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Master Thesis Financial Economics

Conflict Risk Pricing

Examining effects of international conflicts in the U.S stock market

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Abstract

This research paper takes a novel approach to assess the influence of perceived conflict risk in U.S. equity markets. A comprehensive set of conflict risk variables is created using a novel and rich dataset, GDELT. This paper indicates that conflict risk has no significant effect on the U.S. stock market returns. Different conflict risk severity predicts different effects on U.S. stock market volatility. This paper reports mixed results with respect to the relationship between conflict risk and the effects on U.S. stock market volatility. The cross-sectional analysis indicates that conflict risk is not priced, and investors are not to be compensated for this risk. These findings are overall robust for differing event specifications or event windows. This approach and use of dataset contribute to the literature because it adds a new comprehensive measure to examine conflict risk and examine investor behavior.

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1. INTRODUCTION

A fundamental question that has been left unanswered throughout the history of financial markets is why different assets show different returns. In the field of financial economics, this problem is an asset pricing puzzle that is also known as the equity premium puzzle. A second key asset pricing puzzle is the volatility puzzle. Standard global asset pricing models generally assume a complete integration of capital markets and offer an explanation that is based on the concept of risk. Keynes (1919) contributed to examining the relation between conflict and financial markets. His book spawned further research that explores the impact of conflict on financial markets.

The main idea of the risk-based explanation is whether a risk of conflict is a possible explanation for high return to compensate investors. This thesis takes multiple approaches to examine the relation between conflict risk and financial markets, including models that proxy for political uncertainty, fiscal risks, political stability, government military spending or actual war. The difficulty lies in establishing one standard for estimating conflict risk and examining financial economics puzzles.

This paper uses a novel and rich dataset, the global database of event language and tone (GDELT), to examine the relation between conflict risk and the U.S. stock markets. The literature points to the importance of the occurrence of major wars in stock markets and demonstrates that more severe conflicts cause stronger reactions in financial markets. Varying conflict severity can have different consequences for investor behavior.

In addition to the academic interest in this topic, institutions have also been developing a keen interest over the past decades. Previously, there was no room for political scientists at major multi-asset funds and banks such as J.P. Morgan and Citigroup (Wolzak 2018). Currently, large American banks are attracting high-level political analysts to examine political and conflict risk. These analysts` mission is to provide banks, insurers, and pension funds with valuable information on political, conflict-related and geopolitical risks.

This research aims to conduct a detailed examination of the relation between different severities of conflict risk and stock markets. This paper will present the different severities of conflict risk and examine their relation to stock market returns and stock market volatility. A natural question that arises is as follows:

Can a proxy for international conflict risk provide evidence that this risk is priced?

This field of research has an inherent problem from an empirical perspective. Large-scale conflicts are far and few in between. The infrequency provides an obstacle to obtaining the empirical evidence needed to examine the relation between international conflict risk and capital markets.

I delve into different strands of literature on political and conflict risk to examine and build on existing approaches to proxy for conflict risk. I avoid the small sample size problem by focusing on a larger sample that can proxy for different severities of conflict. I assume that publicly-available information is reflected in prices and that financial markets are forward-looking. I also assume that the differences in the probability of an event taking place will be translated into stock prices. This assumption allows me to examine the link between perceived conflict risk on one hand and stock market prices and volatility on the other.

I use a novel and rich dataset named GDELT to construct different perceived conflict risk variables and to avoid the small sample size problem. The GDELT is the largest open database of the human society that has been created. It is a platform that monitors the news media of the world in over 100 languages in broadcast and web formats. The GDELT dataset uses the Conflict and Mediation Event Observation (CAMEO) coding system. One of the major benefits of this coding system is the existence of EventRootCodes. The EventRootCode defines the root-level category that an event code falls under. For example, code 1051 "Demand easing of administrative sanctions" will fall under the EventRootCode 10 "Demand". This eases the aggregation of actions to a certain level. I can examine fine-grained amounts of data with this dataset. This paper will use the dataset to test different perceived conflict risk variables and their effects on stock markets. These news events will impact investor perspectives and serve as proxies for conflict risk as perceived by investors.

I will shed light on the academic results, which have been mixed thus far. I construct a monthly event count that measures conflict risk per proxy of related news for events involving the U.S. The GDELT and its CAMEO coding system allow me to examine a wide array of different conflict severities. These conflicts of differing severities events can have different impacts on the behavior of investors. Realized volatility for conflict risk is examined in a generalized autoregressive conditional heteroskedasticity (GARCH) framework. Finally, time-series predictive regressions and cross-sectional evidence are provided to examine the existence of conflict risk.

This research paper takes a novel approach to assess the influence of perceived conflict risk in U.S. equity markets. A comprehensive set of conflict risk variables is created using a novel and rich dataset, GDELT. This paper finds that conflict risk has no significant effect on the U.S. stock market returns. Different conflict risk severity predicts different effects on U.S. stock market volatility. This paper reports mixed results with respect to the relationship between conflict risk and the effects on U.S. stock market volatility. The cross-sectional analysis indicates that conflict risk is not priced, and investors are not to be compensated for this risk. These findings are overall robust for differing event specifications or event windows. This approach and use of dataset contribute to the literature because it adds a new comprehensive measure to examine conflict risk and investor behavior.

The remainder of this paper is structured as follows. First, I examine existing literature to argue the use of my proxies for perceived conflict risk. Next, I discuss the data that is needed to apply my approaches to the use of GDELT and to the U.S. stock market data. I then present a theoretical framework that describes how I examine the effects of perceived conflict risk. Subsequently, I interpret the empirical results that follow in the results section, Furthermore, I describe the robustness check I apply to examine the robustness of my results and conclude. I finish with my conclusions , research limitations and further research suggestions.

2. LITERATURE REVIEW

2.1 Background literature and special event risk

The literature had adopted multiple approaches to the construction of perceived conflict risk proxies. These different approaches are discussed here. I build upon existing approaches that I find in the literature to produce proxies for conflict risk. I elaborate on the existing approaches and explain how and to what degree I apply parts of them. This allows me to examine how and if perceived conflict risk is priced. This section describes relevant literature on the concept of risk and the effects of special event risk on financial markets.

Global asset pricing models stem from a similar starting point known as the capital asset pricing model (Sharpe, 1964). It uses a risk measure that relates the expected return of an asset to the excess return of the market to proxy for the exposure of this asset to market risk (Lintner, 1965; Black, 1972). Sharpe (1964) argue that dealing with the condition of risk is one of the main obstacles to predicting the behavior of capital markets in the absence of testing a positive microeconomic theory. A base assertion follows that a risk premium is determined, where the prices of assets adjust accordingly to account for the differences in their risk. The capital asset pricing model (CAPM) is the first to reveal the relationship between the price of an asset and a risk-based explanation for this price. The CAPM explains the risk-returns relation in terms of a required risk premium.

Fama and French expand upon this framework in a large part of their academic work. Most notably their paper on common risk factors (Fama and French, 1993). They test whether factors created by size and book-to-market equity (BE/ME) have explanatory power of the cross-section of average returns on New York Stock Exchange (NYSE), Amex and Nasdaq stocks in the sample period of 1963 to 1990. The small market capitalization stocks are riskier than their large counterparts, which indicates that size is a factor. Small companies are riskier than large market-capitalized companies, and therefore outperform larger companies. The value premium refers to the greater risk-adjusted return of value stock over growth stocks.

These results indicate the existence of a size premium and a value premium. The results stem from Fama and French`s construction of portfolios to mimic this size-related risk factor and the BE/ME factor. Their results indicate strong common variation in returns. They conclude that there is a size premium and a value premium on common stock returns in U.S. equity markets and that these factors explain many of the average stock returns in the cross-section. Despite their achievements in this field of study, Fama and French acknowledge that there is an open question that remains unanswered. They acknowledge that there is an option to identify state variables that can explain common variation in stock market returns that are independent of the market. Therefore, there may exist a factor that carries a different risk premium from the general market risk and explains the cross section of stock return in greater detail.

I will now review a strand of literature that explores such a factor regarding conflict risk and asset pricing. The relationship between different forms of conflict risk and asset pricing should help to solve the longstanding puzzle of explaining stock market returns and volatility. The first strand of literature focuses on the effect of rare disasters or special events on financial markets. The impact on financial markets due to market crashes that are caused by special events such as war or other rare disasters are explored in the following paper: (Mehra and Prescott, 1985; Rietz, 1988). Barro (2006) builds upon this framework by exploring the relation between major economic disasters and financial markets. He explains asset-pricing puzzles with the occurrence of a special event such as World War I, the Great Depression, and World War II. The author finds that realistic degrees of risk aversion amongst investors explain the observed equity premium. Berkman, Jacobsen and Lee (2011) follow up on this approach. They consider international political crisis that are likely to cause changes in perceived disaster probability.

The Barro-Rietz framework is expanded by Xavier Gabaix. Gabaix (2009) deducts meaningful results for cross-sectional and time-series variation for expected losses with respect to disasters. Wachter (2009) also expands on the Barro-Rietz framework by introducing a time-varying probability of special events. Her findings suggest that her model can find a high-equity premium and high volatility in the U.S. stock market while generating low means and volatility for the government bill rate.

The inherent problem that is faced by these rare disaster models is a small sample size. It is therefore key to avoid this problem to obtain unbiased parameters and accurate inferences. Berkman, Jacobsen and Lee (2011) bypass this problem by not researching the *actual* wars and instead only examine the probability of a special event such as a war or other rare disaster. I will apply this logic and framework to examine perceived levels of conflict risk and their relation to stock market returns and stock market volatility.

There is an absence of unambiguous research results on the relation between conflict risk or special events such as rare disaster and asset pricing. An undisputed single approach to test the effects of conflict risk on stock markets has yet to be established. Schneider and Troeger (2006) explain the contradictory findings regarding war and other major international conflicts. To illustrate, in 1990 the Dow Jones index plunged by 6.31% when Iraq decided to invade Kuwait. However, Operation Desert Storm, a major U.S. operation, followed the invasion and was accompanied by a 17% gain in the Dow Jones Index throughout the first 4 weeks. Schneider and Troeger (2006) attribute these findings to insufficient understanding of the true dynamic at play behind war and its relation to the economy. The authors ascribe this confusion to "mollifying rhetoric" by political leaders. This creates confusion of the interrelationship between war and the economy and the consequences of armed conflict.

Armed conflicts have considerable consequences. Cranna (1994) shows that impact of conflict on humans` lives, economic growth and the environment creates devastation. These findings contradict the effect of a conflict escalation on international stock markets: the Dow Jones index rose by 17% in 1990 after the first invasion of Iraq. The ambiguous findings might be due to the differences in the severity of the conflict. Another reason might be that the degree of uncertainty of a conflict is a key driver for effects on financial markets.

There is no single approach to measure levels of conflict risk. From a financial economist`s perspective, it is valuable to understand how investors prime their behavior when perceiving conflict risk and what premium they will require for this risk. I will explain the most prominent approaches to measuring conflict risk. I will then elaborate on the overlaps between these approaches and my chosen approach.

2.2 Event analysis and asset pricing: news event analysis approach

This strand of literature will review analysis of news events that are linked to asset pricing issues. This section begins with one of the first studies that explores the theoretical framework between news event and asset pricing (Niederhoffer, 1971). This study examines the broad relation between world events and movement in stock prices. This study also suggests applications that can be used in business research to measure meaning in news. The study classifies world events as relevant when the New York Times covers the subject with a headline that has five to eight columns. The events are classified in 20 categories of meaning. In addition, the events are classified on a seven-point good to bad scale. This approach examines the influence of relevant world events on stock prices. However, the study`s analysis lacks statistical power due to a small number of observations, dependence on the series of large price changes, and the occurrence of their categories.

Goldstein (1992) expands upon this framework. The authors provide a scale that can aggregate individual events to a time-series. The authors conclude that there is no documented set of conflict-cooperation weights for the WEIS (the precursor of CAMEO) event type. The author also demonstrates that detailed information can be aggregated to a workable conflict-cooperation scale. This information leads to a relatively fine-grained time-series that can be used to construct time-series statistics. This new scale makes the previous confusion and controversy over a conflict-cooperation scale superfluous. The scale is widely used in the literature on news event analysis and is present in the dataset of my choice. In addition, the Goldstein scale indicates the severity of an event.

Brune, Hens, Rieger and Wang (2015) extensively focus on news event analysis approaches. The researchers closely examine seemingly contradictory effects that war has on stock markets. The economic rationale behind investor reactions to increasing likelihood of war and actual war stems from underpricing and overpricing. Investors overreact to bad news of war, which leads to underpricing, and overreacts to good news of the end of a war, which leads to overpricing.

A proxy is needed to demonstrate the effects of these differing market reactions to changes in perceived conflict risk. The researchers apply a news event analysis approach that measures the likelihood of war and examine the Iraq war in 2003 for data availability reasons. The researcher uses two independent estimates for the probability that war could take place, which is an approach developed by Wolfer and Zitzewitz (2009). This allows the construction of their own proxy of war likelihood that is based on the news. The researches count how many articles each day`s issue of the New York Times contain the words "war" and "Iraq". The researchers regress the two measures (The Saddameter and their Saddam Security) on their news proxy to demonstrate the relation to the two independent measures of the likelihood of war. Their news variables are valid proxies for the level of conflict where alternative probability measures are available. I apply a similar approach in my paper to proxy for changes in perceived conflict risk in the U.S.

News analysis is inevitably accompanied by the problem of increasing online reporting in the data generating process, which can lead to biased results. Azzimonti (2018) tackles this problem by scaling her raw news conflict count according to the total number of articles in the same month. She investigates political discord and its effects on private investments by constructing a news conflict index. The findings indicate a negative relationship between news index and the aggregate levels of investments in the U.S. This paper intersects two different strands of literature: news event studies and political risk studies. I build upon the approaches as put forth by Azzimonti (2018) and Berkman et al. (2011) to overcome respectively the problems inherent with increasing amount of data and a too small sample size.

My approach sets itself apart from existing literature by conducting a broader examination of perceived conflict risk. The use of a novel and rich dataset in the form of GDELT allows me to construct more fine-grained perceived conflict risk variables. This enables me to deeply examine the relation between changes in perceived conflict risk on one hand and stock market returns and volatility on the other.

Berkman et al (2011) argue that not every crisis is similar. The severity of crises fluctuates, and the more severe a conflict, the stronger the expected market reaction. They apply a dummy variable to indicate a "start" phase, a "during" phase and an "end" of a conflict. The subcategories they examine are, "violence," "violence used during crises," "full-scale war," "gravity of value threat," "part of protracted conflict, ""Use of great power," and "the use of superpower involvement."

