27	0.14	0.01	0.59	0.17	2.38	134.34*
ROA	0.01	0.02	-0.06	0.10	0.99	7.80	763.46*
ln(MTB)	0.50	0.78	-1.56	2.88	0.55	3.75	194.53*
ln(Size)	17.90	1.51	14.58	21.34	0.28	2.65	66.75*
MarketRet	0.01	0.17	-0.56	0.32	-0.97	4.05	451.73*
ln(MarketVol)	3.09	0.32	2.49	3.84	0.48	2.92	120.06*
RiskFree	0.57	1.25	-0.33	4.98	2.29	7.98	1538.51*
Spread	0.14	0.07	0.00	0.30	0.20	2.23	262.99*
Recession	0.22	0.42	0.00	1.00	1.32	2.75	610.14*
PSentiment	980.59	1170.14	-1952.38	4423.99	0.30	3.48	70.73*
ln(EUEPU)	5.20	0.27	4.50	5.86	-0.09	3.12	6.22*
ln(USEPU)	4.92	0.24	4.33	5.46	-0.12	2.82	12.56*
ln(GEPU)	4.96	0.28	4.49	5.59	0.54	2.51	233.13*

Notes: * indicates statistical significance at the 5% level.

Credit default swap spreads exhibit slightly positive skewness and the firm-level political risk variables show similarly mild negative skewness. Most of the firm and market-level independent control variables are positively skewed except for market returns. Equity volatility and the risk-free interest rate display the highest degree of skewness out of all the variables. Kurtosis is present in virtually all variables. The highest degree of kurtosis is displayed by equity volatility, the risk-free interest rate and return on assets.

The normality of the distribution can be further assessed with the Jarque-Bera test, which has the null hypothesis that the values of a given variable are normally distributed. As displayed in the last column in Table 3, the Jarque-Bera test rejects the hypothesis of normality for all variables presumably due to skewness and kurtosis present in the data. All variables are winsorized at the 1% and 99% levels to discard the influence of possible outlier values.

Pearson correlation coefficients between all the variables are computed in Table 4. The overall firm-level political risk measure and the topic-specific variants are all positively correlated with credit default swap spreads. The degree of correlation with credit default swap spreads does not vary much between the political risk measures. The topic-specific measures also exhibit high correlation with the overall measure and between each other with coefficients ranging from 0.73 to 0.90. This is suggestive that they are relatively similar in their information content, which is understandable as all of them are generated from the same discussion related to risk in and uncertainty in earnings calls albeit conditional on different topic-specific language.

Out of all the independent control variables, credit default swap spreads are most correlated with equity volatility which displays the largest positive correlation coefficient of 0.58. The second largest positive correlation coefficient of 0.43 is with implied market volatility. This is an expected result considering how equity volatility is a significant theoretical determinant of credit risk according to the Merton (1974) model. The control variables with the most significant negative correlation with credit default swap spreads are the market-to-book ratio and market returns which display correlation coefficients of -0.40 and -0.21, respectively. The negative correlation is also in line with their theoretically predicted signs.

Table 4. Pearson correlation coefficient matrix.

Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*	*(17)*	*(18)*	*(19)*	*(20)*	*(21)*	*(22)*	*(23)*	*(24)*
(1) ln(CDS)	1.00																							
(2) ln(PRisk)	0.11*	1.00																						
(3) ln(PRiskEconomic)	0.15*	0.83*	1.00																					
(4) ln(PRiskTrade)	0.12*	0.80*	0.88*	1.00																				
(5) ln(PRiskEnvironment)	0.10*	0.73*	0.79*	0.78*	1.00																			
(6) ln(PRiskInstitutions)	0.13*	0.80*	0.88*	0.84*	0.74*	1.00																		
(7) ln(PRiskHealth)	0.10*	0.81*	0.88*	0.85*	0.74*	0.86*	1.00																	
(8) ln(PRiskSecurity)	0.13*	0.83*	0.90*	0.89*	0.79*	0.88*	0.87*	1.00																
(9) ln(PRiskTax)	0.14*	0.78*	0.88*	0.82*	0.72*	0.82*	0.84*	0.83*	1.00															
(10) ln(PRiskTechnology)	0.12*	0.78*	0.86*	0.84*	0.75*	0.82*	0.82*	0.85*	0.79*	1.00														
(11) EquityVol	0.58*	0.16*	0.18*	0.14*	0.13*	0.17*	0.15*	0.15*	0.18*	0.13*	1.00													
(12) Leverage	0.16*	-0.08*	-0.07*	-0.06*	-0.04*	-0.08*	-0.07*	-0.07*	-0.07*	-0.05*	0.04*	1.00												
(13) ROA	-0.21*	-0.12*	-0.13*	-0.13*	-0.08*	-0.13*	-0.10*	-0.13*	-0.15*	-0.09*	-0.22*	0.10*	1.00											
(14) ln(MTB)	-0.40*	-0.21*	-0.23*	-0.22*	-0.17*	-0.22*	-0.18*	-0.21*	-0.24*	-0.17*	-0.37*	0.19*	0.49*	1.00										
(15) ln(Size)	-0.05*	0.30*	0.31*	0.30*	0.25*	0.30*	0.29*	0.29*	0.32*	0.25*	0.14*	-0.24*	-0.37*	-0.51*	1.00									
(16) MarketRet	-0.32*	-0.04*	-0.05*	-0.04*	-0.05*	-0.05*	-0.04*	-0.04*	-0.06*	-0.03	-0.37*	-0.05*	0.05*	0.12*	0.01	1.00								
(17) ln(MarketVol)	0.43*	0.01	0.04*	0.02	0.04*	0.03	0.02	0.02	0.03	0.02	0.44*	0.05*	-0.03	-0.09*	-0.06*	-0.58*	1.00							
(18) RiskFree	0.31*	0.01	0.04*	0.01	0.02	0.03	0.02	0.02	0.03	0.01	0.33*	0.04*	0.03	-0.01	-0.06*	-0.55*	0.61*	1.00						
(19) Spread	0.33*	0.03	0.06*	0.05*	0.02	0.06*	0.04*	0.05*	0.06*	0.05*	0.29*	0.09*	-0.06*	-0.14*	-0.02	0.12*	0.15*	-0.01	1.00					
(20) Recession	0.36*	0.03	0.06*	0.03*	0.05*	0.05*	0.04*	0.05*	0.07*	0.05*	0.36*	0.04*	-0.02	-0.09*	-0.05*	-0.48*	0.40*	0.49*	0.13*	1.00				
(21) PSentiment	-0.23*	-0.14*	-0.15*	-0.13*	-0.10*	-0.15*	-0.14*	-0.14*	-0.15*	-0.10*	-0.25*	0.06*	0.22*	0.29*	-0.19*	0.15*	-0.17*	-0.13*	-0.14*	-0.14*	1.00			
(22) ln(EUEPU)	-0.00	0.01	0.00	0.02	0.02	0.01	0.01	0.01	0.01	0.01	-0.20*	-0.03	-0.03	-0.05*	0.04*	0.04*	-0.14*	-0.46*	-0.22*	-0.05*	0.07*	1.00		
(23) ln(USEPU)	0.21*	0.04*	0.05*	0.04*	0.05*	0.04*	0.03	0.03	0.05*	0.04*	0.10*	0.01	-0.02	-0.10*	0.00	-0.26*	0.22*	0.02	-0.02	0.21*	-0.03	0.55*	1.00	
(24) ln(GEPU)	-0.04*	0.03*	0.02	0.04*	0.04*	0.02	0.02	0.02	0.03	0.03	-0.10*	-0.03	-0.03	-0.05*	0.04*	-0.14*	-0.18*	-0.34*	-0.29*	-0.02	0.08*	0.80*	0.32*	1.00

Notes: * indicates statistical significance at the 5% level.

5 Methodology

This chapter presents the methodology that is utilized to conduct the empirical part of this thesis. The main research objective of this thesis as presented in the first research hypothesis is to examine whether firm-level political risk has a positive effect on corporate credit default swap spreads.

This thesis utilizes panel data regression methodology to analyze the relationship between firm-level political risk and credit default swap spreads. Panel regressions are commonly used in prior literature regarding the determinants of credit default swap spreads such as Galil et al. (2014) and Pereira et al. (2018). Research specifically examining the effect of aggregate and firm-level political risk also feature a panel regression setting, for example Baker et al. (2016), Hassan et al. (2019), Pan et al. (2019) and Wang et al. (2019).

Panel regressions make it possible to take advantage of the cross-sectional and time series properties of the sample in panel data format. Panel data contains more variation than purely cross-sectional or time series data which reduces multicollinearity between variables and produces more informative results (Baltagi, 2005, p. 5). In addition, panel regression methodology allows to consider the effect of unobserved factors that vary either cross-sectionally across panel entities or over time (Baltagi, 2005, p. 4).

The basic form of a panel regression model can be presented as:

$$y_{it} = \alpha + X'_{it}\beta + u_{it}, \tag{13}$$

where

y_{it} = the dependent variable for entity i at time t

α = the constant

X'_{it} = observations of *K* independent variables for entity i at time t

β = the slope or estimated regression coefficient for K independent variables
u_{it} = the total error term (Baltagi, 2005, p. 11).

The total error term u_{it} in Equation 13 can utilize a two-way error component model presented as:

$$u_{it} = \mu_i + \lambda_t + \epsilon_{it}, \qquad (14)$$

where
μ_i = the unobserved panel entity-specific effect
λ_t = the unobserved time series effect
ϵ_{it} = idiosyncratic residual standard errors that are not attributed to μ_i and λ_t (Baltagi, 2005, p. 33).

The first two variables in the error term depict all unobserved factors which can explain variance in standard errors but are omitted from the regression model. The panel entity-specific effects λ_t are heterogenous across panel entities and remain constant over time whereas the time series effects λ_t are panel entity-invariant and vary over time (Baltagi, 2005, pp. 11, 33). Permanent firm characteristics and prevailing macroeconomic trends at different points in time are examples of the panel entity-specific and time series-specific effects, respectively (Baltagi, 2005, pp. 11, 33).

The regression estimates are biased if the unobserved effects are correlated with the independent variables. Panel regressions can take the influence of the unobserved effects into account by utilizing the fixed effects specification in which the unobserved effects are treated as fixed parameters that can be estimated as part of the regression model (Baltagi, 2005, p. 33). The idiosyncratic standard errors are assumed to be independently distributed and uncorrelated with the fixed effects (Baltagi, 2005, p. 33). The fixed effects specification cannot contain variables which are perfectly collinear with the chosen fixed effects including the overall constant or intercept which is panel entity-invariant (Wooldridge, 2012, p. 486).