My approach distinguishes itself from the Berkman et al. (2011) approach and expands it by examining more fine-grained information in the changes of perceived conflict risk probability. The (GDELT) builds upon the WEIS framework with a CAMEO coding system. This allows me to use EventRootCodes to more closely examine certain events that influence the probability of major conflict or crises. For the sake of completeness, I will outline the last strand of literature with respect to conflict risk, political disaster risk models and policy uncertainty.

2.3 Political uncertainty and political risk models

The last strand of literature that I will discuss relates to political risk models and policy uncertainty models. Both concepts are grouped together because they cover the political perspective of conflict risk. The importance of this approach stems from how concerns about policy uncertainty have intensified the global financial crisis, for example. Uncertainty with respect to political policy gave rise to increasing crises in the Eurozone and was a catalyst for partisan policy conflict in the U.S. The international Monetary Fund (IMF) states that uncertainty about fiscal, monetary and regulatory policy led to a decline in the recovery from the global financial crisis from 2008-2009.

Pastor and Veronesi (2012) emphasize the importance of uncertainty of government policies and stock prices. They interpret policy changes broadly and examine government actions that changes the economic environment. Governments might change their policy any time, and this policy change is a moment when previously held beliefs are replaced with a new set of beliefs. The government has two broad incentives for policy change: maximize overall welfare and cover political costs that are incurred during policy change. These costs are now known to investors and they cannot deal with them accordingly, which leads to uncertainty. The political part of the standard deviation of this cost is labelled “political uncertainty”.

Pastor and Veronesi`s findings suggest that average stock prices will fall if policy change is announced. Most actual policy changes are anticipated by investors and contribute to a small positive announcement of returns rather than announcements of larger returns. One explanation for this is that financial markets are forward-looking. The larger negative announcement returns are related to larger stock market reactions because they are surprising. Uncertainty about policy decision is present before the announcement of such a decision. A change in policy is paired with a stock price decrease. If a policy does not change, stock prices increase. The volatilities are also affected by changes in government policy. The authors demonstrate that a new policy with an uncertain policy change will increase volatility.

Sialm (2006) examines in greater depth government uncertainty and consequences by examining the effect of stochastic taxes on asset prices. Busse and Hefeker (2007) have a different take on policy uncertainty. They examine a range of indicators of political risk to identify the relative importance of the flow of foreign direct investments into specific countries. They examine government stability, socioeconomic conditions, religious tensions, democratic accountability and the quality of bureaucracy. The authors indirectly proxy for institutional quality and test the relation between policy uncertainty and foreign direct investments.

Azzimonti (2018) intersects a news event analysis and the approach of a political risk model. A news event analysis proxies for policy uncertainty. The motivation for Azzimonti`s research is the high degree of partisan conflict in recent times. This uncertainty leads to the decreased predictability of investments due to timing, size and fiscal policy uncertainties. A blockage of policy decision leads to suboptimal responses. This causes lower expected return and discourages investments.

Policy uncertainty is proxied through a monthly count between 1981 and 2017 through news events (Azzimonti, 2018). Monthly frequencies for newspaper coverage of articles that report on political disagreements about government policy are counted. These numbers are normalized by the total amount of new articles per month for the whole sample period.

The result is the construction of a partisan conflict index that reports on political risk and the disagreement of lawmakers on policy issues. This serves as a proxy for the policy uncertainty that investors face. Azzimonti`s research focusses on examining the relation between aggregate investments in the U.S. and the partisan conflict index (PCI). The findings support a negative relationship between higher levels of the PCI and the level of aggregate investments in the U.S.

I expand upon these political risk studies by examining the effects of the spectrum of conflict severities and their related events on U.S. stock market returns and volatility. Azzimonti (2018) focusses predominantly on events that measure specific political disagreement and disregards other news events. A second way that my work builds on the techniques used in the literature is moving away from the strict use of newspapers. I will be able to use GDELT to account for all international coverage, including sources such as BBC Monitoring and Google news[1].

3. HYPOTHESIS DEVELOPMENT

I establish important areas of focus from the literature review. I combine the insights from the literature review with the use of GDELT, a novel and rich dataset, to construct multiple approaches to proxy for conflict risk. This research will make it clear how each proxy for conflict risk is perceived by investors. This paper measures the impact that perceived conflict risk has on the behavior of investors and aids in the interpretation of how conflict risk is priced in financial markets.

Berkman et al. (2011) find that the stock market drops by almost 2% in reaction to the start of an international conflict. Their use of the International Crisis Behavior project (ICB) database permits the identification of the trigger event for a major conflict or crisis. Their findings suggest that the more severe the start of a potential conflict, the stronger the reaction of the stock markets.

Brune et al. (2015) indicate that there can be more than one reaction to the increasing severity of conflict. The researchers illustrate a careful partition with respect to the likelihood of war. Their findings suggest that the pre-war phase produces different stock market reactions versus the actual war phase. They refer to this as the war puzzle. During the pre-war phase, an *increase* in the likelihood of war *decreases* market returns. During the actual war phase, if the likelihood of war increases from 99% to 100%, market return *increases*. Similar findings are recorded for stock market volatility. It will be valuable to examine how different events will be perceived among investors and those event` effects on stock market. I therefore examine the relation between perceived conflict risk and financial markets.

Hypothesis 1: Perceived conflict risk will have a negative relation to stock market returns in U.S. equity markets. More severe conflicts will have a larger impact on financial markets in the pre-war phase.

Wachter (2013) examines different investor beliefs and their consequent decisions regarding long-term bonds and stocks. Her findings indicate that beliefs regarding conflict risk affect stock market volatility. An increase in perceived conflict risk probability will results in an increase in stock market volatility. Similarly, a decrease in perceived conflict risk will decrease stock market volatility.

[1] See Appendix A to examine what feeds GDELT precisely.

Hypothesis 2: An increase in perceived conflict risk has a positive relation with stock market volatility in U.S. stock markets.

Pastor and Veronesi (2012) find that a surprising announcement of policy change is followed by greater political uncertainty and a stronger reaction in stock markets. Following the methodology in French, Schwert and Stambaugh (1986) and Amihud (2002), I proxy an autoregressive (1) model. By re-estimating an AR (1) model for my perceived conflict risk proxies, I allow myself to examine *expected* and *unexpected* components of conflict risk. An *expected* conflict risk will exhibit a positive effect on expected excess stock market return. The element of surprise in the form of *unexpected* conflict risk will exhibit a negative effect on excess stock market returns.

Hypothesis 3.1: The expected perceived conflict risk will demonstrate a positive relation with the expected excess stock market return in the U.S. stock market.

Hypothesis 3.2: The unexpected component of conflict risk will have a negative effect on the excess stock market return in the U.S. stock market.

The Barro-Rietz framework for modelling disasters can be extended with a time-varying component. This component examines the predictability of stock market returns and their exposure to conflict risk. Berkman et al (2011) and Gourio (2008) imply that assets that do better during rare events should have lower expected returns. Gourio (2008) investigates what could explain the return in the cross section for industry-expected returns because the returns in these industry portfolios and their variation in the cross-section are well understood. In addition, Berkman et al. (2011) provide cross-sectional evidence that their disaster proxies are priced. I expand upon this approach by adding a wide array of additional conflict risk factors that are exposed to different severities of conflict. This allows me to conduct a deep examination of the cross-sectional relation between my conflict proxies and the 1-month-ahead stock returns in the 30 Fama-French value-weighted industry portfolios. The hypothesis that arises is as follows:

Hypothesis 4: Higher perceived conflict risk yields lower return for value-weighted industry portfolio that have relatively good performance.

4. DATA AND METHODOLOGY

This section will discuss how I retrieve and apply my data. I will examine my U.S. stock market data in the form of value-weighted portfolios.[2] The Fama-French factors are retrievable online and publicly available in the data library from Kenneth French. I will also outline how I will measure the

[2] Publicly available on: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

impact of perceived conflict risk on realized volatility. This section will also demonstrate how I construct my conflict proxies using GDELT.

4.1 U.S. stock market data

The following data is retrieved for common equities in U.S. stock markets. Table 1 contains the descriptive statistics for all relevant market variables for the U.S. equity market. These are stock returns for all common stock that are indicated with shares codes 10 and 11 in the Center for Research in Security Prices (CRSP). I have obtained this data for my sample period, which cover 1st January 1979 to 31st December 2013. Table 1 reports findings on the U.S. excess stock market return (MKTRF), the size (SMB), value (HML) and the risk-free rate (RF). The Fama-French factors are constructed using the six value-weighted portfolios that are formed on size and book-to-market.

MKTRF is the market risk premium minus the risk-free rate. The market risk premium is also known as the excess stock market return, Rm-Rf, and is the value-weighted return of all CRSP firms that are incorporated in the U.S. and listed on NYSE, AMEX, or NASDAQ with a share code of 10 or 11 at the beginning of month *t.* Rf is the risk free rate for month *t* as indicated by the 1-month Treasury bill rate for month *t.* SMB denotes the average return of nine small stock portfolios minus the average of the nine big stock portfolios. SMB is referred to as the size factor. HML is the average return of the two value portfolio minus the average return of the two growth portfolios and is known as the value factor. Rf is the risk-free rate, which is the one-month Treasury bill rate. The returns are monthly returns and are measured from January 1st, 1979 to December 31st, 2013. This a total of 420 months of data.

Table 1:

Descriptive statistics for U.S. equity market

Table 1 present the descriptive statistics for the Fama-French factors and risk-free rate. This table reports the mean, standard deviation, minimum, maximum and the amount of available observations for all variables. The returns are percentages for the six value-weighted portfolios that are formed on size and book-to-market, the six-value weighted portfolio formed on size and profitability, and the value-weighted portfolios formed on size and investment. The sample covers 1st January 1979 to 31st December 2013.

Variables	Mean	Standard Dev.	Minimum	Maximum	Observations
MKTRF	0.651	4.539	-23.240	12.470	420
SMB	0.191	2.922	-15.330	18.750	420
HML	0.318	2.978	-11.100	12.900	420
RF	0.407	0.294	0.000	1.350	420

Table 1 illustrates that the average monthly market risk premium is 0.65%. Compounded yearly, a market risk premium of 8.1%. The monthly standard deviation is 4.54%. The most negative month recorded, October 1987, has a decline of 23.24%. This is not surprising, because on October 19th, 1987, a market crash took place that is commonly known as Black Monday. This global market crash started in Asia and resulted in a decline in the Dow Jones Industrial by 508 points, which is 22.61%. This decline resulted in the month with greatest negative stock market return in the sample. January 1987 is recorded as the highest month for the stock market; that month was the aftermath of a previously bullish market due to U.S. economy stimulation as a response to the 1980s recession.

The average monthly risk-free return is 0.407 or 4.99 on a yearly basis. The small minus big factor is on average 0.191% monthly, which is indicative of the size premium. The high minus low factor indicates a monthly return of 0.318.

4.2 The global data on events and local tone database: GDELT

This section describes the GDELT that I will use to construct conflict risk proxies. The initial GDELT dataset holds 87,298,046 observations form 1st January 1979 to 1st March 2014.

The creators of GDELT has explained GDELT as a new CAMEO-coded dataset that contains more than 200 million geolocated events with global coverage from 1979 to the present. It is evident from the amount of observations and events that GDELT holds multiple events in one observation. One observation can indicate multiple events for any given day. I choose to conduct my analysis using the reduced GDELT 1.0 dataset. Some of the newly-added features in the 2.0 GDELT dataset have no data availability prior to March 2014. The data is based on news reports from a wide variety of international news sources. A machine coded framework, Text Analysis By Augmented Replacement Instructions (TABARI), was used to code events. The international news sources include Africa News, BBC Monitoring, the Washington Post, The New York Times and Google news.

4.2.1 Advantages of using GDELT

The aim of this research is to use GDELT to examine the effects of perceived conflict risk proxies on excess stock market returns. The GDELT is a panel dataset that covers the event that takes place between two actors. The use of this dataset has some inherent advantages as I will illustrate by providing an example of a paper in a related field of study.

Schneider and Troeger (2006) rely on the use of the King and Lowe 10 million international dyadic events dataset, that relies exclusively on Reuters and Agence France Press newswires. This study draws a parallel to this paper and can highlight the dangers in this field of research. First the King and Lowe dataset recognized 450 sub-state actors. This dataset is likely to miss many conflict events that target specific individuals or sub-state groups; these unidentified events will be left out the dataset.

A second concern is the aggregation approach in Schneider and Troeger (2006). There is no clear mention of which actors are included in the study which makes it difficult to examine inferences in empirical research.

The Goldstein scale indicates two separate count variables that are used for conflict and cooperative events. This is a well-thought-out approach but could be a cause for concern when applying time-series models. Simultaneously examining both conflict and cooperation events will lead to multicollinearity issues because both will be highly correlated.

Finally, these studies in the literature consider daily events. It is true that a sudden shock can have consequences for the financial market. I assume that important conflict events are more important in the context of the broader climate of conflict and cooperation. To control for the current climate of conflict and cooperation events that influence investor behavior, I will assume a monthly measure of event count to best proxy for changes in perceived conflict risk.

To overcome these pitfalls, I use the GDELT to examine what actors to include in my dataset. Moreover, I explain my method of action aggregation. I obtain non-biased estimator and construct monthly event counts to avoid these common pitfalls.

4.2.2 The 1.0 GDELT dataset

The GDELT consists of 17 variables per observations. Every observation includes the date, the number of events, and the published number of articles among all news outlets. The CAMEO coding system provides the source and target of the event and provides a full CAMEO code, which is useful for categorizing events. The use of the CAMEO framework allows me to utilize an advantage of this event coding system: the accurate assignment of a type of event that happens between two actors. The CAMEO event coding system is defined in a three-level taxonomy framework. This leaves a level two leaf root node for an event at level three in the taxonomy. This can be illustrated by code “1622” (reduction of military assistance), which yield an EventBaseCode of “162” (reduce or stop material aid, not specified.) The EventBaseCode consists of an EventRootCOde. This defines the root-level category the event code falls under. For example, code “1622” would yield “16” if the EventRootCode is equal to the category “reduce relations” that is indicated by code “16”. The CAMEO framework allows me to examine different gradations of perceived conflict risk and examine their effects on the behavior of investors and financial markets.

Leeteru and Schrodt (2013), the creators of GDELT, state that they use nominal categories, which means that the placement of each category is irrelevant. In addition, their manual argues that the categories are treated as ordinal or almost interval variables. The CAMEO consists of an ordinal increase from 01 to 09 in cooperation events and an ordinal increase for conflict events from 10 to 20.

The WEIS framework for event coding allows for the identification of quadclasses. The CAMEO framework builds upon the WEIS framework, and the quadclass definitions are transferrable. These classes can be categorized in to four conceptual unique categories, from the most co-operative to the most severe conflict events; "verbal cooperations," "material cooperation," "verbal conflict," and "material conflict" are indicated by quadclass number 1 through 4.

The GDELT dataset also contains a Goldstein scale that can serve as a measure of impact of events. The GDELT also provides georeferences for the source and target actors.

4.2.3 GDELT and actors

The GDELT consist of actions that occur between two actors. Actor 1 is the source of the event. Actor 2 is the target of the event. The GDELT follows a hierarchical code system that ensures a level of consistency for users. One of the practical consequences is that it becomes possible to distinguish between domestic and international events.

The aim is to include actors that contribute to the current political climate through international conflict events. Although an act of violence between Nigeria and Cameroon may be important, I do not deem such events important for examining conflict risk in the context of U.S. financial markets. International events that originate from the U.S. or target the U.S. are included in the analysis. This choice is made to best proxy the current political climate. Domestic events are also excluded from the event sample.

4.2.4 GDELT and proxy for perceived conflict risk

I include observations that are above the median of news coverage as measured by the published articles for daily events. The number of events is a rough measure for the importance and impact of events. Investor attention for information is constrained. This attention bias will lead to them acting after they receive repeated news. Events that receive above-median coverage will have the most impact on how investors perceive conflict risk change, which in turn impacts financial markets. The median is a better measure than the mean because the latter can be biased due to extensive reportage of very important events.

I examine the EventRootCodes for all conflict events. The Goldstein score for the "investigate" events is a negative score of 2. I assume that this is an indication of a minor conflict. Table 2 displays all EventRootCodes and their verb abbreviations.

Table 2:

Verb codebook abbreviations

Table 2 reports on the verb codebook abbreviations and their respective EventRootCode as coded in the GDELT between source and target actor.

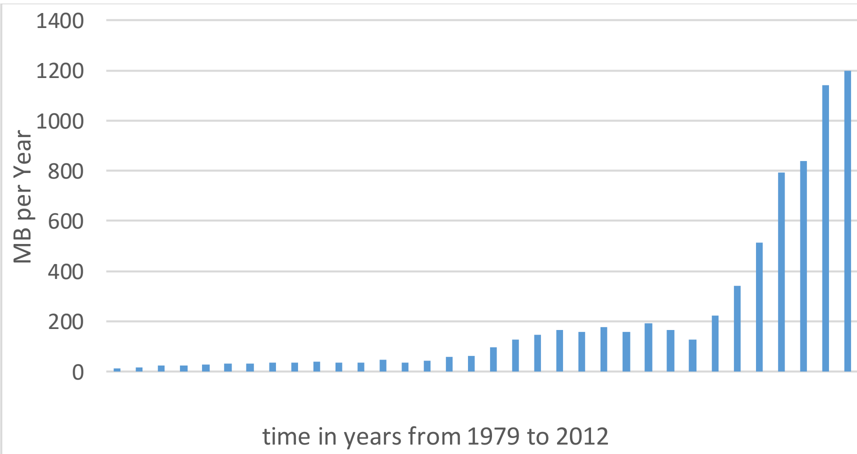
Eventrootcode	Verb codebook abbreviation
9	investigate
10	demand
11	disapprove
12	reject
13	threaten
14	protest
15	exhibit force
16	reduce relations
17	coerce
18	assault
19	fight
20	engage in unconventional mass violence

The GDELT dataset has a problematic feature: the data increases significantly over time due to the frequencies of online reporting. The skewness of data will lead to biased estimators in empirical analyses if not corrected. Figure 1 illustrates that there has been a constant increase in online news reporting since the beginning of the 21^{st} century.

Figure 1:

The amount of online reporting in the GDELT database

Figure 1 reports the total amount of megabytes (MBs) that are available for the GDELT every year. These megabytes are illustrative for the 17 variables that are present per observation and show an increasing trend through time.



Using an approach similar to that of Azzimonti (2018), I scale my raw new conflict count per month by the event count per month. I will normalize all variables by their sample standard deviation to simplify the interpretation of coefficients and apply a log transformation. This transformation will allow me to more easily interpret my estimated coefficients.

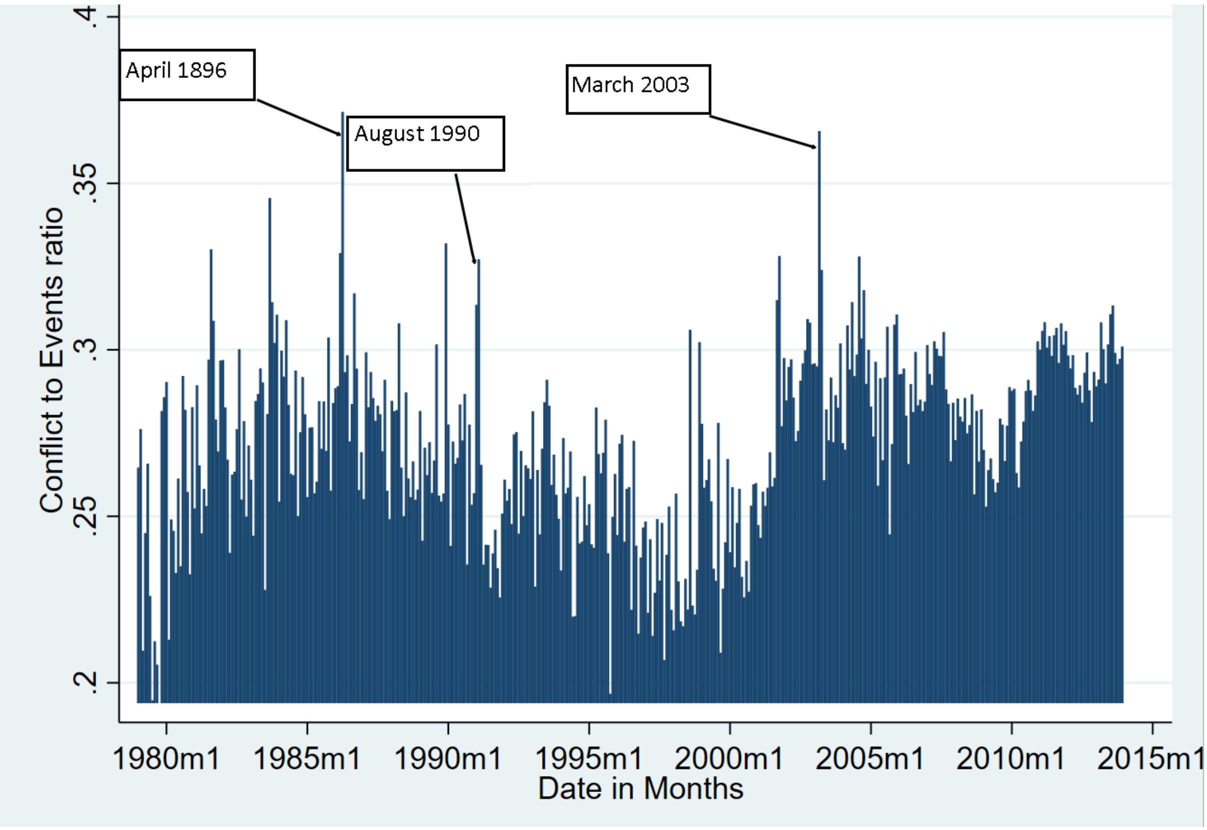
4.2.5 GDELT and validity of a conflict risk proxy

It will be useful to judge if my base conflict risk proxy is indicative for conflict events. Figure 2 depicts a graph of all U.S. international conflict events scaled to all events. This allows me to gauge the behaviour of the conflict risk. Figure 2 allows me to examine if periods of actual international conflict overlap with the score for the behaviour of conflict risk.

Figure 2:

The ratio of conflict event to all events

Figure 2 illustrates all conflict events as a ratio to all events that are available monthly for ingoing and outgoing events with U.S. involvement and with above-median number of articles for January 1979 to December 2013.



The graph indicates several spikes in the ratio of conflict events to total events. I will examine the three most prominent outliers and explain the overall ratio based on the period of conflict with U.S. involvement.

The first outlier is April 1986. In April 1986, the U.S. launched air strikes against Libya to retaliate against the Libyan sponsorship of terrorism against U.S. troops and citizens. The years 1988 and 1989 marked growing tensions between the U.S. under the Reagan presidency and Iraq. The lead up to the Gulf War was the continuing conflict between Iran and Iraq, which ultimately led to the Iraqi invasion of Kuwait by Iraq. The UN Security Council was concerned that this war could spill over the boundaries of the two belligerents. A different outlier was in August 1990, which was when Operation Desert Shield commenced. This operation was intended to build up troops and the defences of Saudi Arabia and to prepare for the later Operation Desert Storm. At the combat phase, coalition forces from 35 nations that were led by the U.S. waged a war in response to the annexations of Kuwait by Iraq.

After this a period of relative calmness emerged. March 20, 2003 marked the first stage of the Iraq war, which lasted over a month. This invasion included 21 days of major combat operations. Combat operations executed by the U.S., the U.K., Australia, and Poland are performed in Iraq to battle insurgents. This conflict aside, the U.S. has been in a constant frenzy of war since the beginning of the 21st century. For example, major U.S. involvement in the Afghanistan conflict remains active today. Other major conflict includes the Iraqi war from 2003 to 2011 and the U.S.-led intervention in Libya in 2011 to overthrow the Gaddafi government and take interim control with a national transitional council.

The time-series in Figure 2 exhibits a similar increase in size that is parallel to the rise of international conflict with U.S. involvement. It appears that such a conflict risk proxy is a good measure for international conflict with U.S. involvement.

4.3 GDELT and descriptive statistics

I also assess different severities of perceived conflict risk. There were 6,949,056 observations from January 1979 to December 2013. Observations took place over a total of 420 months, or 12,784 days, that were aggregated from the sample of daily GDELT.

The tested verbal conflict variables are “Investigate,” “Demand,” “Reject,” “Threaten,” and “Protest.” The test material conflict variables are “Exhibit force,” “Reductions of relations,” “Coerce,” “Assault,” “Fight,” and “Use of unconventional mass violence”. “Investigate” are investigations of events such as crimes, war crimes or military actions. “Demand” are actions that have a verbal demand towards an actor. “Disapprove” entails official complaints, criticism, or accusations. “Reject” covers the rejection of requests and refusal to yield. “Threaten” describes any verbal threat towards an action with any type of action. “Protest” is specified as large demonstrations, strikes, protests, and riots.

The following actions qualify as material conflict. “Exhibit force” describes an increase in military, police, or the mobilizing of executive power such as the military. “Reduce relations” is the reduction of diplomatic relations, halt of negotiations, or expulsion of peacekeepers. “Coerce” is the seizure of property and imposition of administrative sanctions. “Assault” is any type of unconventional violence, abduction, physical assault, sexual assault or killing. “Fight” is the use of conventional military force that is indicated by fighting with small arms, artillery, tanks and aerial weapons; or the violations of a ceasefire. “Use of unconventional violence” is mass expulsion, mass killing, ethnic cleansing and the use of weapons of mass destruction.

Table 3 depicts descriptive statistics from all constructed perceived conflict risk variables. These descriptive statistics are pre-standardization or any other transformation so that the basic descriptive statistics and their ratios can be examined. The mean ratio of conflict events to all events is 0.272. This originates from 3,379,853 conflict-based events and 9,046,076 cooperation events. Every month, 8,047 conflict-based events and 21,538 cooperative events take place.

Table 3 illustrates that the most frequent events are “Disapprove,” “Coerce,” and “Fights,” with respectively rounded values of 0.07, 0.04 and 0.045. “Exhibition of force” has relatively few events in this category with a score of 0.005. The ratio of protests to the total amount of events is relatively low at 0.008. “The use of mass violence” is unconventional and non-frequent, as illustrated by a score of 0.0003. Every conflict risk proxy exhibits a value that are above the critical value for a Dickey-Fuller generalized least squares (GLS) statistic. Therefore, the null-hypothesis of a unit root can be rejected for all variables.

I construct a severity index in addition to the broad measures of all conflicts. The CAMEO framework provides an excellent framework for determining if stock price reactions are different depending on the different severity of conflict. Applying a severity index allows me to better identify periods of high conflict that can cause a shift in the perceived conflict risk probability. Using a similar approach to that of La porta, Lopez-de-Silanes, Shleifer, and Vishny (1988), I add a set of dummy variables to create a conflict severity measure. The conflict severity summarizes the different aspects of a conflict into one measure by adding one for each conflict variable. Table 4 demonstrates that, as expected, this measure is highly significantly correlated with all conflict measures with a 0.96 score.[3]

[3] Table 4 represent the correlation matrix.

Table 3:
Descriptive statistics for all conflict variables

Table 3 reports the descriptive statistics of conflict variables. Panel A reports the mean, standard deviation, minimum and maximum. The sample period for these descriptive statistics is January 1979 to December 2013. This is a total of 420 monthly observations. All conflict denotes the number of conflict-based events that take place scaled by the total number of events monthly. These descriptive statistics represent all events that involve U.S. involvement and exclude domestic events. The variables that are reported on are the following: investigate, demand, disapprove, reject, threaten, protest, exhibit force posture, reduction of relations, coerce, assault, fight and use of mass violence. The severity index is a weighted index of all conflict events weighted by their severity. The critical value at the 1% level for the Dickey Fuller –GLS test are statistics for a test with a null-hypothesis of a unit root equal to -2.57. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

VARIABLES	Mean	Std. Dev.	Min	Max	DF-GLS
All Conflicts	0.2720	0.0273	0.1940	0.3710	-10.467***
Investigate	0.0163	0.0034	0.0051	0.0336	-13.428***
Demand	0.0152	0.0025	0.0081	0.0255	-16.875***
Disapprove	0.0695	0.0088	0.0478	0.0979	-13.704***
Reject	0.0287	0.0042	0.0185	0.0455	-14.479***
Threaten	0.0155	0.0039	0.0067	0.0337	-12.942***
Protest	0.0077	0.0031	0.0017	0.0341	-15.636***
Exhibit Force	0.0046	0.0024	0.0006	0.0174	-12.147***
Reduce Relations	0.0126	0.0029	0.0055	0.0234	-15.523***
Coerce	0.0411	0.0076	0.0149	0.0684	-11.289***
Assault	0.0152	0.0051	0.0049	0.0390	-9.472***
Fights	0.0449	0.0114	0.0139	0.0881	-9.263***
Mass Violence	0.0003	0.0004	0	0.0032	-9.263***
Severity index	1.6460	0.2110	1.0960	2.4690	-9.214***

Table 4 depicts the correlation matrix for all perceived conflict risk variables. This is the total of all correlation coefficients between variables. Most of the correlation coefficients are positively correlated and significant. For example, the more prominent represented variables such as “Disapprove”, “Coerce” and “Fights” are stronger correlated with the two broader conflict measures. This is clearly represented by the correlation coefficient between “All conflicts” and “Fights,” which has a value of 0.77. Another example is the correlation coefficient from “Severity index” and “Disapprove,” which is 0.70.