The two-way fixed effects panel regression model can be then presented as:

$$y_{it} = X'_{it}\beta + \mu_i + \lambda_t + \epsilon_{it}. \tag{15}$$

The alternative to fixed effects is the random effects specification. The unobserved effects remain as part of the total error term in a random effects regression model and the specification is used when the unobserved effects are assumed to be uncorrelated with the independent variables (Wooldridge, 2012, p. 492).

5.1 Baseline regression model

The core methodology is built around a baseline regression model that is used to test the first research hypothesis. The baseline model is a two-way fixed effects panel regression model which includes multiple firm-level and market-level control variables. The format of the baseline model is inspired by the main model specifications used by Hassan et al. (2019) and Pan et al. (2019) which utilize fixed effects panel regressions and feature the firm-level political risk measure as the main independent variable of interest.

The baseline regression model is defined as:

$$\begin{aligned} ln(CDS_{it}) = {} & \beta_1 ln(PRisk_{it}) + \beta_2 EquityVol_{it} + \beta_3 Leverage_{it} \\ & + \beta_4 ln(Size_{it}) + \beta_5 ROA_{it} + \beta_6 ln(MTB_{it}) \\ & + \beta_7 MarketRet_{it} + \beta_8 ln(MarketVol_t) + \beta_9 RiskFree_t \\ & + \beta_{10} Spread_{it} + \beta_{11} Recession_t + \mu_i + \lambda_t + \varepsilon_{it}, \end{aligned} \tag{16}$$

where

$ln(CDS_{it})$ = the natural logarithm of the credit default swap spread

$ln(PRisk_{it})$ = the natural logarithm of the overall firm-level political measure

$EquityVol_{it}$ = annualized 250-day equity volatility

$Leverage_{it}$ = the leverage ratio

$ln(Size_{it})$ = the natural logarithm of book value of total assets

ROA_{it} = the return on assets ratio

$ln(MTB_{it})$ = the natural logarithm of the market-to-book ratio

$MarketRet_t$ = the 12-month equity market index return

$ln(MarketVol_t)$ = the natural logarithm of the VSTOXX implied market volatility index

$RiskFree_t$ = the three-month EURIBOR interest rate

$Spread_t$ = the yield spread between 2-year and 10-year maturity sovereign bonds

$Recession_t$ = the recession dummy

μ_i = firm fixed effects

λ_t = year fixed effects

ε_{it} = the idiosyncratic error term.

In the subsequent regression equations, the firm-level independent control variables are denoted as the vector *FIRM* and the market-level independent control variables are denoted as the vector *MARKET*.

Regarding time series-specific fixed effects, it is not possible to use quarter fixed effects because the baseline model includes quarterly market-level control variables which are panel entity-invariant. The market-level control variables would have to be omitted from the model as they are perfectly collinear with quarter fixed effects. Instead, year fixed effects are used to capture the unobserved effects which are correlated with the independent variables. This approach is akin to Pan et al. (2019) who used year dummies in their baseline regression model.

The choice of using a fixed effects specification over random effects can be further substantiated by utilizing the Hausman (1978) test which assesses whether there are statistically significant differences between the regression estimates obtained by time-varying independent variables when the fixed effects and random effects specifications are used. The null hypothesis of the Hausman test states that the unobserved effects are not correlated with the independent variables which implies that the fixed effects specification is not preferrable over random effects (Wooldridge, 2012, p. 496). Conducting the Hausman test on the baseline regression model results in a p-value of 0.0001. Therefore, the null hypothesis is rejected and the fixed effects specification is more appropriate to be used.

The relatively large number of independent control variables used in the baseline regression model may lead to an issue with multicollinearity which arises when two or more independent variables exhibit high levels of correlation with each other. The inclusion of highly correlated variables in a regression can result in erroneously inflated standard error estimates and thus reduce the statistical precision of regression estimates (Wooldridge, 2012, pp. 94–95).

A simple method to check for multicollinearity is to visually inspect the Pearson correlation coefficient matrix as presented in Table 4 in the previous chapter. The presence of correlation coefficients higher than 0.7 between two independent variables is generally considered to be indicative of alarming multicollinearity that can lead to biased regression estimates (Hair et al., 2014, p. 200). The largest positive correlation coefficient of 0.61 can be found between the control variables *ln(MarketVol)* and *RiskFree*, followed by the coefficient of 0.49 between *RiskFree* and *Recession*. The correlation coefficients for the control variables all fall under the 0.7 threshold. None of the control variables display significantly high correlations with the overall and topic-specific firm-level political risk measures.

The firm-level political risk measures are highly correlated between themselves and display coefficients higher than 0.7. However, their collinearity is not an issue as they are not to be used simultaneously in a regression. In conclusion, a visual inspection of the correlation matrix suggests that multicollinearity is not a major problem especially when higher correlation is limited to between control variables only.

Hair et al. (2014, p. 197) state that multicollinearity can also be expressed as the tolerance value, which is calculated by setting a specific independent variable as the dependent variable and regressing it on other independent variables in a model. They explain that the tolerance value reflects how much of the variation in a particular independent variable is left unexplained by other independent variables. Hair et al. further elaborate that an extension of tolerance is the variance inflation actor (VIF), which is calculated as the inverse of tolerance and used as a common numerical measure of multicollinearity.

VIF values larger than 10 are above a conventional cut-off threshold and signal that a specific independent variable faces estimation difficulties due to the presence of multicollinearity (Hair et al., 2014, p. 200). Table 5 displays the VIF values values for all of the independent variables included in the baseline regression model as well as their corresponding tolerance values. The independent variables attain VIF values which are considerably smaller than the threshold of 10, which confirms that they are not exposed to major issues caused by multicollinearity.

Table 5. Variance inflation factor and tolerance values for the independent variables included in the baseline regression model.

Variable	*VIF*	*1/VIF*
ln(PRisk)	1,12	0,89
EquityVol	1,67	0,60
Leverage	1,09	0,92
ROA	1,37	0,73
ln(MTB)	1,81	0,55
ln(Size)	1,54	0,65
MarketRet	1,99	0,50
ln(MarketVol)	2,06	0,49
Spread	1,28	0,78
RiskFree	1,95	0,51
Recession	1,53	0,65

The fixed effects specification is inefficient when the idiosyncratic standard errors are heteroscedastic and serially correlated. This issue can be alleviated by using clustered standard errors to obtain regression estimates which are robust even in the presence of heteroskedasticity and serial correlation in the panel data (Wooldridge, 2012, pp. 501, 483). Standard errors are clustered at the quarter and firm level in all regressions following the example of previous studies such as Pan et al. (2019) and Gulen and Ion (2016).

5.2 Additional regression models

The second, third and fourth research hypotheses are tested using additional regression models. The additional models are all based on the baseline regression model and further modified include either supplementary or alternative dependent and independent variables.

The second research hypothesis aims to evaluate whether firm-level political risk has a persistent effect on credit default swap spreads. The methodological approach utilized to achieve this objective follows Gulen and Ion (2016) who regress future levels of corporate investment on the level of the EPU index. To be more specific, they utilize multiple panel regression models where the dependent variable leads the independent variables by a specific number of quarters. The lag between the dependent and independent variables is grown incrementally between each regression model to test whether the effect persists for a longer duration.

To test whether the effect of firm-level political risk is persistent, the baseline regression model is modified to so that the dependent variable is the natural logarithm of the credit default swap spread at time $t + l$ where t is the initial period and l indicates how many quarters into the future the dependent variable is leading relative to the initial period t. The value of l ranges from 1 to 12. In other words, the dependent variable is the credit default swap spread that is leading the independent variables up to 12 quarters into the future.

The second regression model is defined as:

$$ln(CDS_{i,t+l}) = \beta_1 ln(PRisk_{it}) + y_1 FIRM_{it} + y_2 MARKET_t + \mu_i + \lambda_t + \varepsilon_{it}, \tag{17}$$

where

$ln(\mathrm{CDS}_{\mathrm{i,t+l}})$ = the natural logarithm of the future credit default swap spread.

The third research hypothesis aims to examine whether the effect of firm-level political risk on credit default swap spreads is heterogenous across different political topics. This objective is achieved by using a modified version of the baseline regression model where the main independent variable of interest is the natural logarithm of the topic-specific firm-level political risk measure *ln(PRiskTopic).*

The third regression model is defined as:

$$ln(CDS_{it}) = \beta_1 ln(PRiskTopic_{it}) + y_1 FIRM_{it} + y_2 MARKET_t + \mu_i + \lambda_t + \varepsilon_{it}, \tag{18}$$

where

$ln(PRiskTopic_{it})$ = the natural logarithm of the topic-specific firm-level political risk measure.

The fourth research hypothesis is aims to examine whether the effect of firm-level political risk is pronounced in politically sensitive industries. This objective is achieved by modifying the baseline regression model to include an interaction term between the firm-level political risk measure and an industry dummy variable. The methodological approach is inspired by Baker et al. (2016) and Wang et al. (2019) who utilized interaction terms between the EPU index and dummy variables denoting politically sensitive industries.

The industry dummy variable is set to have a value of one if firm *i* belongs to the ICB industry group denoted by the dummy and zero otherwise. Industry dummies are created for all industries represented in the sample. The interaction term between the firm-level political risk measure and the industry dummy will display any heterogeneity across different industries. A positive and statistically significant coefficient for the interaction term indicates that the effect of firm-level political risk is stronger for firms in a particular industry.

The fourth regression model is defined as:

$$\begin{aligned} ln(CDS_{it}) = {} & \beta_1 ln(PRisk_{it}) + \beta_2\, ln(PRisk) \times Industry_{it} \\ & + \beta_3 Industry_i + y_1 FIRM_{it} + y_2 MARKET_t \\ & + \mu_i + \lambda_t + \varepsilon_{it}, \end{aligned} \tag{19}$$

where

$ln(PRisk) \times \ Industry_{it}$ = the interaction term between firm-level political risk and the ICB industry dummy

$Industry_i$ = the ICB industry dummy.

In this thesis, the Finance, Health Care, Energy and Utilities industries are expected to be more reliant on government contracts or subjected to a greater regulatory burden which makes them sensitive to politics following the notion introduced in previous studies such as Baker et al. (2016) and Kaviani et al. (2020).

The industry dummy variable $Industry_t$ represents a permanent firm characteristic which does not change over time. Therefore, the industry dummies are dropped by default in the actual regressions due to their perfect collinearity with firm fixed effects. However, the interaction term $ln(PRisk) \times \ Industry_{it}$ is time-varying and appropriate to be used in conjunction with firm fixed effects.