Table 4:

The correlation matrix for all conflict variables

Table 4 reports correlation coefficients between the different conflict risk variables. The correlation coefficient is stated for every conflict risk variable. These correlation coefficients are representative for the sample period of January 1979 to December 2013. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	AC	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	Severity index
All Conflicts	1.00													
Investigate (9)	0.35 ***	1.00												
Demand (10)	0.24 ***	-0.01	1.00											
Disapprove (11)	0.70 ***	0.12 **	0.24 ***	1.00										
Reject (12)	0.05	-0.05	-0.07	0.07	1.00									
Threaten (13)	0.47 ***	0.01	0.11 **	0.33 ***	-0.05	1.00								
Protest (14)	0.32 ***	-0.07	0.08	0.17 ***	0.08 *	***	1.00							
Exhibit of Force (15)	0.27 ***	-0.06	0.16 ***	0.21 ***	0.02	0.37 ***	0.08 *	1.00						
Reduce Relations (16)	-0.01	-0.10 **	0.00	-0.03	0.03	0.05	0.14 ***	-0.04	1.00					
Coerce (17)	0.54 ***	0.41 ***	-0.03	0.15 ***	-0.11 **	0.01	0.03	-0.15 ***	-0.09 *	1.00				
Assault (18)	0.55 ***	0.15 ***	0.09 *	0.23 ***	-0.15 ***	0.07	0.22 ***	-0.01	-0.10 **	0.39 ***	1.00			
Fights (19)	0.77 ***	0.19 ***	0.08 *	0.39 ***	-0.14 ***	0.34 ***	0.11 **	0.22 ***	-0.17 ***	0.32 ***	0.37 ***	1.00		
Use Mass Violence (20)	-0.02	0.10 **	0.01	-0.11 **	-0.06	0.10 **	0.01	0.02	0.02	-0.11 **	-0.03	0.05	1.00	
Severity Index	0.96 ***	0.29 ***	0.14 ***	0.53 ***	-0.06	0.40 ***	0.28 ***	0.23 **	-0.03	0.60 ***	0.62 ***	0.87 **	0.00	1.00

The correlation coefficients are mostly positive and highly significant. The verbal conflict events and the material conflict events differ in their nature of correlation. Verbal conflict events are stronger and more positively correlated with other verbal conflict events. The same holds for material conflict events that are positive and more strongly correlated with other material conflict events. This could indicate tit-for-tat policies by the involved countries.

5. THEORETICAL FRAMEWORK

This section examines how conflict risk is priced. First, this section tests the effects of U.S. involvement in conflict risk on U.S. excess stock market returns. Second, the section examines the effect of increasing conflict risk and its effects on U.S. stock market volatility, followed by a time-series analysis to produce predictive regressions with expected and unexpected components of conflict risk. Finally, cross-sectional evidence is used to examine the link between cross-sectional sensitivities of conflict risk for value-weighted industry portfolios and 1-month-ahead returns.

5.1 Standardizing perceived conflict risk variables.

Azzimonti (2018) is built upon to adjust my conflict risk variables. Every individual conflict risk variable will be in line with the following approach. $X_{i,t}$ will denote the scaled frequency of event counts per conflict variable. I compute the time-series variance δ_i^2. Here, *i* represents every conflict measure and t denotes the month from my sample period. I divide $X_{i,t}$ by the standard deviation, which will be denoted as Y_t. This provides me with a unit standard deviation. I compute the mean of Y_t for every variable in each month and name it Z_t. I compute M, which is the mean value of Z_t in the interval T_2. I multiply Z_t by (100/ M) for every t to obtain standardized counts for my perceived conflict risk variables. These standardized measures are transformed by the natural logarithm. This eases the comparison between covariates and aids interpretation.

5.2 Contemporaneous stock returns

The following methodology is used to examine the effect of international conflicts that cause crises and their effects of financial markets. The first test is of the overall impact of the monthly amount of conflicts on the U.S. stock market returns in any given month t.

$$Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t, \quad (1)$$

In Equation (1), $Excess\ Return_{t}^{US}$ is the monthly excess return for the U.S. stock market in month *t.* The excess return is the monthly excess return on the value-weighted portfolio consisting of all NYSE, AMEX, and NASDAQ firms that are available in CRSP. The risk-free return is deducted from these returns to obtain excess stock market returns.

A simple ordinary least square regressions (OLS) applies to the two broad conflict measures "All-conflict" and "Severity index" as well as to the variables of different perceived conflict risk severity: "Investigate", "Demand", "Disapprove", "Reject", "Threaten", "Protest", "Exhibit force", "Reduction of relations", "Coerce", "Assault," "Fight, " and Use of mass violence". Each conflict measure is normalized and transformed logarithmically before applying equation (1).

A simple ordinary least square regression (OLS) applies to the 2 broad conflict measures "All-conflict" and "Severity index" as well as for the variables of different perceived conflict risk severity. To reiterate these are: "Investigate", "Demand", "Disapprove", "Reject", "Threaten", "Protest", "Exhibit force", "Reduction of relations", "Coerce", "Assault"," Fight" and "Use of mass violence". Each conflict measure is normalized and transformed logarithmically before applying equation (1).

5.3 Realized volatility

The effects of conflict risk are extended regarding realized volatility. I obtain the monthly aggregated stock market volatility through the realized volatility. I therefore estimate a generalized auto regressive conditional heteroskedasticity model (GARCH). Specifically, I apply a GARCH (1) model with an exogenous variable. This tests if the volatility of U.S. stock market returns is related to the occurrence of conflict events. Using a similar approach to that of Engle and Patton (2001). A model with an exogenous regressor is chosen because it is simple and robust (Engle, 2002).

This GARCH process makes use of two steps. The reason for the two-step process is because I am interested in the volatility effects and in controlling for the impact of conflictual events on the mean returns. Hence, I capture the volatility effects as the conditional variance of the error term while controlling for effects on the mean returns. Hence, equation (2) is as follow:

$$Excess\ Return_{t}^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t \,,$$

$$\varepsilon_t \sim N(0, \sigma_t^2 \,) \,,$$

$$\sigma_t^2 \;=\; \beta_0 \;+\; \beta_1\, \varepsilon_t^2 \;\; + \; \beta_2\, \sigma_{t-1}^2 + \; \beta_3 Conflict_t \; + \; \varepsilon_t. \;\; (2)$$

From this specification it follows that the variance depends on past squared residuals, past variance, and the conflict risk variable. In this paper, I expect that my findings will produce a positive relation between conflictual events and stock market volatility.

5.4 Time-series: predictive regressions

One additional approach is to use the time-series evidence to examine conflict risk, where expected and unexpected components of conflict risk test their effects on excess stock market returns. Thereafter, I follow the cross-sectional analysis that is also predictive in nature. I apply a two-step Fama and Macbeth (1973) regression to study the relation between conflict sensitivity and 1-month-ahead returns across 30 value-weighted Fama-French industry portfolios. Using an approach similar to that of French, Schwert, Stambaugh (1986) and Amihud (2002), I use an AR (1) model to proxy for the level of *expected* and *unexpected* conflict risk. The benefit of including *unexpected* conflict risk via an autoregressive process is that the two-step process gains importance in terms of the explanatory power of the variation. Including an *unexpected* component helps to explain variation over time that exist in market returns. I can interpret the coefficient of the *unexpected* conflict risk variable as indirect evidence of the relation between the expected level of conflict risk and the *expected* market risk premium. I will assume that investors follow an AR (1) process. They apply this to proxy for levels of *expected* conflict risk. Investors determine the *expected* conflict risk for any month based on information available from the previous month. These investors require a return based on their expectations to be compensated for their predicted conflict risk. Perceived conflict risk is assumed to follow the following AR (1) process:

$$Conflict_t = \alpha + \beta_1 Conflict_{t-1} + \varepsilon_t \, . \quad (3)$$

$Conflict_t$ is the standardized logged ratio of events per perceived conflict risk variable. This conflict variable is regressed by its auto regressive component. Therefore, $Conflict_{t-1}$ is representative of the proxied perceived conflict risk measure of the previous month.

The fitted values from equation (3) will serve as the *expected* levels of perceived conflict risk and the residuals values from equation (3) as the *unexpected* levels of perceived conflict risk. The AR (1) process is a two-step process where the first equation is equation (3). The second step is the inclusion of both *expected* and *unexpected* conflict risk in a similar model illustrated by equation (4).

$$Excess\ Return_t^{US} = \alpha + \beta_1 Expected\ Conflict_t \quad + \beta_2 Unexpected\ Conflict_t + \varepsilon_t \, . \quad (4)$$

Equation (3) and (4) apply to all my perceived conflict risk proxies. Note that equation (3) is therefore re-estimated for each conflict proxy.

5.5 Time-series evidence: cross-sectional

To obtain a more thorough understanding and possible explanation of what constitutes variation in expected returns, I examine cross-sectional evidence with respect to conflict risk. This cross-sectional analysis applies to 30 value-weighted industry portfolios.

I run a two-step Fama and Macbeth (1973) regression to study the cross-sectional relationship between crisis sensitivity and one-month-ahead returns across 30 Fama-French industry portfolios. Berkman et al. (2011) motivates the choice of value-weighted industry portfolios because previous research has been generating poor results in terms of explaining the difference in expected returns among these portfolios. Fama and French (1997) provide another explanation for the use of value-weighted industry portfolios. They find that the CAPM and the Fama-French 3 factor model unsatisfactorily explain the substantial heterogeneity in expected returns for value-weighted industry portfolios.

Lewellen,Nagel , Shanken and Jay (2010) provide another valid argument for the use of value-weighted industry portfolios. They argue that asset pricing test are often misleading, in the sense that apparently strong explanatory power(high cross-sectional R^2s and small pricing errors) can provide weak support for a model. Obtaining high cross-sectional R^2 in other models is easy due to the tendency of any proposed factor to line up with expected returns. If a factor is slightly correlated with the HML or SMB and not with the residuals from a three-factor model, it will be significant with respect to expected returns.

Lewellen et al. (2010) stress that this is problematic and cannot be easily solved as a sampling issue. I can resolve the problems caused by a strong factor structure of size-B/M portfolios. I can perform my cross-sectional tests on portfolios that are sorted by industry betas. In addition to the unexplained heterogeneity in industry portfolios, these tests can help to examine if my conflict risk factors are priced. Therefore, I use 30 Fama-French value-weighted portfolios.

I include the unexpected changes in perceived conflict probability to measure the sensitivity in each industry. The residual values from equation (3) represent the unexpected conflict risk. I use these values as indicative of the unexpected changes in conflict risk or every proxy. This will be considered as a factor that is additional to the Fama-French factors.

I use a 60-month window to estimate the following time-series regression. This 60-month observations window is indicated by the following subscripts: $\tau = t - 60$ to $t - 1$. This rolling window applies to all time-series regressions and is used to estimate the factor loadings for the Fama-French factors and to estimate the conflict sensitivity for each industry portfolio, as indicated by *i.* The first step of regressions is as follows:

$$RI_{i,\tau} = \alpha_{i,t-1} + \beta_{i,t-1}^{MKTRF} MKTRF_{\tau} + \beta_{i,t-1}^{SMB} SMB_{\tau} + \beta_{i,t-1}^{HML} HML_{\tau} + \beta_{i,t-1}^{Conflict} Conflict_{\tau} + \eta_{i,\tau} \,. \quad (5)$$

$RI_{i,\tau}$ represent the excess return on the value-weighted industry portfolio *i,* in month τ. $MKTRF_{\tau}$, is the representation of the Fama-French factor commonly known as the market factor. SMB_{τ} and HML_{τ} are the Fama-French factors that represent size and value premiums for month *t* respectively. $Conflict_{\tau}$ is the *unexpected* conflict risk. Recall that this *unexpected* conflict risk factor is obtained through equation (3) and re-estimated per proxy.

The 30 value-weighted portfolios from the Fama-French database represent portfolios of stock from NYSE, AMEX and NASDAQ through CRSP. These stocks are sorted into their specific industry portfolio based on their four-digit SIC code. Using an approach similar to that of Nagel (2005), I apply a slight adjustment for interpretational purposes to the $\beta_{i,t-1}^{Conflict}$ variable. I rank $\beta_{i,t-1}^{Conflict}$ into decile ranks each month and scale them back to ranges between zero and one. The main benefit of this procedure is that sensitivity towards errors are reduced. In addition, the procedure aids the interpretation of the coefficient estimates. After these adjustments, the second step for the Fama and Macbeth (1973) regressions are performed. I run the second-stage cross-sectional regression in each month *t*.

$$RI_{i,t} = \gamma_t + \gamma_{MKTRF,t}\, \beta_{i,t-1}^{MKTRF} + \gamma_{SMB,t}\, \beta_{i,t-1}^{SMB} + \gamma_{HML,t}\, \beta_{i,t-1}^{HML} + \gamma_{Conflict,t}\, \beta_{i,t-1}^{Conflict} + \varepsilon_{i,t}. \quad (6)$$

In this second step the cross section of portfolio returns is regressed against the factor exposures, at each time step. This step computes cross-sectional regression on the returns of the estimates of the β`s estimated from equation (6). The same βs from equation (6) are used for every regression. My aim here is to measure the exposure of return to each factor loadings over time. Finally, I calculate the average risk premium that is associated with each factor.

6. RESULTS

I have outlined the existing literature, the methodology, and how I expand upon used approaches. I describe the theoretical framework that I use to examine how conflict risk is priced, thereby answering my hypotheses. The analysis section will start by examining the stock returns for the U.S. and examining volatility effects for the relevant factors. Hereafter, I follow the predictive tests in the form of industry portfolio analyses. The last section of this chapter will address the robustness issue.

6.1 Perceived conflict risk and U.S. stock market returns

A simple regression analysis evaluates the effects on the monthly U.S. market excess returns as a dependent variable. This regression uses dummy variables to include all the perceived conflict risk variables. All regressions are corrected for the potential presence of autocorrelation or heteroscedasticity. This results in regression coefficients and *t*-statistics that consider heteroskedastic and autocorrelation-robust standard errors.

Following Azzimonti (2018), the scaled variables for perceived conflict risk and their frequency count per month are standardized by their standard deviation. The mean value is obtained from this series. This series is then normalized to 100 to obtain a normalized time-series index. This normalized time-series is transformed with a logarithm transformation.

Table (5) allows me to examine the hypothesized negative effects for higher degrees of conflict severity. All coefficients are to be interpreted in percentages. The *t*-statistic for the variable “All conflict” is 0.42. This *t*-statistic is far from the critical value for the *t*-statistics and results in a *p*-value of 0.675. I therefore cannot reject the null-hypothesis that the variable “All conflict “is significantly different from zero. Therefore, the variable “All conflict” does not carry enough explanatory power.