6 Empirical results

The empirical results are presented and discussed in this chapter. The regression models introduced in the previous chapter are used to test the four research hypotheses posed by this thesis. This chapter also presents the results of additional tests which aim to assess the robustness of the main empirical findings obtained using the baseline regression model.

6.1 The effect of firm-level political risk on credit default swap spreads

The first research hypothesis examines whether firm-level political risk has a positive effect on credit default swap spreads. The research hypothesis is tested using the baseline regression model as defined in Equation 16. Table 6 presents the empirical results for four different model specifications of the baseline regression model which are incrementally more demanding regarding the inclusion of firm and market-level control variables.

The first model in column (1) of Table 6 includes natural logarithm of the overall firm-level political risk measure *ln(PRisk)* as the only explanatory variable and does not feature any control variables. The overall firm-level political risk variable *ln(PRisk)* has a positive coefficient (0.027) and attains statistical significance at the 5% level. The adjusted R-squared value displayed in column (1) is 69.5% with only one independent variable, which indicates that the majority of variance in credit default swap spreads is captured by the firm and year fixed effects. In other words, most of the variance in credit default swap spreads can be explained by permanent differences between firms and aggregate-level trend that varies over time across years in the sample.

The results in column (1) can be compared to Pan et al. (2019) who found that a model with firm fixed effects, year dummies and the overall firm-level political risk measure as the only independent variable can explain 59.7% and 73.5% of the variance in long-term debt and leverage ratios, respectively. They also documented that the firm-level political risk measure displays a statistically significant effect in regression models without fixed effects and control variables.

Table 6. Results for the baseline regression model estimating the effect of firm-level political risk on credit default swap spreads.

	ln(CDS)		
Variable	*(1)*	*(2)*	*(3)*
ln(PRisk)	0.027**	0.014**	0.012*
	(2.68)	(2.05)	(1.97)
EquityVol		1.961***	1.672***
		(8.41)	(7.47)
Leverage		0.715***	0.744***
		(3.58)	(3.81)
ROA		-2.566***	-2.664***
		(-3.66)	(-4.02)
ln(MTB)		-0.344***	-0.286***
		(-6.64)	(-6.80)
ln(Size)		-0.085	-0.075
		(-1.37)	(-1.26)
MarketRet			-0.245*
			(-1.82)
ln(MarketVol)			0.398***
			(4.54)
RiskFree			0.083
			(0.86)
Spread			-0.029
			(-0.07)
Recession			-0.009
			(-0.15)
Obs.	3374	3374	3374
Adj. R-sq	0.695	0.806	0.827
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the credit default swap spread. Robust standard errors are clustered at the firm and quarter level. T-statistics displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The firm-level independent control variables are added to the model specification in column (2), where *ln(PRisk)* remains statistically significant at the 5% level with a positive coefficient of 0.014. The inclusion of firm-level controls lowers the explanatory power of *ln(PRisk)* by a noticeable amount, as the size of the coefficient is roughly half the size compared to the coefficient displayed in column (1) without firm-level controls. The firm-level controls considerably improve the model's ability to explain variation in credit default swap spreads as the adjusted R-squared value in column (2) rises to 80.6%.

The full baseline regression model is formed in column (3) where both the firm-level and market-level independent control variables are included in the model specification. The adjusted R-squared value of the third model rises to 82.7%. However, the increase is relatively minor compared to the difference in explanatory power between the first and second model specifications. Market-level controls therefore explain only a small incremental amount of the variance in credit default swap spreads, although most of their explanatory power could already subsumed by year fixed effects. *ln(PRisk)* remains statistically significant in column (3) but the significance level drops to only 10%. In addition, the coefficient of *ln(PRisk)* (0.012) decreases by a minimal amount which implies that the inclusion of market-level controls does not greatly reduce the explanatory power of overall firm-level political risk.

Except for *ln(Size)*, all firm-level control variables are statistically significant. The only market-level control variables that display significant explanatory power are *MarketRet* which has a negative coefficient (-0.245) that is statistically significant at the 10% level and *ln(MarketVol)* which has positive coefficient (0.398) that is highly statistically significant at the 1% level. The coefficient signs displayed by most control variables follow theoretical predictions apart from *RiskFree* and *Recession*. The fact that most control variables follow their theoretical predictions is reassuring as it suggests that the full sample is to a certain extent comparable to data used in other studies.

Empirical results support the notion that firm-level political risk has a statistically significant effect positive effect on credit default swap spreads, which is not subsumed by firm and market-level controls nor unobserved fixed effects. The main takeaway from the results displayed by the full baseline regression model is that a 1% change in overall firm-level political risk is associated with a 0.012% increase in credit default swap spreads. It should be noted that the effect has limited economic significance. Using other log-transformed variables as comparison, a 1% increase in *ln(MarketVol)* and *ln(MTB)* are associated with a 0.398% increase and a -0.286% decrease in credit default swap spreads, respectively. Nonetheless, the evidence is enough to confirm the first research hypothesis as firm-level political risk has a positive effect on credit default swap spreads.

6.2 The persistent effect of firm-level political risk

The second research hypothesis examines whether firm-level political risk has a persistent effect on credit default swap spreads. The second hypothesis is tested using the second regression model as defined in Equation 17. Table 7 presents empirical results for twelve different model specifications of the second regression model. The dependent variable in the second model is the natural logarithm of the future credit default swap spread at time *t+l*. In the first model in column (1) the value of *l* is 1 so the model tests how each independent variable at the initial quarter *t* affects credit default swap spreads leading by *t+1* or one quarter into the future. The value of *l* is incrementally increased in each successive specification so in the second model in column (2) the dependent variable is leading by *t+2* or two quarters and so forth.

Table 7 shows that the effect of *ln(PRisk)* diminishes in the first and second quarters following the initial period as indicated by the smaller coefficient values and lack of statistical significance in columns (1) and (2). The model in column (3) shows that the strength of the effect picks up in the third future quarter in which the coefficient of *ln(PRisk)* is positive (0.015) and statistically significant at the 5% level. Although statistical significance is lost and the coefficients diminish slightly in the two subsequent quarters, the effect persists until six quarters into the future. The effect peaks in the sixth future quarter as seen in column (6) where the coefficient of *ln(PRisk)* reaches its highest value (0.020) and attains statistical significance at the 5% level. After the sixth future, the coefficient values display a downward trend and do not regain statistical significance.

The effect of firm-level political risk and how it develops over time is illustrated in Figure 3 where the coefficients of *ln(PRisk)* from each column in Table 7 and from the full baseline regression model in Table 6 for the initial quarter *t* are plotted along with their associated upper and lower bounds as determined by the 95% confidence interval.

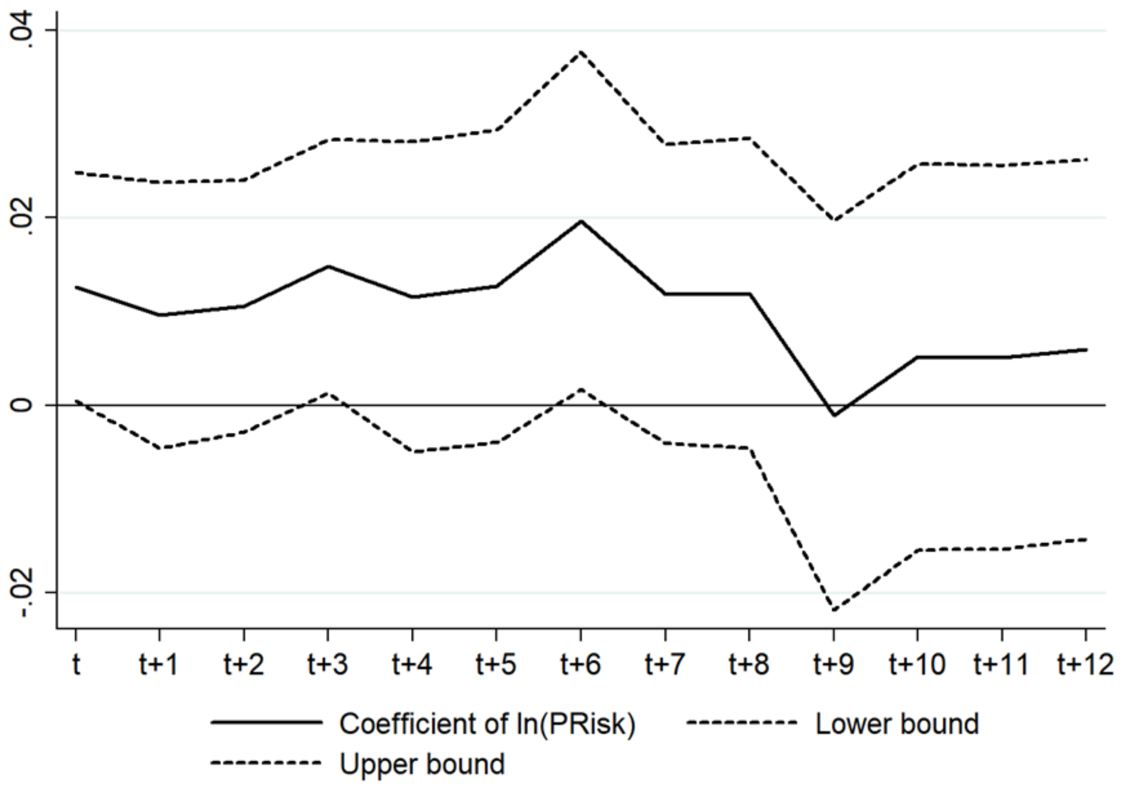

Figure 3. The persistence of the effect of firm-level political risk on credit default swap spreads.

Figure 3 depicts a persistent trend in which the effect of firm-level political risk is initially weaker one quarter into the future but grows gradually stronger until it reaches a peak in the sixth future quarter following the initial quarter *t*. The magnitude of the effect diminishes in the subsequent quarters. The full effect seems to be realized with a delay considering that the coefficient of *ln(PRisk)* is larger and more statistically significant when the dependent variable is the credit default swap spread three quarters or six quarters into the future compared to the baseline model which represents the initial quarter.

The lagged effect induced by firm-level political risk is in line with Pan et al. (2019) who presented results indicating that the negative effect of overall firm-level political risk on leverage ratios and long-term debt ratios is at its strongest five quarters into the future after the initial quarter. Similarly, Gulen and Ion (2016) documented that the negative effect of EPU shocks on future corporate investment peaks during the fifth quarter after the initial period, which leads to authors to declare that the influence of aggregate political risk is lagged. However, the results contradict Wang et al. (2019) who found that the positive effect of EPU on credit default swap spreads peaks immediately in the initial quarter. They still concluded that the influence of a shock to EPU in the initial quarter is persistent considering that the positive effect on future credit default swap spreads diminishes gradually during the subsequent eight quarters.