The severity index produces a similar result. This is evidence to reject my hypothesis that the two broad conflict measures have a negative relation to stock market return in the U.S. equity markets for international conflict involving the U.S. This combined and weighted severity index over all conflict events indicates a -0.568 coefficient accompanied by a -0.34 *t*-statistic. These results do not bear enough statistical weight for interpretation. As a result, the weighted severity index does not differentiate significantly from zero. These results apply to the two broad perceived conflict risk measures. Next, I will examine the different degrees of conflict severity in Table (5).

The variables in Table (5) are kept in their ordinal scale of conflict severity. For the verbal conflict, these variables are “Investigate,” “Demand,” “Disapprove,” “Reject,” “Threaten,” and “Protest.” The variation in severity for verbal conflict events do not produce significant results with respect to the U.S. equity markets. The variable “Disapprove” has a t-statistic of -1.48 and is closest to a threshold that is widely considered to be statistically significant. However, all these conflict proxies are not statistically different from zero, and therefore the null-hypothesis cannot be rejected. Hence, the coefficients for these variables are not different from zero.

The rest of the variables include more severe conflicts and are labeled as material conflicts: “Exhibit force,” “Reduce relations,” “Coerce,” “Fights,” and “Use of mass violence.” Like verbal conflicts, the *t*-statistics indicate non-significant results. It is therefore futile to interpret these coefficients. A 1% increase in the variable “Exhibit force” in month *t,* for example, would otherwise be associated with a 0.056% decline in excess stock market return in month *t.* However, I cannot reject the null-hypothesis and conclude that the coefficients do not significantly differ from zero for these variables. Extrapolating this result to an increase of one standard deviation provides following result: An increase in one standard deviation of the amount of conflict events indicated as “Exhibit force” is associated with a 1.904% increase in excess stock market return in U.S. equity markets.

There does not seem to be striking similarity in the relationship between either verbal or material conflict events and the excess stock market return in the U.S. Investors do not seem to behave differently or perceive conflict risk differently regarding excess mean returns whenever events of a verbal or material nature occur. Several explanations could shed light on these results, such as my assumptions regarding what investors pay attention to. I assume that events qualify as relevant only when the number of articles is above the median. I assume that this number of articles serves as a measure of relative impact and importance of events. I do not deem this assumption to be too strict, but an additional measure of relative importance and impact of events could be helpful.[4]

Another explanation might be that a simple linear OLS regression is not the best tool to examine the relationship between conflict risk and the stock market. Certain material or verbal events can have catastrophic consequences in a certain context. The relation between variables might potentially help to examine perceived conflict risk effects on stock markets. This potential interaction effect will represent the combined effect of variables on the dependent variable. To give an example, the amount of “Exhibit force” events might depend heavily on the amount of “Disapprove” events. Such as interaction effect could aid in the interpretation of results.

A simple regression analysis applies to evaluate the effects on the monthly U.S. market excess returns as a dependent variable. This regression uses dummy variables to include all the perceived conflict risk variables. All regressions are corrected for the potential presence of autocorrelation or heteroskedasticity. Resulting in regression coefficients and t-statistics that consider heteroskedastic and autocorrelation-robust standard errors.

Following (Azzimonti, 2018) the scaled variables for perceived conflict risk and their frequency count per month are standardized by their standard deviation. From this series the mean value is obtained. This series is then normalized to 100, to obtain a normalized time-series index. This normalized time-series is transformed with a logarithm transformation.

Table (5) allows me to examine the hypothesized negative effects for higher degrees of conflict severity. All coefficients are to be interpreted in percentages. The t-statistic for the variable “all conflict” is -0.42. This t-statistic is far off from the critical value for the t-statistics and results in a

[4] Neither the GDELT 1.0 database nor retrievable raw GDELT data can be used to asses the value for a similar measure of relative importance and impact. Average tone for example lacks reliable data availability ex-ante March 2014.

p-value of 0.675. I can therefore not reject the null-hypothesis that the variable “all conflict” is significantly different from zero. The variable “all conflict” does therefore not carries enough explanatory power. The severity index shows a similar result. For the 2 broad conflict measures this is evidence to reject my hypothesis that conflicts exhibit a negative relation to stock market return in the U.S. equity markets for international U.S. involved conflicts. This combined and weighted severity index over all conflict events shows a -0.568 coefficient accompanied by a -0.34 t-statistics. This result as well does not bear enough statistical weight for interpretation. As a result, the weighted severity index does seem to differentiate significantly from zero. These results apply for the two broad perceived conflict risk measures. Next, I will examine the different degrees of conflict severity through Table (5).

The variables in Table (5) are kept in their ordinal scale of conflict severity. For the verbal conflict these are “Investigate”, “Demand”, “Disapprove”,” Reject”, “Threaten” and “Protest”. The variation in severity for verbal conflict event do not show significant results with respect to U.S. equity markets. The variable “Disapprove” with a t-statistics of -1.48 is closest to a widely considered statistically significant threshold. However, all these conflict proxies are not statistically different from zero and therefore the null-hypothesis cannot be rejected. Concluding that coefficients for these variables are not different from 0.

The rest of the variables are more severe conflict events and are labelled as material conflicts. Here in this research I distinguish: “exhibit force”, “reduce relations”, “coerce”, “fights” and “use of mass violence”. Like verbal conflict the t-statistics indicate non-significant results. Interpretation of the coefficients is therefore futile. A 1% increase in for example the variable “exhibit force” in month *t* would otherwise be associated with a 0.056% decline in excess stock market return in month *t.* However, for these variables I cannot reject the null-hypothesis and conclude that the coefficients do not significantly differ from zero. Extrapolating this result to a one standard deviation increase gives me the following result. A one standard deviation increases in the amount of conflict events indicated as “exhibit force” is associated with a 1.904% increase in excess stock market return in U.S. equity markets.

There does not seem to be striking similarity in the direction of a relationship for either verbal or material conflict events and the excess stock market return in the U.S. With respect to the excess mean returns, investors do not seem to behave differently or perceive conflict risk differently whenever events of a verbal or material nature occur. Several explanations could shed light on these results. First, my assumption with respect to what investors pay attention to. I assume that events qualify as relevant only when the number of articles is above the median. I assume that this number of articles serves as a measure of relative impact and importance of events. I do not deem this assumption too strict however an additional measure of relative importance and impact of events could serve helpful.

Another explanation might be that a simple linear ordinary least squares regression is not the best tool to examine the conflict risk and stock market relationship. Certain events material or verbal can have catastrophic consequences in a certain context. The relation among variables might serve as potential aid in examining perceived conflict risk effects on stock markets. This potential interaction effect will represent the combined effect of variables on the dependent variable. To give an example, the amount of “exhibit force” events might depend heavily on the amount of “disapprove” events. If such an interaction effects were to be present it could aid in examining the relation between perceived conflict risk and the stock market relationship.

Table 5:

Effects of perceived conflict risk on international U.S. equities

Results for equation (1) through $Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t$. where $Excess\ Return_t^{US}$ is the monthly excess return on U.S. stock markets for 1st January 1979 to 31st December 2013. $Conflict_t$ represents each conflict variable and is constructed by the number of events in month *t*. For category, the variable scaled by the total event count for that month *t*, standardized by their sample standard deviation. A natural logarithm transformation applies to every conflict risk variable. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level. The *t*-statistics are based on heteroskedasticity-consistent standard errors.

	Constant	Conflict
Log(All Conflicts)		
Coefficient (%)	4.765	-0.894
T-statistic	(0.49)	(-0.42)
Log(Severity index)		
Coefficient (%)	3.264	-0.568
T-statistic	(0.43)	(-0.34)
Log (Investigate)		
Coefficient (%)	-3.106	0.820
T-statistic	(-0.65)	(0.79)
Log (Demand)		
Coefficient (%)	0.364	0.063
T-statistic	(0.05)	(0.04)
Log (Disapprove)		
Coefficient (%)	13.09	-2.706
T-statistic	(1.55)	(-1.48)
Log (Reject)		
Coefficient (%)	-4.866	1.201
T-statistic	(-0.63)	(0.72)
Log (Threaten)		
Coefficient (%)	3.278	-0.574
T-statistic	(0.78)	(-0.62)
Log (Protest)		
Coefficient (%)	-3.115	0.830
T-statistic	(-1.15)	(1.38)
Log (Exhibit force)		
Coefficient (%)	0.901	-0.056
T-statistic	(0.51)	(-0.14)
Log (Reduce relations)		
Coefficient (%)	0.438	0.047
T-statistic	(0.11)	(0.05)
Log (Coerce)		
Coefficient (%)	-5.254	1.287
T-statistic	(-1.05)	(1.18)
Log (Assault)		
Coefficient (%)	1.942	-0.284
T-statistic	0.70	-0.46
Log (Fights)		
Coefficient (%)	1.942	-0.284
T-statistic	(0.70)	(-0.46)
Log(Use of Mass Violence)		
Coefficient (%)	-0.555	0.262
T-statistic	(-0.38)	(0.87)

6.2 Realized volatility effects

This section examines the perceived conflict risk effects on stock market volatility for U.S. equity markets. I elect to choose a GARCH (1,1) model to examine the realized market volatility. I expect an increase in conflict probability to increase stock market volatility and a decrease in conflict probability to decrease in stock market volatility. I apply a GARCH (1,1) model for all perceived conflict factors. Table 6A reports the results for the two broad conflict proxies and the verbal conflict event proxies. Table 6B reports the material conflict events and their GARCH (1,1) output.

The first column of table 6A and 6B represent the result for conflict risk variables on the mean of the excess stock returns in U.S. equity markets. A coefficient that is indicative of the effect and a constant is provided for every variable. The effects of the two broad measures "All conflicts" and "Severity index" are depicted in Table 5 with respect to their statistical significance. Furthermore, the effects on the excess mean of stock returns for the U.S. are mostly similar in Tables 5, 6A and 6B.

A few conflict risk specifications differ. The conflict risk specifications for "Disapprove," "Protest," and "Coerce" indicate a significant difference from zero for their coefficient with respect to a 10% significance threshold. Their coefficients can be interpreted as percentage changes and are
- 2.522, 0.806 and 1.898 respectively. The interpretation for disapproval conflict events, for example, would be as follows. A 1% increase of "Disapprove" events in month *t* is associated with a 2.522% decrease in excess stock market return in U.S. equity markets. This supports my hypothesis that increasing conflict risk decreases excess stock market returns. However, the positive coefficients of "Protest" and "Coerce" provide conclusive evidence. A possible explanation is that certain events are real signals of war for investors and therefore indicate a positive relation with excess stock market return.

The second result is with respect to the modeling of the stock market volatility, which is referred to as the second step in the GARCH specification. For this sample period the observed ARCH and GARCH coefficients are represented by β_1 and β_2 respectively in the GARCH (1,1) model. β_1 and β_2 are the coefficients for the squared error term and the variance term lagged. The coefficients β_1 and β_2 in Tables 6A and 6B are significant at a 1% threshold except for one conflict risk specification. The "Threaten" conflict risk specification does not indicate significant results for β_1 and β_2. This result can be interpreted as the presence of conditional heteroskedasticity in this dataset.

The last column in tables 6A and 6B represents the effects of the conflict risk specifications on the volatility of the U.S. stock market. The findings on the two broad conflict measures are negative and significant. The all conflict variable reports a coefficient of -4.811 and is significant at a 10% significance threshold. The conflict severity index depicts a similarly-sized and significant coefficient of -4.009 at a 5% significance threshold. Respectively, this indicates that a 1% increase in conflictual events would decrease stock market volatility by 4.81% and 4.01%. This contradicts my initial prediction that an increase in conflict risk would increase stock market volatility.

There is no clear direction for the relationship between conflict-specific events. The coefficient and their respective significance do not indicate a general direction for the relationship that is represented in the last column of table 6A. The variables “Investigate,” “Disapprove,” and “Protest” demonstrate non-significant results, and because of these variables and the realized volatility, I therefore confirm the null-hypothesis. The coefficients for these variables are therefore not different from zero, and there is no relation between conflict risk specifications and volatility.

Increases in events that are coded as “Demand” indicate significant results at a 1% significance threshold and a coefficient of -4.11. This means a 1% increase in a “Demand”-type event decreases stock market volatility by 4.11%. On the other hand, both “Reject” and “Threaten” indicated positive coefficients with values of 4.93 and 0.57 respectively. The interpretations of “Demand” and “Reject” are similar. For example, a 1% increase in “Reject” events would increase stock market volatility by 4.93%. Table 6A does not provide unambiguous evidence to support a direction for the relation between conflict risk and stock market volatility.

The conflict risk variables that stem from material conflict tell a more conclusive story. All these conflict risk variables can be found in last column for Table 6B. “Coerce,” “Assault,” and “Fight” all pass the significance thresholds respectively for the 5%, 10% and 1 % threshold. The value of the coefficients for these conflict factors are -2.733, -1709, and -2.170 respectively. The interpretation of these statistics is that a 1% increase in “Fight” events causes a 2.17% decrease in U.S. stock market results. Table 6B depicts a negative relation between material conflict events and stock market volatility.

My hypothesis states a positive relation between increasing conflict risk and stock market volatility. The two broad conflict measures indicate contradictory evidence, and the verbal conflict events indicate mixed evidence. The material conflict events also do not support a positive relation between conflict risk and stock market volatility.

I hypothesized a positive relation between increasing conflict risk and stock market volatility. Episodes that reflect war or special events with U.S. involvement, such as World War II or the Organization of Petroleum Exporting Countries (OPEC) oil shock in 1973 are followed by greater stock market volatility. The specifications for material conflict might serve as catalysts of economic activity and hereby stimulate economic growth. Therefore, material conflict events would indicate a negative relationship with U.S. stock market volatility. Several explanations fit this story.

An explanation for this finding could be similar as to Brune, Hens, Rieger and Wang (2015), but then with respect to stock market volatility as opposed to stock market returns. Material conflict events can change the investor`s perception of the likelihood of war to a 100% chance. There are multiple explanations for the negative relationship between these conflicts and stock market volatilities. War can be perceived as a stimulus package for the U.S. economy. In times of economic growth, stock market volatility decreases, while the opposite is true during recession.

Another reason for my findings is that the effects I examine are long-term effects on volatility, which differs from some of the literature. For example, Schwert (1989) demonstrates that stock market volatility increases in a brief period and immediately after a panic event but provides no evidence for long-term effects on volatility. Schwert`s work does not support my findings of a negative relation between material conflict events and long-term effects on volatility.

An extension of this line of thinking is that investors are inclined to hold on to their stocks. The number of trading days in the month and the actual trading activity are positively related to stock market volatility. Therefore, material conflict risk is not exogenous and positively influences economic activity. A potential consequence of this could be lower trading volume causing low stock market volatility, as indicated by the negative coefficients found in Table 6B in the last column. Overall, I conclude that there are no unambiguous inferences that can be made regarding conflict risk-specific variables and their relation to stock market volatility. However, material conflicts exhibit a negative relation between conflict risk variables and stock market volatility.