Regarding the longevity of the effect, Gulen and Ion (2016) noted that it can take up to two to three years in total for the level of corporate investment to recover back to normal after a positive shock to aggregate political risk. As mentioned previously in this thesis, a decline in investment growth carries negative implications for future corporate profit and credit risk (Abaidoo & Kwenin, 2013, p. 29; Wisniewski & Lambe, 2015, p. 454). Therefore, the investments channel could provide one possible explanation why firm-level political risk has a long-lasting influence on credit default swap spreads.

Taken together, the results suggest that overall firm-level political risk has a statistically significant and lagged positive effect on credit default swap spreads that persists for several quarters into the future. This empirical evidence is in line with a persistent effect which supports the confirmation of the second research hypothesis.

Table 7. Results for the second regression model estimating the persistent effect of firm-level political risk on credit default swap spreads.

	$\ln(CDS_{i,t+1})$	$\ln(CDS_{i,t+2})$	$\ln(CDS_{i,t+3})$	$\ln(CDS_{i,t+4})$	$\ln(CDS_{i,t+5})$	$\ln(CDS_{i,t+6})$	$\ln(CDS_{i,t+7})$	$\ln(CDS_{i,t+8})$	$\ln(CDS_{i,t+9})$	$\ln(CDS_{i,t+10})$	$\ln(CDS_{i,t+11})$	$\ln(CDS_{i,t+12})$
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
ln(PRisk)	0.009	0.010	0.015**	0.012	0.013	0.020**	0.011	0.012	-0.001	0.005	0.005	0.006
	(1.25)	(1.54)	(2.21)	(1.44)	(1.56)	(2.19)	(1.49)	(1.44)	(-0.10)	(0.48)	(0.48)	(0.59)
EquityVol	1.201***	0.668***	0.576**	0.652***	0.825***	0.766***	0.450*	0.441*	0.216	-0.141	-0.281	-0.164
	(5.16)	(2.73)	(2.64)	(3.47)	(4.24)	(3.49)	(1.79)	(1.89)	(0.93)	(-0.57)	(-1.17)	(-0.63)
Leverage	0.765***	0.648***	0.510*	0.364	0.261	0.119	0.069	0.033	0.069	-0.149	-0.126	-0.126
	(3.91)	(2.75)	(1.90)	(1.35)	(0.96)	(0.42)	(0.23)	(0.10)	(0.23)	(-0.50)	(-0.39)	(-0.35)
ROA	-2.316***	-1.983***	-1.859**	-1.085*	-1.579**	-1.607**	-1.184*	-0.338	0.938	0.281	-0.331	0.412
	(-3.42)	(-2.78)	(-2.65)	(-1.76)	(-2.17)	(-2.30)	(-1.77)	(-0.59)	(1.51)	(0.40)	(-0.45)	(0.50)
ln(MTB)	-0.255***	-0.211***	-0.156***	-0.101**	-0.048	0.002	0.029	0.045	0.045	0.0393	0.042	0.052
	(-5.89)	(-4.75)	(-3.62)	(-2.30)	(-0.98)	(0.05)	(0.58)	(0.85)	(0.80)	(0.71)	(0.78)	(0.90)
ln(Size)	0.002	0.076	0.051	0.070	0.095	0.151*	0.211**	0.225***	0.185**	0.253***	0.244***	0.267***
	(0.04)	(1.19)	(0.80)	(1.02)	(1.28)	(1.93)	(2.67)	(2.98)	(2.52)	(3.51)	(3.34)	(3.59)
MarketRet	-0.046	-0.232	-0.288*	-0.413**	-0.352**	-0.067	0.049	-0.025	-0.388**	-0.594***	-0.377**	-0.136
	(-0.30)	(-1.34)	(-1.71)	(-2.47)	(-2.27)	(-0.39)	(0.29)	(-0.17)	(-2.20)	(-3.42)	(-2.08)	(-0.75)
ln(MarketVol)	-0.147*	-0.414***	-0.225**	-0.388***	-0.303**	-0.052	-0.108	-0.119	-0.304***	-0.302***	0.008	0.030
	(-1.68)	(-5.46)	(-2.49)	(-4.70)	(-2.46)	(-0.57)	(-1.03)	(-1.26)	(-3.73)	(-2.94)	(0.12)	(0.29)
RiskFree	0.172*	-0.024	-0.049	0.046	0.110	-0.045	0.027	0.072	-0.017	-0.027	-0.196**	-0.240***
	(1.81)	(-0.24)	(-0.52)	(0.52)	(1.47)	(-0.63)	(0.37)	(0.97)	(-0.26)	(-0.34)	(-2.28)	(-3.13)
Spread	-0.378	-1.808***	-1.419***	-1.523***	-1.313***	-0.439	-0.838*	-1.304***	-0.377	-0.158	0.810**	0.807
	(-0.93)	(-4.60)	(-3.10)	(-3.76)	(-3.00)	(-0.89)	(-1.78)	(-3.21)	(-1.10)	(-0.43)	(2.06)	(1.58)
Recession	0.025	0.001	-0.182**	-0.283***	-0.127*	0.034	-0.052	-0.154**	-0.131***	-0.102*	-0.013	0.102
	(0.25)	(0.01)	(-2.55)	(-5.16)	(-2.01)	(0.73)	(-1.11)	(-2.34)	(-3.02)	(-1.86)	(-0.37)	(1.52)
Obs.	3253	3128	3010	2886	2768	2645	2533	2413	2293	2181	2076	1974
Adj. R-sq.	0.785	0.749	0.729	0.727	0.724	0.707	0.695	0.716	0.732	0.734	0.738	0.749
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the future credit default swap spread at time t+l. Each column represents a different specification of the second regression model per Equation 17 with incremental values of l. Robust standard errors are clustered at the firm and quarter level. T-statistics displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

6.3 The effect of topic-specific firm-level political risk

The third research hypothesis examines whether the effect of firm-level political risk on credit default swap spreads varies between political topics. The third hypothesis is tested using the third regression model defined in Equation 18 which features the topic-specific firm-level political risk measure as the main independent variable of interest. The empirical results are presented in Table 8 which includes eight different model specifications of the third regression model so that each variant of the topic-specific political risk measure has a separate model.

Table 8 displays that all eight topic-specific political risk measures are statistically significant and obtain positive coefficients. The Economic policy & Budget topic has the largest positive coefficient of 0.020 and is closely followed by the Environment topic with a coefficient of 0.018. The topics with the weakest effects are Technology & Infrastructure and Trade which have positive coefficients of 0.014 and 0.012, respectively. The Economic policy & Budget, Environment, Health and Tax topics are highly statistically significant at the 1% level. The remaining topics Trade, Institutions & Political process, Security & Defense and Technology & Infrastructure are statistically significant at the 5% level.

Interestingly, almost all topic-specific variants display both a slightly larger coefficient and a higher level of statistical significance compared to the overall firm-level political risk measure in the full baseline regression model in Table 3 which has a coefficient of 0.012 that is statistically significant at the 10% level. The only exception is the Trade topic which has an approximately similar coefficient in size but is more statistically significant at the 5% level.

The statistical significance attained by all eight topic-specific measures can be compared to Hassan et al. (2019) who reported a significant positive relationship between the topic-specific firm-level political risk and corporate lobbying expenditures related to the same topic in the following quarter. To be more specific, the authors conduct a fixed effects panel regression in which all the topic-specific measures are combined into a single explanatory variable and future lobbying expenditures categorized by topic serve as the dependent variable. The positive relationship remains statistically significant at the 1% level when the interaction term between firm and topic is used as fixed effects, therefore focusing only on the variation within firms and topics. Their finding implies that topic-specific firm-level political risk is statistically significant even when unobserved differences between political topics are considered, which is in line with the results displayed in Table 8 where every topic-specific variant is statistically significant at the conventional levels.

Table 8. Results for the third regression model estimating the effect of topic-specific firm-level political risk on credit default swap spreads.

	ln(CDS)							
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
ln(PRiskEconomic)	0.020***							
	(2.84)							
ln(PRiskEnvironment)		0.018***						
		(2.83)						
ln(PRiskTrade)			0.012**					
			(2.36)					
ln(PRiskInstitutions)				0.013**				
				(2.29)				
ln(PRiskHealth)					0.016***			
					(2.71)			
ln(PRiskSecurity)						0.015**		
						(2.28)		
ln(PRiskTax)							0.016***	
							(2.73)	
ln(PRiskTechnology)								0.014**
								(2.31)
Obs.	3374	3374	3374	3374	3374	3374	3374	3374
Adj. R-sq.	0.828	0.827	0.827	0.827	0.827	0.827	0.827	0.827
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the credit default swap spread. Robust standard errors are clustered at the firm and quarter level. T-statistics displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The finding that the Economic policy & Budget topic is ranked highest in terms of the coefficient size is not surprising considering that it is related to the type of economic policy uncertainty that is also measured by the EPU index which has a significant positive effect on credit default swap spreads (see e.g., Wang et al., 2019; Wisniewski & Lambe, 2015).

Another comparison can be made to Hassan et al. (2019) who examined whether different political topics have heterogenous effects on corporate lobbying expenses by running individual regressions for each topic-specific variant as the main independent variable. Their results show that the Healthcare topic has by far the largest coefficient. However, they also report that the second and third largest coefficients are displayed by the Economic Policy & Budget and Environment topics, respectively. This result resembles their position in Table 8 as the two topic-specific measures with the largest coefficient values.

Contrasting results are presented by Pan et al. (2019) who found that the Tax topic does not exhibit a statistically significant effect on long-term debt ratios whereas only the Environment, Trade and Technology & Infrastructure topics exert statistically significant effects on leverage ratios. Their results also suggested that the Environment topic has only a moderate impact on long-term debt and leverage ratios relative to other topics and the effect of the Economic policy & Budget topic is either amongst the weakest or non-significant.

The empirical results indicate that firm-level political risk continues to exhibit a positive relationship with credit default swap spreads when examined on a more detailed level using different political topics. Reaching a conclusion regarding the third research hypothesis proves to be more challenging. It must be ultimately acknowledged that the sizes of the coefficients displayed by the different topic-specific variants in Table 8 do not vary by large margin. The relative difference in effect size is quite small even when comparing the Economic policy & Budget topic which has the largest coefficient (0.020) and the Trade topic which has the smallest coefficient (0.012) together. Both Hassan et al. (2019) and Pan et al. (2019) reported considerably larger variation in coefficient sizes between the topic-specific political risk measures. In contrast, the economic significance of the variation between topics as displayed in Table 8 is quite small.