Table 6A:
Regression results for the effect of perceived conflict risk variables on the realized U.S. stock market volatility

This table reports the GARCH (1,1) model results following equation (2). $Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 Conflict_t + \varepsilon_t$ (2). where excess return is the excess stock return for U.S. equity markets from January 1979 to December 2013. For every $Conflict_t$, the variable scaled by the total event count for that month *t* is standardized by their sample standard deviation, and a natural logarithm transformation applies to each conflict risk variable. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Mean		Volatility			
	constant	conflict	constant	β_1	β_2	conflict
Log (All conflicts)						
Coefficient (%)	0.669	0.010	21.590*	0.113***	0.864***	-4.811*
Z-statistic	(0.07)	(0.00)	(1.83)	(3.84)	(30.15)	(-1.79)
Log (Severity index)						
Coefficient (%)	-0.848	0.340	17.900**	0.113***	0.863***	-4.009**
Z-statistic	(-0.11)	(0.20)	(2.09)	(3.91)	(30.49)	(-2.03)
Log (Investigate)						
Coefficient (%)	-4.375	1.107	8.290	0.116***	0.854***	1.877
Z-statistic	(-1.14)	(1.33)	(1.45)	(3.77)	(25.69)	(-1.43)
Log (Demand)						
Coefficient (%)	2.401	-0.368	18.590***	0.102***	0.858***	-4.110***
Z-statistic	(0.50)	(-0.36)	(3.22)	(3.83)	(23.29)	(-3.10)
Log (Disapprove)						
Coefficient (%)	12.30*	-2.522*	1.746	0.112***	0.858***	-0.439
Z-statistic	(1.92)	(-1.82)	(0.17)	(3.47)	(25.35)	(-0.19)
Log (Reject)						
Coefficient (%)	-4.423	1.123	-22.701***	0.123***	0.827***	4.925***
Z-statistic	(-0.60)	(0.70)	(-3.24)	(3.74)	(16.78)	(3.40)
Log (Threaten)						
Coefficient (%)	3.821	-0.657	0.327	0.146**	-0.061	0.568**
Z-statistic	(1.02)	(-0.79)	(0.25)	(2.46)	(-0.29)	(2.22)
Log (Protest)						
Coefficient (%)	-2.913	0.806*	-2.991	0.114***	0.850***	0.632
Z-statistic	(-1.38)	(1.72)	(-0.68)	(3.38)	(20.08)	(0.62)

Table 6B:

Regression results for the effect of perceived conflict risk variables on the realized U.S. stock market volatility

This table reports the GARCH (1,1) model results following equation (2). $Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 Conflict_t + \varepsilon_t$ (2), where excess return is the excess stock return for U.S. equity markets from January 1979 to December 2013. For every $Conflict_t$, the variable scaled by the total event count for that month *t* is standardized by their sample standard deviation, and a natural logarithm transformation applies to each conflict risk variable. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Mean		Volatility			
	constant	conflict	constant	β_1	β_2	conflict
Log (Exhibition of Force)						
Coefficient (%)	1.419	-0.156	3.319	0.108***	0.858***	-0.796
Z-statistic	(0.64)	(-0.32)	(1.16)	(3.55)	(27.04)	(-1.16)
Log (Reduction of relations)						
Coefficient (%)	-1.228	0.424	-6.188	0.112***	0.863***	1.257
Z-statistic	(-0.28)	(0.44)	(-0.73)	(3.69)	(28.09)	(0.71)
Log (Coerce)						
Coefficient (%)	-8.013	1.898*	12.120**	0.115***	0.856***	-2.733**
Z-statistic	(-1.51)	(1.65)	(2.27)	(3.68)	(27.70)	(-2.19)
Log (Assault)						
Coefficient (%)	0.253	0.098	6.920*	0.111***	0.873***	-1.709*
Z-Statistic	(0.09)	(0.16)	(1.75)	(0.029)	(33.33)	(-1.71)
Log (Fights)						
Coefficient (%)	2.658	-0.417	9.517***	0.112***	0.858***	-2.170***
Z-statistic	(0.464)	(-0.53)	(2.86)	(4.13)	(30.27)	(-2.62)
Log (Use of mass violence)						
Coefficient (%)	0.457	0.0890	-0.235	0.227***	0.720***	0.089
Z-statistic	(0.31)	(0.29)	(-0.06)	(3.14)	(7.64)	(0.11)

6.3 Time-series regression

There may be observable effects of the *expected* and *unexpected* portions of the perceived conflict risk on excess stock market returns. An AR (1) model will test the persistence of pricing in a time-series framework for conflict risk. In addition, an analysis on the industry level will indicate whether there is evidence of priced-in conflict risk in the cross section.

6.3.1 Time-series evidence

To determine *expected* and *unexpected* conflict risk equation (3) is re-estimated for every conflict risk proxy. I examine the total conflict proxy to illustrate the significance levels that result for equation (3). If I run equation (3) for all conflicts, the intercept indicates a value of 1.923 (with a *t*-statistic of 10.48). The coefficient that matches this constant is 0.582 for the measure of all conflicts (with a *t*-statistic of 12.21). Both are highly significant.

The fitted values from equation (3) that are estimated over the whole sample period can serve as the expected conflict risk. By re-estimating equation (3), I obtain the unique expected conflict risk variables for all specifications. The residuals will serve as the unexpected components of conflict risk. The inclusion of this unexpected component may be helpful for variations in market excess returns over time. Berkman et al. (2011) state that an unexpected disaster risk component will aid the interpretation of the relationship between *expected* conflict risk and the expected market risk premium, which is evidenced by the inclusion of such an unexpected component. Where the fitted values for equation (3) serve as the expected values of conflict risk, the residuals from equation (3) serve as the unexpected component of conflict risk.

Table 7 depicts the results of equation (4). The dependent variable is the monthly excess return of the U.S. equity market. The third and fourth columns represent the expected and unexpected conflict risk effects. Equation (4) is re-estimated for each conflict specification.

The results do not support my hypothesized relation between expected conflict risk, unexpected conflict risk, and excess stock market return in the U.S. equity markets. The null-hypothesis for almost all coefficients cannot be rejected and is therefore not statistically different from zero. All conflict risk specifications do not indicate a positive relation with excess stock market returns except in the form of “Reject” events. Where a 1% increase in the expected “Reject” conflict event is associated with a 7.257% increase in excess stock returns in the U.S. The rest of the expected conflict risk variables are not significantly different from zero. I conclude that there is no observable relationship between unexpected conflict risk and U.S. excess stock market return and a weak relation between expected conflict risk and U.S. excess stock market return.

Table 7:
Time-series results for expected and unexpected conflict risk

This table reports the findings of equation (4): $Excess\ Return_t^{US} = \alpha + \beta_1 Expected\ Conflict_t + \beta_2 Unexpected\ Conflict_t + \varepsilon_t$, where $Excess\ Return_t^{US}$ is the monthly excess U.S. stock market return in percentages for 1st January 1979 to 31st December 2013. The $Expected\ Conflict_t$ risk is the fitted value for equation (3). Equation (3) is specified as follows: $Conflict_t = \alpha + \beta_1 Conflict_{t-1} + \varepsilon_t$, where $Conflict_t$ can represent any different conflict risk specification. The residuals from equation (3) are used as $Unexpected\ Conflict_t$ risk. Equation (3) is re-estimated per conflict specification. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level. The *t*-statistics are based on heteroskedasticity-consistent standard errors.

Variables	constant	expected conflict risk	unexpected conflict risk
All conflict			
Coefficient (%)	3.397	-0.599	-1.019
t-Statistics	(0.20)	(-0.16)	(-0.38)
Investigate			
Coefficient (%)	1.421	-0.170	1.077
t-statistic	(0.12)	(-0.06)	(0.94)
Demand			
Coefficient (%)	14.39	-2.993	0.150
t-Statistics	(0.46)	(-0.44)	(0.11)
Disapprove			
Coefficient (%)	6.351	-1.242	-2.812
t-Statistics	(0.29)	(-0.26)	(-1.48)
Reject			
Coefficient (%)	-33.940	7.527*	0.127
t-Statistics	(-1.64)	(1.67)	(0.08)
Threaten			
Coefficient (%)	-9.783	2.279	-1.033
t-Statistics	(-0.91)	(0.97)	(-1.07)
Protest			
Coefficient (%)	-9.923	2.328	0.602
t-Statistics	(-1.23)	(1.31)	(0.92)
Exhibit Force			
Coefficient (%)	2.419	-0.396	0.083
t-Statistics	(0.58)	(-0.43)	(0.16)
Reduce Relations			
Coefficient (%)	10.850	-2.228	0.303
t-Statistics	(0.66)	(-0.62)	(0.30)
Coerce			
Coefficient (%)	-3.142	0.825	1.450
t-Statistics	(-0.31)	(0.38)	(1.08)
Assault			
Coefficient (%)	0.057	-0.866	0.152
t-Statistics	(1.28)	(-0.88)	(0.17)
Fight			
Coefficient (%)	0.022	-1.815	0.138
t-Statistics	(0.53)	(-1.50)	(0.13)
Mass Violence			
Coefficient (%)	0.021	0.375	0.277
t-Statistics	(0.87)	(0.27)	(0.72)
Severity index			
Coefficient (%)	7.492	1.490	-0.152
T-statistic	(7.49)	(0.64)	(0.07)

I examine the results of a supremum Wald test to test potential causes for the non-significant results with respect to *unexpected* conflict risk. A Wald test tests the presence of a structural break in the data. Performing a Wald test on the regression from equation (3) for the variable "All conflict" indicates that the coefficient is not stable over time. The Wald test produces a test statistic with a value of 25.29 that translates to a *p*- value 0f 0.0001. The null-hypothesis that no structural break is present in this data is rejected. The test indicates a break in the data around month 9 of 2001, which is September 2001. Normally, the outbreak of a special event can cause a structural break in research data. September 2001 marked the beginning of the war in Afghanistan and other conflicts in the Middle East. A structural break can bias estimators, and a robustness check would be in place for these results. Section 6.4 details a robustness check for this break.

6.3.2 Cross-sectional evidence

The previous section highlights the pricing of conflict risk through predictive regressions in a time-series framework. Using an approach similar to that of Berkman et al. (2011), I expand upon this research by examining the cross-sectional framework and their 1-month ahead return in the value-weighted industry portfolio with newly-constructed conflict risk variables. In general assets that do better during a conflict or crisis should exhibit lower expected excess returns. Thirty value-weighted industry portfolios are used to examine this hypothesis. I apply a Fama and Macbeth (1973) regression to examine the relation between conflict sensitivity and the 1-month ahead returns for each industry portfolio.

The motivation for the use of value-weighted industry portfolios as test asset is similar to that of Berkman et al. (2011), because these value-weighted industry portfolios have been generating poor results in terms of explaining the difference in expected returns among these portfolios. Furthermore, the CAPM and the Fama-French 3 factor model unsatisfactorily explain the substantial heterogeneity in expected returns for value-weighted industry portfolios (Fama and French, 1997; Lewellen,Nagel and Shanken , 2010).

I use the Fama-French factors and the unexpected change in conflict risk to examine the cross-sectional evidence on the pricing of conflict risk. This cross-sectional evidence on pricing conflict risk serves as a sensitivity analysis for conflict risk among industries. Each conflict sensitivity is represented by the residuals from the re-estimated equation (3).

I use a 60-month rolling window and run the time-series regression to be consistent with other research in this area. Equation (5) use these time-series regressions in a 60-month window ($\tau = t - 60$ to $t - 1$) to obtain the factor loadings for the Fama-French factors and the conflict sensitivity for each industry portfolio *i*.

For interpretational purposes, I scale the $\beta_{i,t-1}^{Conflict}$ from equation (5) into deciles and rank each month. This transformed coefficient is scaled back to between zero and one. Nagel (2005) indicates that this adjustment renders results less sensitive to errors. The next step is the cross-sectional regressions. Equation (6) shows how I perform the cross-sectional regression for every month *t.* This results in monthly risk premium for every factor in equation (6). The market risk premiums are averaged for all factors and the results are reported in Table 8A and Table 8B.

Table 8A provides the time-series averages for the estimates of the risk premiums on a monthly estimate. The table depicts the risk premiums for the Fama-French factors in the first three columns. The forth column depicts the factor that resembles conflict risk. I use Newey-West (1987) standard error correction to avoid any problems with autocorrelation.

The three Fama-French factors are expected to show a positive sign. These common risk factors show mixed results and are not significant, this contradicts my expectation. I can therefore argue that the common risk factors do not explain the variation in the cross section of the 30 value-weighted industry portfolios. This result is not completely surprising since these portfolios are not sorted on size or book-to-market.

The fourth column in Table 8A depicts the risk premium for conflict risk sensitivity, which enables me to examine if perceived conflict risk is priced in the cross section. Table 8A does not indicate support for my hypothesis that perceived conflict risk is priced in the cross section. The two broad conflict measures as proxied by "All conflict" and "Severity index" are not significant at a 10% significance threshold; they have *t*-statistics of 1.26 and 1.64 respectively. The conflict risk factor that reflects "verbal conflict" in column 4 of Table 8 do not indicate significant results for conflict sensitivity either. I conclude that for these conflict factors, industry portfolios do not perform relatively better during periods of high-conflict events and conflict risk is not priced for these conflict variables. These findings assume that investors do not require a premium as compensation for these conflict risks.

Table 8B reports the findings on material conflict variables. Like Table 8A, the first three columns indicate the Fama-French factors and are not significant. The fourth column indicates the conflict proxy sensitivity for the material conflicts that are coded with "Exhibit force," "Reduce relations," "Coerce," "Assault," "Fight," and "Mass violence." All events that are coded with "Assault" indicate significant results and are therefore suited for inferences. The proxy perceived conflict risk for "Assault "type events indicate a coefficient of 0.341 and a *t*-statistic of 2.27.

This result contradicts my hypothesis that if conflict risk is priced, the average of the time-series that represent the risk premium would be negative. Instead for these "Assault" type events the values are positive. A negative value would imply that industry portfolios that do relatively well when there is an increase in conflict risk will yield lower returns on average. The "Assault" conflict risk specification demonstrates that the monthly average risk premium is 0.341 and is statistically significant at a 5% threshold. This implies that the average difference in returns between the bottom “Assault” crisis sensitivity stock and the top “Assault” crisis sensitivity stock is there 0.341%. The least conflict-risk sensitive “Assault” industry decile portfolio outperforms the most conflict risk-sensitive “Assault” industry decile portfolio. This is not in line with the risk-based approach. The industry portfolios that do relatively well during periods of high “Assault” conflict risk yield higher returns on average. Table 8A and 8B do not provide conclusive evidence to support my hypothesis that conflict risk is priced.

The results in Tables 8A and 8B are not sufficiently conclusive evidence to support my hypothesis with respect to the pricing of conflict risk. I cannot accept that the perceived conflict risk is priced in the U.S. equity market. Investors therefore do not require a risk premium compensation for this risk.

Table 8A:

Averaged risk premiums for the perceived conflict sensitivities and the 3 Fama-French factors

This table reports findings for the monthly average risk premiums from equation (6), following a two-step Fama and Macbeth (1973) regression. $RI_{i,t} = \gamma_t + \gamma_{MKTRF,t}\,\beta_{i,t-1}^{MKTRF} + \gamma_{SMB,t}\,\beta_{i,t-1}^{SMB} + \gamma_{HML,t}\,\beta_{i,t-1}^{HML} + \gamma_{Conflict,t}\,\beta_{i,t-1}^{Conflict} + \varepsilon_{i,t}$ (6). Here $RI_{i,t}$ represents the excess returns for the "i" industry portfolios in month "t" for the sample period February 1979 through December 2013. Where the β`s resemble factor loadings, for respectively $MKTRF, t$, SMB, t and HML, t and $Conflict, t$ is obtained by re-estimating equation (5) : $RI_{i,\tau} = \alpha_{i,t-1} + \beta_{i,t-1}^{MKTRF} MKTRF_\tau + \beta_{i,t-1}^{SMB} SMB_\tau + \beta_{i,t-1}^{HML} HML_\tau + \beta_{i,t-1}^{Conflict} Conflict_\tau + \eta_{i,\tau}$. These time-series regressions apply over a rolling window of 60 months. The t-statistics are, based on autocorrelation-adjusted Newey-West standard errors for two lags and are presented, between the parentheses. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Variables	MKTRF	SMB	HML	Conflict
All conflict				
Coefficient	-0.056	0.072	0.212	0.187
t-Statistics	(-0.16)	(0.38)	(1.11)	(1.26)
Severity index				
Coefficient	-0.112	0.062	0.182	0.241
t-Statistics	(-0.32)	(0.32)	(0.95)	(1.64)
Investigate				
Coefficient	-0.023	0.079	0.204	0.208
t-statistic	(-0.06)	(0.42)	(1.06)	(1.25)
Demand				
Coefficient	-0.072	0.108	0.199	-0.200
t-Statistics	(-0.20)	(0.57)	(1.03)	(-1.32)
Disapprove				
Coefficient	-0.066	0.092	0.227	0.121
t-Statistics	(-0.19)	(0.5)	(1.20)	(0.74)
Reject				
Coefficient	-0.097	0.115	0.240	0.081
t-Statistics	(-0.29)	(0.60)	(1.25)	(0.63)
Threaten				
Coefficient	0.065	0.054	0.233	-0.013
t-Statistics	(0.17)	(0.28)	(1.20)	(-0.08)
Protest				
Coefficient	-0.206	0.102	0.217	0.139
t-Statistics	(0.06)	(0.55)	(1.12)	(1.01)

Table 8B:
Averaged risk premiums for the perceived conflict sensitivities and the 3 Fama-French factors

This table reports findings for the monthly average risk premiums from equation (6), following a two-step Fama and Macbeth (1973) regression. $RI_{\,i,t} \; = \gamma_t \, + \, \gamma_{MKTRF,t} \, \beta_{i,t-1}^{MKTRF} + \, \gamma_{SMB,t} \, \beta_{i,t-1}^{SMB} \, + \, \gamma_{HML,t} \, \beta_{i,t-1}^{HML} + \gamma_{Conflict\,,t} \, \beta_{i,t-1}^{Conflict} \, + \, \varepsilon_{i,t}$ (6). Here $RI_{\,i,t}$ represents the excess returns for the "i" industry portfolios in month "t" for the sample period February 1979 through December 2013. Where the β`s resemble factor loadings, for respectively $MKTRF, t$, SMB, t and HML, t and $Conflict\,, t$ is obtained by re-estimating equation (5) : $RI_{\,i,\tau} \; = \alpha_{i,t-1} + \, \beta_{i,t-1}^{MKTRF} MKTRF_\tau + \, \beta_{i,t-1}^{SMB} SMB_\tau \, + \, \beta_{i,t-1}^{HML} HML_\tau \, + \, \beta_{i,t-1}^{Conflict} Conflict_\tau + \, \eta_{i,\tau}$. These time-series regressions apply over a rolling window of 60 months. The t-statistics are, based on autocorrelation-adjusted Newey-West standard errors for two lags and are presented, between the parentheses. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Variables	MKTRF	SMB	HML	Conflict
Exhibit Force				
Coefficient	0.020	0.107	0.193	0.054
t-Statistics	(0.06)	(0.57)	(0.97)	(0.33)
Reduce Relations				
Coefficient	-0.139	0.106	0.167	-0.061
t-Statistics	(-0.39)	(0.57)	(0.86)	(-0.38)
Coerce				
Coefficient	-0.114	0.077	0.238	0.079
t-Statistics	(-0.33)	(0.41)	(1.24)	(0.63)
Assault				
Coefficient	-0.105	0.045	0.244	0.341**
t-Statistics	(-0.30)	(0.23)	(1.25)	(2.27)
Fight				
Coefficient	-0.135	0.060	0.202	0.111
t-Statistics	(-0.39)	(0.32)	(1.05)	(0.77)
Mass Violence				
Coefficient	0.140	0.491*	0.280	-0.100
t-Statistics	(0.33)	(1.74)	(0.95)	(-0.42)

The results do not indicate a risk premium for perceived conflict risk. One of the reasons for this could be that investors do not find a risk premium appropriate because the risk is not attached to certain assets. A natural consequence would be that this risk is diversifiable, and therefore no compensation for exposure to this risk is needed.

Another explanation for these results is as follows. There have been recent critiques of the Fama and Macbeth (1973) regression procedure. Various problems have been addressed in this multi-step approach and the gamma estimations, such as a cross-sectional independence problem. The Fama and Macbeth (1973) procedure uses OLS in cross-sectional models for panels. This assumes that the variance covariance matrix of the residuals η at each point t is proportional to a diagonal matrix. If this is not the case, then the gamma γs will be consistent but not efficient (Baek and Bilson, 2015). As a result, the parameters demonstrate false t-statistics. Wrong t-statistics can cause type I or type II errors and therefore lead to wrong inferences from results.

An additional critique of the Fama and Macbeth (1973) approach is the errors-in-variable problem, which is that the cross-sectional regressions assume that the betas are given. For example, the results for the betas that arise from the time-series regression using a rolling window are the true and unobservable betas. The resulting errors in the betas affect the precision by which the parameters of the cross-sectional regression are estimated. Hence, the validity of the conclusion with respect to these parameters is there questionable.

6.4 Robustness tests

As explained in the methodology, I make argued assumptions regarding my choice of the construction of a wide array of proxies for perceived conflict risk. This robustness section examines how my results persist or change when assumptions change. First, I will examine if my results depend on my sample period. By testing for a structural break in my data, I can examine if my results are prone to differ for different event windows. Second, I determine the speed with which investors reliably process and analyze information. I do so by examining the effects of the previous month`s news event with respect to all conflict risk measures. Finally, I tweak my underlying assumptions about what events I include in my sample. With respect to the war puzzle, it will be interesting to only examine outgoing U.S. -involved events. This might serve as more conclusive evidence that events that mimic war can serve as stimuli packages for an economy, for example. The results can be found in the Appendix. Appendix A, B, C and D will be discussed here.

First, I examine a potential structural break in my data with a Wald test for my AR (1) model, as described in equation (4). This Wald test examines whether the coefficients in a time-series regression vary over the periods defined by an unknown break date. The null-hypothesis for this test states that the estimates of the coefficients are constant through the sample period. “All conflict” has an intercept of 1.923, a *t*-statistic of 10.48 and a coefficient of 0.582 that has a *t*-statistic of 14.59. I now perform a Wald test for my variable “All conflict”. The Wald test provides me with a test statistic of 37.77 and indicates that I need to reject the null-hypothesis. The test reports that here is a structural break present in September 2001. This structural break can influence my results. To test this, I will re-estimate my equations for this later event window between September 2001 and December 2013.

The returns of the market are lower than the risk-free rate for this sample period, as illustrated in Appendix B (Table 9). Appendix B (Table 11) indicates that the two broad conflict measures indicate higher values that suggest more conflict in the period after September 2001. The correlation for this later event window is more positive and slightly stronger (see Appendix B, Table 10).

Appendix B (Table 12) demonstrates that my broad conflict measures are now positive values that indicate a large increase in size. The severity index is significant at a 5% threshold. The amount and severity of conflict exhibit a large increase in this later event window. The results indicate an opposite reaction to my predictions for this event window, judging by the positive and significant coefficients for “Protest” and “Coerce.” Appendix B (Tables 13A and 13B) report that except for “Coerce,” event types do not show significant support for any effects of conflict risk on stock market volatility. The time-series evidence indicates mostly similar results, except that the coefficient for “Fight”-type conflict risk is now significant and negative (Appendix B, Table 15A and table Table 15B). Comparing the results from the base case and this robustness check yields the conclusion that there is a structural break in the data. The effects of perceived conflict risk on excess stock market return, volatility, time-series regression, or cross-sectional regression are not robust for different event windows. The coefficients are therefore not stable throughout time.

Another robustness check examines if investor behavior differs for news events that are lagged by a month. News events in the previous month might influence the perception or reaction of investors. To check for this, I re-apply my analysis with a 1-month-lagged conflict risk variable. Appendix C (Table 16) reports similar signs and sizes for the coefficients and their effect on mean excess stock market return are also not statistically significant. The GARCH specification produces similar results with respect to conflict risk effects on stock market volatility. The effects are similar but less strong in the 1-month lagged specification (Appendix C Table 17A and Table 17B). Appendix C (Table 18) exhibits similar results for unexpected or expected conflict risk. “Protest” however shows a positive effect for unexpected “Protest” risk. The “Fight”-type unexpected risk shows a negative and significant value of -2.286 indicative for a negative relation between unexpected “Fight” type events and excess stock market return. The cross-sectional evidence shows no indication of a clear relation between conflict risk and pricing the cross section.

Finally, I check if the inclusion of only events that have the U.S. as a source influences my results. I therefore focus only on outgoing events which the U.S. imposes on other actors. Appendix D (Table 20) demonstrates relatively more frequent and severe conflicts are initiated by the U.S. as opposed to the conflict event counts in my base case analysis. My results on excess mean returns are like my base case in terms of significance (Appendix D Table 22). The GARCH specification demonstrates similar results for conflict risk types and stock market volatility (Appendix D, Table 23A and Table 23B). The two broad conflict measures are both negative and significant as in my base case, and the effects are less strong. Material conflict events are less strong and similarly negative, and significant effects are observable (Appendix D, table 23B). Appendix D (Table 24) indicates similarly insignificant results with respect to the time-series evidence that includes separate components for *expected* and *unexpected* conflict risk. The cross-sectional evidence reports that the “Use of mass violence”- type events is priced in the cross section. Appendix D (Table 25) reports that verbal conflict events are not priced in when applying the Fama and Macbeth (1973) framework. The material event results demonstrate that the value-weighted industry portfolios are sensitive. Therefore, "Use of mass violence" is priced in.

My robustness section suggests that there is a structural break in the GDELT event database and this should be kept in mind for follow-up research. A 1-month lagged specification of conflict risk variables do not bear any significant explanatory weight. Only including outgoing event from the U.S. results in relatively more severe events than in the base case analysis.

7. CONCLUSION

In this paper I build upon existing news event analysis to proxy for different severities of conflict risk. I use a novel and rich dataset, GDELT, to construct a wide array of conflict risk-specific variables and two broad conflict measures. I conduct an in-depth examination of the relation between conflict risk and U.S. excess stock market returns. This research approach finds that there is no relation between perceived conflict risk and excess stock market return in the U.S. stock market. The GARCH specification indicates that U.S. stock market volatility is influenced by the changes in perceived conflict risk. Distinguishing between *expected* and *unexpected* conflict risk effect on U.S. stock market does not add any explanatory power to my findings. I do not find unambiguous evidence for the existence of risk premiums when examining conflict risk in a cross-sectional framework.

I find no relation between excess mean stock return in the U.S. market and conflict risk for most conflict variables and a weak relation for a few variables. With respect to contemporaneous stock market return, investors do not discriminate between verbal and material events. This finding is surprising because the existing literature concludes that including international conflict event have a negative effect on contemporaneous stock returns on country level (Berkman et al., 2011; Chen, Lu and Yang, 2014). Berkman et al. (2011) specifically address the stock market reaction of individual countries to international crisis in which those countries were actors. Their findings suggest that a crisis has a stronger impact on stock returns if a country is a crisis actor. I do not find that excess stock market return exhibit a stronger negative stock reaction for more severe events. The following paragraphs cover potential explanation for my findings.

First, my assumption of what investor pay attention to plays a crucial role in obtaining my results. I assume that an event qualifies as relevant only when the number of articles is above the median. I assume that this number of articles is a measure of relative impact and importance of events. This assumption may not be strict enough. An additional measure of relative importance and impact events would be helpful.

Another explanation might be that a simple linear OLS regression is not the best tool to examine the conflict risk and stock market relationship. Certain verbal or material events can have catastrophic consequences in a certain context. The relation between variables might serve as potential aid to examine the effects of perceived conflict risk on stock markets. An interaction effect will represent the combined effect of variables on the dependent variable. For example, the amount of "Exhibit force" events might depend heavily on the amount of "Disapprove" events. If such interaction effects are present, they could aid in the interpretation of results.

Furthermore, I provide evidence of a negative relation between increasing conflict risk and U.S. stock market volatility. The two broad conflict measures also indicate these contradictory findings. The verbal conflict event demonstrates mixed results. The material conflict events report a negative relation between conflict risk and stock market volatility. This evidence contradicts my hypothesis that increased conflict risk increase stock market volatility.

A potential explanation for this could be the war puzzle developed by Brune et al. (2011). The war puzzle indicates a switch in the reaction of stock market returns whenever the likelihood of war tips from 99% to 100%. This war puzzle might aid in the interpretation of these results with respect to realized volatility. Both the broad conflict measures heavily rely on frequent material conflict events, as is evident from the descriptive statistics. A negative relation is observable for these two measures. This war puzzle explanation might serve useful to why investors interpret these events as "good news". War may be well-perceived because it can be a stimulus package for the U.S. economy. This incentivizes investors to hold on to their stock. Because of that, trading volume decreases and this leads to a decrease in stock market volatility.

A different reason for my findings is the effects I examine are long-term effects on volatility unlike the focus of some existing literature. Schwert (1989) demonstrates that stock market volatility increases for a brief period immediately after a panic event. However, Schwert`s paper does not provide evidence for long-term effects on volatility. This could be a potential reason why I find a contradictory negative relation with respect to conflict risk and excess stock market returns.