Regarding the statistical precision of the coefficient estimates, half of the topic-specific political risk measures are highly statistically significant at the 1% level and the other half are significant at the 5% level. The result can be interpreted to mean that for some political topics the observed positive effect on credit default swap spreads is less likely to have been caused by pure chance compared to other topics. Nevertheless, all topic-specific measures are statistically significant at the conventional levels. The overall results do not support the notion that firm-level political risk measures associated with different political topics have considerably heterogenous effects on credit default swap spreads. Accordingly, the third research hypothesis is not confirmed due to the lack of substantial evidence.

6.4 The effect of firm-level political risk in politically sensitive industries

The fourth research hypothesis states that the impact of firm-level political risk on credit default swaps is pronounced for firms in politically sensitive industries. The hypothesis is tested using the fourth regression model as defined in Equation 19 which features interaction terms between the overall firm-level political risk measure and industry dummy variables. The empirical results are displayed in Table 9 which includes nine different specifications of the fourth regression model so that each industry interaction term has a separate model.

It is evident from the empirical results displayed in Table 9 that firms belonging to the industries which are epected to be more politically sensitive do not exhibit statistically significant interactions with firm-level political risk. The interaction terms *ln(PRisk) × Financials*, *ln(PRisk) × Health* and *ln(PRisk) × Utilities* do not achieve statistical significance. Although the interaction term *ln(PRisk) × Utilities* has the highest positive coefficient

(0.030) out of all the industry interaction terms, the result is only indicative as it fails attain statistical significance.

Table 9. Results for the fourth regression model estimating the effect of firm-level political risk on credit default swap spreads in different industries.

	ln(CDS)								
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
ln(PRisk)	0.012*	0.017**	0.010	0.011*	0.013*	0.010	0.011*	0.012*	0.013**
	(1.90)	(2.31)	(1.61)	(1.74)	(1.99)	(1.37)	(1.82)	(1.84)	(2.26)
ln(PRisk) × Financials	0.002								
	(0.13)								
ln(PRisk) × ConsDisc		-0.026*							
		(-1.74)							
ln(PRisk) × ConsStap			0.021						
			(1.07)						
ln(PRisk) × BasicMat				0.011					
				(1.25)					
ln(PRisk) × Industrials					-0.011				
					(-0.82)				
ln(PRisk) × Utilities						0.030			
						(1.47)			
ln(PRisk) × Health							0.010		
							(0.34)		
ln(PRisk) × Telecom								0.003	
								(0.24)	
ln(PRisk) × Energy									-0.026
									(-1.08)
Obs.	3374	3374	3374	3374	3374	3374	3374	3374	3374
Adj. R-sq.	0.898	0.836	0.819	0.761	0.819	0.846	0.804	0.888	0.801
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the credit default swap spread. T-statistics in parentheses. Robust standard errors are clustered by firm and quarter. Statistical significance at the 10%, 5% and 1% levels are denoted as *, ** and ***, respectively.

Interestingly, only the Consumer Discretionary industry exhibits signs of a significant interaction. The *ln(PRisk) × ConsDisc* interaction term is statistically significant at the 1% level and obtains a negative coefficient of -0.026. The negative interaction term can be interpreted to mean that the relationship between firm-level political risk and credit default swap spreads is either negative or becomes weaker when the Consumer

Discretionary dummy has a positive value. In other words, the results suggest that the effect that firm-level political risk has on credit default swap spreads is less pronounced for firms in the Consumer Discretionary industry. This finding could be explained by the characteristics of that particular industry. Hassan et al. (2019) noted that firms in the retail trade industry have the smallest mean values of firm-level political risk. They argue that consumer retail firms are among the least dependent on government spending and do not face significant regulatory burdens.

Overall, the evidence purported by the regression estimates in Table 9 does not confirm the existence of a statistically significant interaction between overall firm-level political risk and credit default swap spreads of firms in politically sensitive industries. Therefore, the fourth hypothesis is rejected.

There are several factors which may explain the lack of statistical significance for the interaction terms. One reason could be the relatively small sample sizes, considering that the number of observations for a single industry group range from 781 firm-quarter observations for Financials to 159 observations for Energy. In comparison, the full sample utilized in the main regression contains 3374 firm-quarter observations. Larger sample sizes provide more statistical power to regressions and help in attaining accurate regression estimates. Accordingly, the possibility of obtaining statistically significant results decreases as the sample size gets smaller. The variation in coefficient sizes between the interaction terms and the existence of both positive and negative signs could also be caused by the sample size issue. The different sample sizes between industries as displayed in Table 2 could introduce bias by distorting the coefficient and standard error estimates.

Another reason could be related to the nature of overall firm-level political risk measure itself. Hassan et al. (2019) found that industry-sector fixed effects explain only 6.38% of the variation exhibited by the overall firm-level political risk measure in their full sample whereas firm fixed effects explain 91.69% of the variation. They argue that based on this decomposition it is evident that the variation in firm-level political risk is not related to industry-level trends or aggregate factors. In a sense, the non-significant results for the interaction terms in Table 9 support the conclusions by Hassan et al. (2019) where the overall firm-level political risk measure truly represents unique political risk exposure of individual firms which is not correlated across firms inside the same industry.

6.5 Robustness tests

Two additional tests are conducted to assess the robustness of the baseline results. The first set of robustness tests considers the influence of political sentiment, which describes the expected outcome of political risk. The second set of robustness tests aims to disentangle the effect of firm-level political risk from the influence of aggregate political risk.

6.5.1 Controlling for political sentiment

Hassan et al. (2019) assert that the discussion in a conference call regarding an issue which generates political risk can be accompanied by discussion of said issue in a positive or negative sentiment. They argue that the effect induced by firm-level political risk could be conditional on its expected outcome, compelling that the sentiment towards political risk should be controlled for. Table 10 displays the results for the robustness tests controlling for the political sentiment measure *PSentiment*. Following Hassan et al. (2019), the political sentiment measure is standardized by dividing the variable by its standard deviation. The standardized variable is more uniform in scale which eases the interpretation of the regression estimates.

The model in column (1) is the baseline regression model as defined in Equation 16 which includes *PSentiment* as an additional variable. The results show that *PSentiment i*s a reliable determinant of credit default swap spreads as it has a negative coefficient (-0.025) that is highly statistically significant at the 1% level. The negative coefficient implies that credit default swap spreads tend to decrease when firm-level political risk is associated with a more positive sentiment. The explanatory power of *ln(PRisk)* is not subsumed by the inclusion of *PSentiment* considering that *ln(PRisk)* remains statistically significant at the 10% level and displays a positive coefficient (0.12) that is similar in size as in the standard baseline model.

Table 10. Results for the robustness tests controlling for political sentiment.

	ln(CDS)	
Variable	*(1)*	*(2)*
ln(PRisk)	0.012*	0.003
	(1.77)	(0.39)
PSentiment (Standardized)	-0.025***	-0.064***
	(-2.79)	(-2.32)
ln(PRisk) × PSentiment (Standardized)		0.009
		(1.44)
Obs.	3374	3374
Adj. R-sq.	0.828	0.828
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes

Notes: The dependent variable is the natural logarithm of the credit default swap spread. Robust standard errors are clustered at the firm and quarter level. T-statistics displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The model in column (2) features the interaction term *ln(PRisk) × PSentiment* that is used to further assess whether the effect of firm-level political risk varies according to higher or lower values of *PSentiment*. The interaction term fails to attain statistical significance, suggesting that there is no discernible relationship between the effect of firm-level political risk and the value of the political sentiment measure. In other words, the effect on credit default swap spreads is not distinctly stronger or weaker when the sentiment towards firm-level political risk is either more positive or more negative.

According to the results, the positive relationship between firm-level political risk and credit default swap spreads is robust to controlling for differing political sentiment. There is no evidence that the effect induced by firm-level political risk is conditional on either positive or negative political sentiment. The results are in line with Hassan et al. (2019) who found that overall firm-level political risk has a statistically significant positive relationship with equity volatility and a negative relationship with corporate investment as well as employment growth after controlling for political sentiment. In addition, they did not find a significant interaction between firm-level political risk and political sentiment.

6.5.2 Controlling for aggregate political risk

The second set of robustness tests aims to ensure that the baseline results do not suffer from omitted variable bias induced by aggregate political risk. It can be reasoned that the observed effect of firm-level political risk could be caused by the credit default swap market responding to simultaneous aggregate political risk shocks. Pan et al. (2019) state that a portion of domestic aggregate political risk is likely to have originated from other countries due to increased cointegration and spillover effects in the financial markets. Accordingly, Table 11 presents results for the robustness tests where the European EPU index is assumed to proxy for aggregate political risk pertaining to the domestic European market whereas the US EPU and Global EPU indices proxy for aggregate political risk relating to foreign markets.

Table 11 features three models based on the baseline regression model in which the three different aggregate political risk measures have been added as additional variables. The results for the model in column (1) indicate that the baseline results are robust to aggregate political risk originating from the domestic European market. Firm-level political risk even seem to be complemented by the inclusion of *ln(EUEPU)* as *ln(PRisk)* attains statistical significance at the 5% level which is higher compared to the baseline model.

Controlling for aggregate political risk originating from the US and foreign markets on the global level only slightly reduces the explanatory power of firm-level political risk as *ln(PRisk)* has the coefficient value of 0.010 in both columns (2) and (3) where *ln(USEPU)* and *ln(GEPU)* are used as controls, respectively. The inclusion of *ln(GEPU)* causes a more substantial decline in the statistical precision of the coefficient estimate, although PRisk remains statistically significant at the 10% level. The presence of *ln(GEPU)* increases standard errors to the point where *ln(PRisk)* loses statistical significance altogether. However, the difference between controlling for US EPU and Global EPU is negligible in practice. The p-value for *ln(PRisk)* in column (2) is 0.099 whereas in column (3) the p-value is 0.1001, which is only barely over the threshold required to remain statistically significant at the 10% level.

Table 11. Results for the robustness tests controlling for aggregate political risk.

	ln(CDS)		
Variable	*(1)*	*(2)*	*(2)*
ln(PRisk)	0.012**	0.010*	0.010
	(2.09)	(1.68)	(1.68)
ln(EUEPU)	0.313***		
	(3.89)		
ln(USEPU)		0.326***	
		(3.28)	
ln(GEPU)			0.388***
			(4.27)
Obs.	3374	3374	3374
Adj. R-sq.	0.830	0.831	0.831
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the credit default swap spread. Robust standard errors are clustered at the firm and quarter level. T-statistics displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Overal, the results displayed in Table 11 suggest that the effect of firm-level political risk on credit default swap spreads is independent from the effect of aggregate political risk related to the domestic European market seeing that the European EPU has no discernible deteriorating effect on the regression estimates. The results are not as straightforward when aggregate political risk originating from foreign markets outside of Europe is considered. The effect is not completely subsumed by US EPU and Global EPU considering that controlling for either of the two variables only slightly reduces the explanatory power of firm-level political risk. However, the precision of the baseline results is somewhat weakened by the presence of the foreign market aggregate political risk variables which either reduce or completely eliminate the statistical significance of firm-level political risk. The loss of statistical significance for firm-level political risk when controlling for Global EPU could arise due to the variance inflation caused by including additional variables into the regression model, which inevitably increases the standard errors of the coefficient estimates.

The results are contrary to Pan et al. (2019) who documented that firm-level political risk remains statistically significant and has identical explanatory power over leverage and long-term debt ratios as in their base results when Global EPU is used as a control. In addition, Pan et al. found that the effect of Global EPU is insignificant whereas in Table 11 all three aggregate political risk variables are highly statistically significant at the 1% level and obtain coefficient estimates considerabily higher than firm-level political risk.

The greater significance of the foreign aggregate political risk variables could be related to the prior findings by Boutchkova et al. (2012) who argued that multinational firms are more exposed to non-diversifiable global political risk due to their greater dependency on foreign trade revenue. Conversely, multinational firms are less affected by domestic aggregate political risk. For example, Liu and Zhong (2017) found that the credit default swap spreads of firms which are more internationally diversified are less affected by political risk associated with national elections and Hill et al. (2019) presented results suggesting that that internationally diversified British firms are less exposed to domestic political risk induced by the Brexit referendum. The sample utilized in this thesis only includes firms that are listed on major European stock market indices which are more likely to be internationally diversified multinationals and therefore more exposed to foreign aggregate political risks on the global level.

7 Conclusions

This thesis analyzes the relationship between firm-level political risk and corporate credit default swap spreads in the European market. The research objective is accomplished by taking advantage of a novel measure of firm-level political risk developed by Hassan et al. (2019) and analyzing the credit default swap spreads of 132 European firms during the period from the first quarter of 2008 to the second quarter of 2019. The methodological approach is built around on a baseline panel regression model featuring firm-specific and market-level control variables to isolate the effect of various factors that are deemed to be determinants of credit default swap spreads. In addition, firm and time fixed effects are utilized to account for the influence of unobserved factors.

The first research hypothesis of this thesis proposes that firm-level political risk has a positive effect on credit default swap spreads. Empirical results conducted using the baseline regression model indicate that the firm-level political risk measure has a positive effect on credit default swap spreads which is statistically significant after controlling for firm-specific and market-level determinants of credit risk. The results imply that heightened firm-level political risk is linked to increased credit default swap spread levels, although the economic significance of the effect is relatively small. Therefore, the first research hypothesis is confirmed.

Robustness tests regarding the baseline results aim to disentangle the effect of firm-level political risk from the influence political sentiment and simultaneous aggregate political risk shocks which could be driving the observed behavior in the credit default swap markets. The findings imply that controlling for the expected outcome of political risk as described by political sentiment is inconsequential. Moreover, the effect induced by firm-level political risk does not change based on more positive or negative political sentiment. The explanatory power and statistical significance of firm-level political risk is not subsumed by aggregate political risk relating to the domestic European market. However, taking aggregate political risk associated with foreign markets also into consideration leads to weaker results. Controlling for global aggregate political risk renders firm-level political risk statistically insignificant, although the coefficient estimate is not greatly affected.

Subsequent empirical tests are conducted to further assess the characteristics of firm-level political risk. The second research hypothesis states that firm-level political risk has a persistent effect on credit default swap spreads. The full effect of firm-level political risk is realized with a delay considering that both the statistical significance and the strength of the effect are at their highest when examining credit default swap spreads four and six quarters into the future compared to the immediate effect in the initial quarter. The results suggest that the positive effect of firm-level political risk can persist for up to six quarters after an initial shock before displaying signs of diminishing, which is supportive of persistence and leads to confirming the second research hypothesis.

The topic-specific variants of the firm-level political risk measure are utilized to test the third research hypothesis which posits that the effect on credit default swap spreads varies by topic. The empirical results are indicative of slight heterogeneity between the effects induced by different political topics. Political risks concerning government economic policy and environmental issues seem to invoke the strongest reaction. However, the variation in explanatory power across the topic-specific political risk measures is quite small which makes it challenging to assert with confidence that the effect differs substantially by topic. All eight topics-specific measures are statistically significant as well. Considering the arguably negligible statistical and economic differences between topics, the third research hypothesis is rejected.

The fourth and final research hypothesis assumes that the effect of firm-level political risk is pronounced for firms in industries that are deemed to be sensitive to politics according to prior literature. The results show that none of the politically sensitive Financials, Utilities and Healthcare industries exhibit statistically significant interactions with firm-level political risk. Interestingly, the only statistically significant result is the negative interaction displayed by the Consumer Discretionary industry, which suggests that the credit default swap spreads of firms operating in that industry are less affected by firm-level political risk. Although the results could be indicative towards some level of heterogeneity across industries, the fourth hypothesis concerning politically sensitive industries is rejected as it is not supported by empirical evidence.

As stated by Hassan et al. (2019), the firm-level political risk measure could be subject to a degree of differential measurement error even though the authors conduct a multiple validation tests to check against this possibility. The novelty of the firm-level political risk measure means that its validity as a proxy for political risk is not yet backed by the consensus of subsequent studies such as is the case with the EPU index by Baker et al. (2016). This means that the results obtained in this thesis must be interpreted using individual judgement. The relatively small number of firms included in the sample sets another inherent limitation. The empirical results presented in this thesis could suffer from bias caused by the small sample size utilized in the empirical tests. The sample size bias could have particularly substantial implications for testing the fourth research hypothesis.

This analysis should be repeated with a larger dataset of credit default swap spreads in future research to mitigate the small sample size issue encountered in this study. In lieu of the industry-level interaction effects analyzed in this thesis, future research could examine interaction effects with other cross-sectional characteristics that prior studies have linked to heightened sensitivity to political risk such foreign trade dependency (Boutchkova et al., 2012), tax rates, external financing reliance, corporate lobbying (Kaviani et al., 2020) as well as the degree of investment irreversibility and credit ratings (Pan et al., 2019). Another interesting approach would be to extend the dataset with credit default swap spread data prior to 2008 to ascertain whether the effect of firm-level political risk was different during the period before the onset of the Global Financial Crisis compared to the crisis and post-crisis periods which are examined in this thesis.

A second suggestion would be to take advantage of the currently ongoing development of the firm-level political risk measure undertaken by Hassan et al. (2019). Notably, the authors of the original study have developed additional firm-level measures which specifically pertain to the risk and sentiment related to Brexit (Hassan, Hollander, van Lent & Tahoun, 2020) and the spread of epidemic diseases such as SARS, Ebola and COVID-19 (Hassan, Hollander, van Lent, Schwedeler & Tahoun, 2020). Analyzing the market response to these new topics would give further understanding of how politics and government actions affect credit default swap spreads and by extension the credit risk of individual companies.

References

Abaidoo, R., & Kwenin, D. O. (2013). Corporate profit growth, macroeconomic expectations and fiscal policy volatility. *International Journal of Economics and Finance*, 5(8), 25–38. https://doi.org/10.5539/ijef.v5n8p25

Acharya, V. V., Engle, R. F., Figlewski, S., Lynch, A. W., & Subrahmanyam, M. G. (2009). Centralized Clearing for Credit Derivatives. In V. V. Acharya & M. Richardson (Eds.), *Restoring Financial Stability: How to Repair a Failed System* (pp. 251–268). Wiley.

Annaert, J., De Ceuster, M., Van Roy, P., & Vespro, C. (2013). What determines euro area bank CDS spreads? *Journal of International Money and Finance, 32*(1), 444–461. https://doi.org/10.1016/j.jimonfin.2012.05.029

Ashraf, B. N., & Shen, Y. (2019). Economic policy uncertainty and banks' loan pricing. *Journal of Financial Stability, 44*, 100695. https://doi.org/10.1016/j.jfs.2019.100695

Augustin, P., Subrahmanyam, M. G., Tang, D. Y., & Wang, S. Q. (2016). Credit Default Swaps: Past, Present, and Future. *Annual Review of Financial Economics, 8*(1), 175–196. https://doi.org/10.1146/annurev-financial-121415-032806

Aunon-Nerin, D., Cossin, D., Hricko, T., & Huang, Z. (2002). *Exploring for the determinants of credit risk in credit default swap transaction data: Is fixed-income markets' information sufficient to evaluate credit risk?* (FAME Research Paper No. 65). International Center for Financial Asset Management and Engineering. https://dx.doi.org/10.2139/ssrn.375563

Backshall, T., Giesecke, K., & Goldberg, L. (2012). Credit-Risk Modeling. In F.J. Fabozzi & S.V. Mann (Eds.), *The Handbook of Fixed Income Securities* (8th ed.) (pp. 1025–1044). McGraw-Hill.

Bai, J., & Wu, L. (2016). Anchoring Credit Default Swap Spreads to Firm Fundamentals. *Journal of Financial and Quantitative Analysis*, 51(5), 1521–1543. https://doi.org/10.1017/S0022109016000533

Baker, S., Bloom, N., & Davis, S. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics, 131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Baltagi, B. H. (2005). *Econometric Analysis of Panel Data* (3rd ed.). John Wiley & Sons.

Bank for International Settlements. (2020, May 7). *Statistical release: OTC derivatives statistics at end-December 2019.* https://www.bis.org/publ/otc_hy2005.pdf

Baum, C. F., & Wan, C. (2010). Macroeconomic uncertainty and credit default swap spreads. *Applied Financial Economics, 20*(15), 1163–1171. https://doi.org/10.1080/09603101003781455

Bekaert, G., Harvey, C. R., Lundblad, C. T., & Siegel, S. (2014). Political risk spreads. *Journal of International Business Studies, 45*(4), 471–493. https://doi.org/10.1057/jibs.2014.4

Bekaert, G., & Hodrick, R. J. (2011). *International financial management* (2nd ed.). Pearson Education.

Benzschawel, T. (2012). *Credit risk modelling: Facts, theory and applications*. Risk Books.

Bernanke, B. S. (1983). Irreversibility, Uncertainty, and Cyclical Investment. *The Quarterly Journal of Economics, 98*(1), 85–106. https://doi.org/10.2307/1885568

Bialkowski, J., Gottschalk, K., & Wisniewski, T. P. (2008). Stock market volatility around national elections. *Journal of Banking and Finance, 32*(9), 1941–1953. https://doi.org/10.1016/j.jbankfin.2007.12.021

Black, F., & Cox, J. C. (1976). Valuing Corporate Securities: Some Effects of Bond Indenture Provisions. *The Journal of Finance, 31*(2), 351-367. https://doi.org/10.2307/2326607

Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy, 81*(3), 637–654. http://dx.doi.org/10.1086/260062

Blanco, R., Brennan, S., & Marsh, I. W. (2005). An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps. *The*

Journal of Finance, 60(5), 2255–2281. https://doi.org/10.1111/j.1540-6261.2005.00798.x

Bloom, N. (2014). Fluctuations in Uncertainty. *The Journal of Economic Perspectives, 28*(2), 153–175. https://doi.org/10.1257/jep.28.2.153

Bonaime, A., Gulen, H., & Ion, M. (2018). Does policy uncertainty affect mergers and acquisitions? *Journal of Financial Economics, 129*(3), 531–558. https://doi.org/10.1016/j.jfineco.2018.05.007

Bonfim, A. N. (2015). *Understanding Credit Derivatives and Related Instruments* (2nd ed.). Academic Press.

Boutchkova, M., Doshi, H., Durnev, A., & Molchanov, A. (2012). Precarious Politics and Return Volatility. *The Review of Financial Studies, 25*(4), 1111–1154. https://doi.org/10.1093/rfs/hhr100

Brogaard, J., & Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science, 61*(1), 3–18. https://doi.org/10.1287/mnsc.2014.2044

Callen, J. L., Livnat, J., & Segal, D. (2009). The Impact of Earnings on the Pricing of Credit Default Swaps. *The Accounting Review, 84*(5), 1363–1394. https://doi.org/10.2308/accr.2009.84.5.1363

Chacko, G., Sjöman, A., Motohashi, H., & Dessain, V. (2016). *Credit Derivatives: A Primer on Credit Risk, Modeling, and Instruments (*2nd ed.). Pearson Education.

Chan, K. C., & Chen, N.-F. (1991). Structural and Return Characteristics of Small and Large Firms. *The Journal of Finance, 46*(4), 1467–1484. https://doi.org/10.1111/j.1540-6261.1991.tb04626.x

Chen, R., Fabozzi, F. J., & O'Kane, D. (2013). Credit Default Swap Valuation. In F. J. Fabozzi (Ed.), *Encyclopedia of Financial Models Vol.I (*pp. 525–539). John Wiley & Sons.

Choudhry, M., & Lizzio, M. (2015). *Advanced Fixed Income Analysis* (2nd ed.). Butterworth-Heinemann.

Ciby, J. (2013). *Advanced credit risk analysis and management.* Wiley.

Corò, F., Dufour, A., & Varotto, S. (2013). Credit and liquidity components of corporate CDS spreads. *Journal of Banking and Finance, 37*(12), 5511–5525. https://doi.org/10.1016/j.jbankfin.2013.07.010

Crouhy, M., Galai, D., & Mark, R. M. (2014). *The essentials of risk management* (2nd ed). McGraw-Hill Education.

Das, S. R., Hanouna, P., & Sarin, A. (2009). Accounting-based versus market-based cross-sectional models of CDS spreads. *Journal of Banking and Finance, 33*(4), 719–730. https://doi.org/10.1016/j.jbankfin.2008.11.003

Dattatreya, R. F., Fabozzi, F. J., & Focardi, S. M. (2012). "Risks Associated With Investing In Fixed Income Securities". In F.J. Fabozzi & S.V. Mann (Eds.), *The Handbook of Fixed Income Securities* (8th ed.) (pp. 21–32). McGraw-Hill.

Davis, S. J. (2016). *An Index of Global Economic Policy Uncertainty* (NBER Working Paper No. 22740). National Bureau of Economic Research. https://doi.org/10.3386/w22740

Duffie, D., & Singleton, K. J. (2003). *Credit Risk: Pricing, Measurement, and Management*. Princeton University Press.

Economic Policy Uncertainty. (n.d. a). *Europe Monthly Index.* Policy Uncertainty. Retrieved December 12, 2020, from https://www.policyuncertainty.com/europe_monthly.html

Economic Policy Uncertainty. (n.d. b). *Global Economic Policy Uncertainty Index.* Policy Uncertainty. Retrieved December 12, 2020, from https://www.policyuncertainty.com/global_monthly.html

Elton, E. J., Gruber, M. J., Agrawal, D., & Mann, C. (2001). Explaining the rate spread on corporate bonds. *Journal of Finance, 56*(1), 247–277. https://doi.org/10.1111/0022-1082.00324

Ericsson, J., Jacobs, K., & Oviedo, R. (2009). The Determinants of Credit Default Swap Premia. *Journal of Financial and Quantitative Analysis, 44*(1), 109–132. https://doi.org/:10.1017/S0022109009090061

Euro Area Business Cycle Network. (n.d. a). *Chronology of Euro Area Business Cycles*. EABCN. Retrieved September 1, 2020, from https://eabcn.org/dc/chronology-euro-area-business-cycles

Euro Area Business Cycle Network. (n.d. b). *Recession indicators*. EABCN. Retrieved September 1, 2020, from https://eabcn.org/dc/recession-indicators

Fabozzi, F.J., Mann, S.V., & Cohen, A.B. (2012). "Corporate Bonds". In F.J. Fabozzi & S.V. Mann (Eds.), *The Handbook of Fixed Income Securities* (8th ed.) (pp. 259–286). McGraw-Hill.

Gad, M., Nikolaev, V. V., Tahoun, A., & van Lent, L. (2020). Firm-level Political Risk and Credit Markets. *SSRN Electronic Journal, 3395266*. https://doi.org/10.2139/ssrn.3395266

Galil, K., Shapir, O. M., Amiram, D., & Ben-Zion, U. (2014). The determinants of CDS spreads. *Journal of Banking and Finance, 41*, 271–282. https://doi.org/10.1016/j.jbankfin.2013.12.005

Gambetti, P., Gauthier, G., & Vrins, F. (2019). Recovery rates: Uncertainty certainly matters. *Journal of Banking and Finance, 106*, 371–383. https://doi.org/10.1016/j.jbankfin.2019.07.010

Gulen, H., & Ion, M. (2016). Policy uncertainty and corporate investment. *Review of Financial Studies, 29*(3), 523–564. https://doi.org/10.1093/rfs/hhv050

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate Data Analysis: Pearson New International Edition* (7th ed.). Pearson Education.

Hassan, T. A., Hollander, S., van Lent, L., & Tahoun, A. (2019). Firm-Level Political Risk: Measurement and Effects. *The Quarterly Journal of Economics, 134*(4), 2135–2202. https://doi.org/10.1093/qje/qjz021

Hassan, T. A., Hollander, S., van Lent, L., Schwedeler, M., & Tahoun, A. (2020). *Firm-level Exposure to Epidemic Diseases: COVID-19, SARS, and H1N1* (NBER Working Paper No. 26971). National Bureau of Economic Research. https://doi.org/10.3386/w26971

Hassan, T. A., Hollander, S., van Lent, L., & Tahoun, A. (2020). *The Global Impact of Brexit Uncertainty* (NBER Working Paper No. 26609). National Bureau of Economic Research. https://doi.org/10.3386/w26609

Hausman, J. A. (1978). Specification Tests in Econometrics. *Econometrica, 46*(6), 1251–1271. https://doi.org/10.2307/1913827

Hill, P., Korczak, A., & Korczak, P. (2019). Political uncertainty exposure of individual companies: The case of the Brexit referendum. *Journal of Banking and Finance, 100*, 58–76. https://doi.org/10.1016/j.jbankfin.2018.12.012

Hull, J. (2015). *Options, Futures, and Other Derivatives* (9th ed.). Pearson Education.

Hull, J., Predescu, M., & White, A. (2004). The relationship between credit default swap spreads, bond yields, and credit rating announcements. *Journal of Banking and Finance, 28*, 2789–2811. https://doi.org/10.1016/j.jbankfin.2004.06.010

Hull, J., & White, A. (2000). Valuing Credit Default Swaps I: No Counterparty Default Risk. *Journal of Derivatives, 8*(1), 29–40. https://doi.org/10.3905/jod.2000.319115

Jarrow, R. A., & Turnbull, S. M. (1995). Pricing Derivatives on Financial Securities Subject to Credit Risk. *The Journal of Finance, 50*(1), 53–85. https://doi.org/10.1111/j.1540-6261.1995.tb05167.x

Kaviani, M. S., Kryzanowski, L., Maleki, H., & Savor, P. (2020). Policy uncertainty and corporate credit spreads. *Journal of Financial Economics, 138*, 838–865. https://doi.org/10.1016/j.jfineco.2020.07.001

Li, J. & Born, J. A. (2006). Presidential election uncertainty and common stock returns in the United States. *Journal of Financial Research, 29*(4), 609–622. https://doi.org/10.1111/j.1475-6803.2006.00197.x

Liu, J., & Zhong, R. (2017). Political uncertainty and a firm's credit risk: Evidence from the international CDS market. *Journal of Financial Stability*, *30*, 53–66. https://doi.org/10.1016/j.jfs.2017.03.006

Longstaff, F. A., Mithal, S., & Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *Journal of Finance, 60*(5), 2213–2253. https://doi.org/10.1111/j.1540-6261.2005.00797.x

Mengle, D. (2007). Credit Derivatives: An Overview. *Economic Review, 92*(4), 1–24. https://www.frbatlanta.org/-/media/documents/research/publications/economic-review/2007/vol92no4_mengle.pdf

Merton, R. C. (1974). On the pricing of corporate debt: the risk structure of interest rates. *The Journal of Finance, 29*(2), 449–470. https://doi.org/10.1111/j.1540-6261.1974.tb03058.x

Niederhoffer, V., Gibbs, S., & Bullock, J. (1970). Presidential Elections and the Stock Market. *Financial Analysts Journal, 26*(2), 111–113. http://www.jstor.org/stable/4470664

Nodari, G. (2014). Financial regulation policy uncertainty and credit spreads in the US. *Journal of Macroeconomics, 41*, 122–132. https://doi.org/10.1016/j.jmacro.2014.05.006

Pan, W. F., Wang, X., & Yang, S. (2019). Debt maturity, leverage, and political uncertainty. *North American Journal of Economics and Finance, 50*(4), 100981. https://doi.org/10.1016/j.najef.2019.04.024

Pantzalis, C., Stangeland, D. A., & Turtle, H. J. (2000). Political elections and the resolution of uncertainty: The international evidence. *Journal of Banking and Finance, 24*, 1575–1604. https://doi.org/10.1016/S0378-4266(99)00093-X

Pástor, L., & Veronesi, P. (2012). Uncertainty about government policy and stock prices. *The Journal of Finance, 67(*4), 1219-1264. https://doi.org/10.1111/j.1540-6261.2012.01746.x

Pástor, L., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, *110*(3), 520–545. https://doi.org/10. 1016/j.jfineco.2013.08.007

Pereira, J., Sorwar, G., & Nurullah, M. (2018). What drives corporate CDS spreads? A comparison across US, UK and EU firms. *Journal of International Financial Markets, Institutions and Money, 56*, 188–200. https://doi.org/10.1016/j.intfin.2018.02.002

Riley, W. B., & Luksetich, W. A. (1980). The Market Prefers Republicans: Myth or Reality. *The Journal of Financial and Quantitative Analysis, 15*(3), 541–560. https://doi.org/10.2307/2330399

Rugman, A. M., & Collinson, S. (2009). *International Business* (5th ed.). Pearson Education.

Schönbucher, P. J. (2003). *Credit Derivatives Pricing Models*. Wiley.

Smales, L. A. (2017). "Brexit": A Case Study in the Relationship Between Political and Financial Market Uncertainty. *International Review of Finance, 17*(3), 451–459. https://doi.org/10.1111/irfi.12100

Stulz, R. M. (2010). Credit Default Swaps and the Credit Crisis. *The Journal of Economic Perspectives, 24*(1), 73–92. https://doi.org/10.1257/jep.24.1.73

van Deventer, D. R., Imai, K., & Mesler, M. (2013). *Advanced financial risk management: Tools and techniques for integrated credit risk and interest rate risk management* (2nd ed.). John Wiley & Sons Singapore.

Waisman, M., Ye, P. & Zhu, Y. (2015). The effect of political uncertainty on the cost of corporate debt. *Journal of Financial Stability, 16*, 106–117. https://doi.org/10.1016/j.jfs.2015.01.002

Wang, H., Zhou, H., & Zhou, Y. (2013). Credit default swap spreads and variance risk premia. *Journal of Banking and Finance,* 37(10), 3733–3746. https://doi.org/10.1016/j.jbankfin.2013.02.021

Wang, X., Xu, W., & Zhong, Z. (2019). Economic policy uncertainty, CDS spreads, and CDS liquidity provision. *Journal of Futures Markets*, *39*(4), 461–480. https://doi.org/10.1002/fut.21982

Wisniewski, T. P., & Lambe, J. B. (2015). Does economic policy uncertainty drive CDS spreads? *International Review of Financial Analysis*, 42, 447–458. https://doi.org/10.1016/j.irfa.2015.09.009

Wooldridge, J. M. (2012). *Introductory Econometrics: A Modern Approach* (5th ed.). Cengage Learning.

Yu, H., Fang, L., Du, D., & Yan, P. (2017). How EPU drives long-term industry beta. *Finance Research Letters, 22*, 249–258. https://doi.org/10.1016/j.frl.2017.05.012

Appendices

Appendix 1. List of all firms included in the full sample

Name	*Ticker*	*Country*	*ICB Industry*
3i Group PLC	III	UK	Financials
Accor SA	AC	France	Consumer Discretionary
Aegon NV	AGN	Netherlands	Financials
Air Liquide SA	AIR	France	Basic Materials
Akzo Nobel NV	AKZA	Netherlands	Basic Materials
Allianz SE	ALV	Germany	Financials
Alstom SA	ALOT	France	Industrials
Anglo American PLC	AAL	UK	Basic Materials
Assicurazioni Generali SpA	G	Italy	Financials
AstraZeneca PLC	AZN	UK	Health Care
Atlantia SpA	ATL	Italy	Industrials
Aviva PLC	AV.	UK	Financials
AXA SA	MIDI	France	Financials
BAE Systems PLC	BA.	UK	Industrials
Banco Comercial Portugues SA	BCP	Portugal	Financials
Bankinter SA	BKT	Spain	Financials
Barclays PLC	BARC	UK	Financials
BASF SE	BAS	Germany	Basic Materials
Bayer AG	BAYN	Germany	Health Care
Bayerische Motoren Werke AG	BMW	Germany	Consumer Discretionary
BNP Paribas SA	BNP	France	Financials
Bouygues SA	ENT	France	Industrials
BP PLC	BP.	UK	Energy
British American Tobacco PLC	BATS	UK	Consumer Staples
BT Group PLC	BT.A	UK	Telecommunications
Carrefour SA	CRFR	France	Consumer Staples
Casino Guichard Perrachon SA	CSO	France	Consumer Staples
Ceconomy AG	CEC	Germany	Consumer Discretionary
Centrica PLC	CNA	UK	Utilities
Clariant AG	CLN	Switzerland	Basic Materials
Commerzbank AG	CBK	Germany	Financials
Compagnie de Saint Gobain SA	SGO	France	Industrials
Compass Group PLC	CPG	UK	Consumer Discretionary
Continental AG	CON	Germany	Consumer Discretionary
Daily Mail and General Trust PLC	DMGT	UK	Consumer Discretionary
Daimler AG	DAI	Germany	Consumer Discretionary
Danone SA	BSN	France	Consumer Staples
Deutsche Bank AG	DBK	Germany	Financials

Deutsche Lufthansa AG	LHA	Germany	Consumer Discretionary
Deutsche Post AG	DPW	Germany	Industrials
Deutsche Telekom AG	DTE	Germany	Telecommunications
Diageo PLC	DGE	UK	Consumer Staples
E.ON SE	EOAN	Germany	Utilities
Edison SpA	EDNR	Italy	Utilities
EDP Energias de Portugal SA	ECP	Portugal	Utilities
EnBW AG	EBK	Germany	Utilities
Endesa SA	ELE	Spain	Utilities
Enel SpA	ENEL	Italy	Utilities
Engie SA	ENGI	France	Utilities
Eni SpA	ENI	Italy	Energy
Experian PLC	EXPN	UK	Industrials
Fresenius SE & Co KGaA	FRE	Germany	Health Care
GlaxoSmithKline PLC	GSK	UK	Health Care
Hannover Rueck SE	HNR1	Germany	Financials
Havas SA	HAV	France	Consumer Discretionary
HeidelbergCement AG	HEI	Germany	Industrials
Heineken NV	HB	Netherlands	Consumer Staples
Henkel AG & Co KgaA	HEN3	Germany	Consumer Discretionary
Iberdrola SA	IBE	Spain	Utilities
Imperial Brands PLC	IMB	UK	Consumer Staples
ING Groep NV	INGA	Netherlands	Financials
Intesa Sanpaolo SpA	ISP	Italy	Financials
ITV PLC	ITV	UK	Consumer Discretionary
J Sainsbury PLC	SBRY	UK	Consumer Staples
KBC Groep NV	KB	Belgium	Financials
Kering SA	KER	France	Consumer Discretionary
Kingfisher PLC	KGF	UK	Consumer Discretionary
Koninklijke DSM NV	DSM	Netherlands	Basic Materials
Koninklijke Philips NV	PHIL	Netherlands	Health Care
LafargeHolcim Ltd	LHN	Switzerland	Industrials
Lagardere SCA	MMB	France	Consumer Discretionary
LANXESS AG	LXS	Germany	Basic Materials
Legal & General Group PLC	LGEN	UK	Financials
Leonardo SpA	LDO	Italy	Industrials
Lloyds Banking Group PLC	LLOY	UK	Financials
L'Oreal SA	OR	France	Consumer Discretionary
LVMH SE	LVMH	France	Consumer Discretionary
Marks and Spencer Group PLC	MKS	UK	Consumer Discretionary
Mediobanca S.p.A.	MB	Italy	Financials
Merck KGaA	MRK	Germany	Health Care
Munich Re Group	MUV2	Germany	Financials
National Grid PLC	NG.	UK	Utilities

Natixis SA	KN	France	Financials
Naturgy Energy Group SA	CTG	Spain	Utilities
Nestle SA	NESN	Switzerland	Consumer Staples
Next PLC	NXT	UK	Consumer Discretionary
Novartis AG	NOVN	Switzerland	Health Care
Orange SA	ORA	France	Telecommunications
Pearson PLC	PSON	UK	Consumer Discretionary
Pernod Ricard SA	RCD	France	Consumer Staples
Peugeot SA	PGT	France	Consumer Discretionary
PostNL NV	PNL	Netherlands	Industrials
Prudential PLC	PRU	UK	Financials
Publicis Groupe SA	PUB	France	Consumer Discretionary
Rank Group PLC	RNK	UK	Consumer Discretionary
Relx PLC	REL	UK	Consumer Discretionary
Renault SA	RENU	France	Consumer Discretionary
Rentokil Initial PLC	RTO	UK	Industrials
Repsol SA	REP	Spain	Energy
Rio Tinto PLC	RIO	UK	Basic Materials
Roche Holding AG	ROG	Switzerland	Health Care
Rolls-Royce Holdings PLC	RR.	UK	Industrials
Royal Bank of Scotland Group PLC	RBS	UK	Financials
Sanofi SA	SQ	France	Health Care
Schneider Electric SE	QT	France	Industrials
Scor SE	SCO	France	Financials
Siemens AG	SIE	Germany	Industrials
Smiths Group PLC	SMIN	UK	Industrials
Societe Generale SA	SGE	France	Financials
Sodexo SA	SDX	France	Consumer Discretionary
Solvay SA	SOL	Belgium	Basic Materials
SSE PLC	SSE	UK	Utilities
Swiss Re AG	SREN	Switzerland	Financials
Swisscom AG	SCMN	Switzerland	Telecommunications
Tate & Lyle PLC	TATE	UK	Consumer Staples
Telefonica SA	TEF	Spain	Telecommunications
Telekom Austria AG	TKA	Austria	Telecommunications
Tesco Corp	TSCO	UK	Consumer Staples
Thales SA	CSF	France	Industrials
Total SA	TAL	France	Energy
UBS Group AG	UBSG	Switzerland	Financials
Unione di Banche Italiane SpA	UBI	Italy	Financials
United Utilities Group PLC	UU.	UK	Utilities
Valeo SA	FR	France	Consumer Discretionary
Vinci SA	DG	France	Industrials
Vivendi SA	EX	France	Consumer Discretionary

Vodafone Group PLC	VOD	UK	Telecommunications
Volkswagen AG	VOW3	Germany	Consumer Discretionary
Wendel SE	MF	France	Industrials
Wolters Kluwer NV	WSG	Netherlands	Consumer Discretionary
WPP PLC	WPP	UK	Consumer Discretionary
Zurich Insurance Group AG	ZURN	Switzerland	Financials
N	132		