I distinguish between an *expected* and *unexpected* component of conflict risk. Both components did not seem to bear statistical relevance. Therefore, no relationship is observable. This result is robust to other robustness tests. Berkman et al. (2011) provide similar results with respect to the *expected* component of conflict risk. Potential reasons for my findings for the *unexpected* component might be similar to the explanation provided for contemporaneous stock return. Additionally, another potential explanation might be that conflict risk is tail heavy and are not characterized by a linear relationship. The distribution of events that are of importance for investors might exhibit a fat tail. The problem with a fat-tailed distribution is that the variance is typically high and underestimated in past data. Investor should possibly approach conflict risk from an extreme value theory approach.

Furthermore, I find no evidence for a cross-sectional predictability to the Fama-French factors. This finding is not surprising. Like findings of Gourio (2008a) and Fama and French (1997), they find similar evidence that the Fama-French factors do not describe the cross section of industry returns well.

The results do not indicate a risk premium for perceived conflict risk. One of the reasons for this could be that investors do find a risk premium appropriate because the risk is not attached to certain assets. A natural consequence would be that this risk is diversifiable, and therefore no compensation for exposure to this risk is needed.

Another explanation for these results are as follows. There have been recent critiques of the Fama and Macbeth (1973) regression procedure. Various problems have been addressed in this multi-step approach and the gamma estimations, such as cross-sectional independence problem. The Fama and Macbeth (1973) procedure uses OLS in cross-sectionals models for panels. This assume that the variance covariance matrix of the residuals N at each point t is proportional to a diagonal matrix. If this is not the case, then the gamma γs will be consistent but not efficient in that case according to Baek and Bilson (2015). As a result, the parameters demonstrate false t-statistics. Wrong t-statistics can cause type I or type II errors and therefore lead to wrong inferences from results.

An additional critique of the Fama and Macbeth (1973) approach is the errors-in-variable problem, which is that the cross-sectional regressions assume that the betas are given. For example, the results for the betas that arise from the time-series regression using a rolling window are the true and unobservable betas. The resulting errors in these betas affect the precision by which the parameters of the cross-sectional regression are estimated. Hence, the validity of the conclusion with respect to these parameters is therefore questionable.

Furthermore, the evidence from my sample period is consistent but contradicts previous findings. A reason might be the emphasis on more recent data in this paper. Lastly, I will look at certain limitations of this research and give potential future research possibilities.

7.1 Limitations

Firstly, I would like to reiterate that one of the explanations for my findings might be due to an attention bias among investors. Investors do not rely on every event that takes place and are restrained by their limited attention capacity. I assume that above-median coverage events are useful for investors. I use the variable “Number of Articles” to proxy for the importance of an observation. A more extensive measure of importance and impact of events would be useful. The GDELT dataset does not contain records for the variable: “Average Tone” ex-ante March 2014. This would be a great addition in further research. This variable reports the average tone for each article and can therefore more in depth proxy for the importance and impact of events.

A different limitation stem from the CAMEO code categorization. This GDELT dataset lacks trigger dates or end dates for international crisis. Using an approach similar to that of Berkman et al. (2011), it would be nice if further research could distinguish between a start phase, a during phase and an end phase of war. Where one would have to either by hand detect trigger dates for each as the date when the earliest actor in the international crisis perceives crisis.

A last limitation or concern is the potential presence of a latent variable. A variable that is not directly observed but is inferred from other variables that are observed. This variable cannot be measured directly but might influence results.

7.2 Further research

In combination with Berkman et al. (2011) and Azzimonti (2018) this paper provides new steps with respect to the analysis of perceived conflict risk in asset pricing. Due to the gap in prior literature on studies done on conflict risk, there are several avenues for future research.

Firstly, it would be useful to test different models to examine the relation between conflict risk and stock market returns. Possibly a quadratic or discontinuous model describes the relation between conflict risk and stock market return better. A different research avenue is examining the potential interaction effect and thus an interacted combined effect of conflict risk events.

Furthermore, further research can extend how conflict risk is priced as a cross-sectional risk factor. One could examine conflict risk as an observable stock characteristic. Thereby examining the contemporaneous relation between expected future conflict risk that agents might asses in determining expected returns. Using an approach similar to that of Ang, Hodrick, Xing and Zhang (2009), one could build portfolios that are sorted on conflict risk sensitivity. Hereby expanding upon the cross-sectional evidence.

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Appendices

Appendix A: What feeds GDELT

Here is a list that comprise of all that feeds GDELT:

AfricaNews, Agence France Presse, Associated Press Online, Associated Press Worldstream, BBC Monitoring, Christian Science Monitor, Facts on File, Foreign Broadcast Information Service, United Press International, and the Washington Post.

In addition to this there are sources that examine the inter and national news coverage from prominent newspapers the New York Times, major international united states national stories from the Associated Press and all national and international news published by Google news. From google news the sport, entertainment and strictly economic section is excluded.

Appendix B:

Appendix B: Robustness check 2 reports the results for a different event window.

Table 9:

Descriptive statistics for U.S. equity market different event window

Table 9 present the descriptive statistics for the Fama-French factors and risk-free rate. This table reports the mean, standard deviation, minimum, maximum and the amount of available observations for all variables. The returns are percentages for the six value-weighted portfolios that are formed on size and book-to-market, the six-value weighted portfolio formed on size and profitability, and the value-weighted portfolios formed on size and investment. The sample covers 1st September 2001 to 31st December 2013.

Variables	Mean	Standard Dev.	Minimum	Maximum	Observations
MKTRF	0.547	4.521	-17.23	11.35	148
SMB	0.403	2.450	-6.23	6.71	148
HML	0.128	2.548	-11.10	7.76	148
RF	0.127	0.140	0.00	0.44	148

Table 10:

The correlation matrix for all conflict variables different event window

Table 10 reports correlation coefficients between the different conflict risk variables. The correlation coefficient is stated for every conflict risk variable. These correlation coefficients are representative for the sample period of September 2001 to December 2013. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	AC	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	Severity index
All Conflicts	1.00													
Investigate (9)	0.20 *	1.00												
Demand (10)	0.15	0.31 ***	1.00											
Disapprove (11)	0.58 ***	-0.23 **	0.38 ***	1.00										
Reject (12)	0.44 ***	-0.37 ***	0.03	0.11	1.00									
Threaten (13)	0.53 ***	-0.12	0.02 **	0.57 ***	0.21 *	1.00								
Protest (14)	0.47 ***	0.11	-0.05	0.01	0.34 ***	0.25 ***	1.00							
Exhibit of Force (15)	0.35 ***	-0.29 ***	0.22 **	0.54 ***	0.16	0.64 ***	0.17 *	1.00						
Reduce Relations (16)	-0.27 ***	-0.11	0.22 **	-0.20 *	0.09	0.24 **	0.20 *	-0.26 ***	1.00					
Coerce (17)	0.39 ***	0.42 ***	-0.27 **	-0.21 *	-0.17 *	-0.23 **	0.21 **	-0.40 ***	-0.10 *	1.00				
Assault (18)	0.42 ***	0.24 **	-0.11	0.17 *	0.06	-0.21 *	0.25 **	-0.38 ***	-0.14 **	0.52 ***	1.00			
Fights (19)	0.64 ***	-0.04	0.03	0.26 **	0.03	0.22	0.11	0.14	0.08	0.16	0.38 ***	1.00		
Use Mass Violence (20)	0.26	0.09 **	-0.08	0.01 **	0.11	0.12 **	0.15	0.03	0.01	0.06 **	0.25	0.32	1.00	
Severity Index	0.93 ***	0.18 *	0.00	0.325 ***	0.31 ***	0.33 ***	0.45 ***	0.16	0.2 *	0.54 ***	0.63 ***	0.77 ***	0.33 ***	1.00

Table 11:

Descriptive statistics for all conflict variables different event window

Table 11 reports the descriptive statistics of conflict variables. Panel A reports the mean, standard deviation, minimum and maximum. The sample period for these descriptive statistics is September 2001 to December 2013. This is a total of 420 monthly observations. All conflict denotes the number of conflict-based events that take place scaled by the total number of events monthly. These descriptive statistics represent all events that involve U.S. involvement and exclude domestic events. The variables that are reported on are the following: investigate, demand, disapprove, reject, threaten, protest, exhibit force posture, reduction of relations, coerce, assault, fight and use of mass violence. The severity index is a weighted index of all conflict events weighted by their severity. The critical value at the 1% level for the Dickey Fuller –GLS test are statistics for a test with a null-hypothesis of a unit root equal to -2.57. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

VARIABLES	Mean	Std. Dev.	Min	Max	DF-GLS
All Conflicts	0.2900	0.0166	0.2445	0.3643	-7.499***
Investigate	0.0172	0.0023	0.0120	0.0255	-7.034***
Demand	0.0156	0.0016	0.0121	0.0201	-8.562***
Disapprove	0.0719	0.0064	0.0577	0.0910	-6.173***
Reject	0.0267	0.0024	0.0210	0.0371	-7.407 ***
Threaten	0.0175	0.0035	0.0118	0.0337	-5.931***
Protest	0.0079	0.0027	0.0024	0.0228	-6.689***
Exhibit Force	0.0049	0.0018	0.0026	0.0136	-5.456***
Reduce Relations	0.0119	0.0018	0.0086	0.0186	-8.832***
Coerce	0.0447	0.0050	0.0298	0.0565	-6.116***
Assault	0.0181	0.0039	0.0010	0.0290	-4.780***
Fights	0.0527	0.0051	0.0375	0.0640	-8.740***
Mass Violence	0.0004	0.0003	0	0.0020	-10.379***
Severity index	1.804	0.1208	1.4975	2.2338	-7.333***

Table 12:

Effects of perceived conflict risk on international U.S. equities different event window

Results for equation (1) through $Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t$. where $Excess\ Return_t^{US}$ is the monthly excess return on U.S. stock markets for 1st September 2001 to 31st December 2013. $Conflict_t$ represents each conflict variable and is constructed by the number of events in month *t*. For category, the variable scaled by the total event count for that month *t*, standardized by their sample standard deviation. A natural logarithm transformation applies to every conflict risk variable. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level. The *t*-statistics are based on heteroskedasticity-consistent standard errors.

	Constant	Conflict
Log (All Conflicts)		
Coefficient (%)	-48.837	10.581
T-statistic	(-1.46)	(1.48)
Log (Investigate)		
Coefficient (%)	-3.398	0.848

T-statistic	(-0.32)	(0.37)
Log (Demand)		
Coefficient (%)	-5.241	1.252
T-statistic	(-0.35)	(0.39)
Log (Disapprove)		
Coefficient (%)	16.259	-3.390
T-statistic	(0.73)	(-0.71)
Log (Reject)		
Coefficient (%)	-24.008	5.420
T-statistic	(-1.33)	(1.37)
Log (Threaten)		
Coefficient (%)	-0.771	0.280
T-statistic	(-0.06)	(0.10)
Log (Protest)		
Coefficient (%)	-11.928***	2.724***
T-statistic	(-2.66)	(2.81)
Log (Exhibit force)		
Coefficient (%)	1.592	-0.226
T-statistic	(0.29)	(-0.19)
Log (Reduce relations)		
Coefficient (%)	-4.381	1.087
T-statistic	(-0.37)	(0.42)
Log (Coerce)		
Coefficient (%)	-33.718**	7.312***
T-statistic	(-1.97)	(2.01)
Log (Assault)		
Coefficient (%)	-12.744	2.793*
T-statistic	-1.60	1.68
Log (Fights)		
Coefficient (%)	-17.442	3.778
T-statistic	(-0.99)	(1.03)
Log(Use of Mass Violence)		
Coefficient (%)	-0.709	0.284
T-statistic	(-0.31)	(0.58)
Log (Severity Index)		
Coefficient (%)	-54.109*	11.644**
T-statistic	(-1.98)	(2.00)

Table 13A:

Regression results for the effect of perceived conflict risk variables on the realized U.S. stock market volatility different event window

This table reports the GARCH (1,1) model results following equation (2). $Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 Conflict_t + \varepsilon_t$ (2). where excess return is the excess stock return for U.S. equity markets from September 2001 to December 2013. For every $Conflict_t$, the variable scaled by the total event count for that month t is standardized by their sample standard deviation, and a natural logarithm transformation applies to each conflict risk variable. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Mean		Volatility			
	Constant	Conflict	Constant	β_1	β_2	Conflict
Log (All conflicts)						
Coefficient (%)	-45.68*	9.953*	24.10	0.251***	0.704***	-5.172
Z-statistic	(-1.74)	(1.77)	(0.34)	(2.63)	(5.99)	(-0.34)
Log (Severity Index)						
Coefficient (%)	-48.15**	10.42**	13.59	0.246***	0.721***	-2.948
Z-statistic	(-2.12)	(2.16)	(0.20)	(2.68)	(6.82)	(-0.21)
Log (Investigate)						
Coefficient (%)	-9.890	2.302	-2.701	0.241***	0.718***	0.570
Z-statistic	(-0.96)	(1.03)	(-0.10)	(2.85)	(6.94)	(0.10)
Log (Demand)						
Coefficient (%)	1.613	-0.178	18.26	0.248***	0.673***	-3.860
Z-statistic	(0.10)	(-0.05)	(0.76)	(2.70)	(5.27)	(-0.74)
Log (Disapprove)						
Coefficient (%)	18.51	-3.806	12.34	0.249**	0.684***	-2.593
Z-statistic	(0.93)	(-0.89)	(0.37)	(2.55)	(5.41)	(-0.36)
Log (Reject)						
Coefficient (%)	-18.96	4.358	31.90	0.268***	0.678***	-7.024
Z-statistic	(-1.43)	(1.50)	(0.69)	(2.75)	(5.68)	(-0.68)
Log (Threaten)						
Coefficient (%)	-3.042	0.822	-7.070	0.238***	0.713***	1.517
Z-statistic	(-0.30)	(0.39)	(-0.38)	(2.90)	(6.50)	(0.39)
Log (Protest)						
Coefficient (%)	-9.396*	2.239*	6.143	0.218***	0.732***	-1.371
Z-statistic	(-1.71)	(1.87)	(0.52)	(2.75)	(7.05)	(-0.50)

Table 13B:
Regression results for the effect of perceived conflict risk variables on the realized U.S. stock market volatility different event window

This table reports the GARCH (1,1) model results following equation (2). $Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 Conflict_t + \varepsilon_t$ (2), where excess return is the excess stock return for U.S. equity markets from January 1979 to December 2013. For every $Conflict_t$, the variable scaled by the total event count for that month *t* is standardized by their sample standard deviation, and a natural logarithm transformation applies to each conflict risk variable. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Mean		Volatility			
	Constant	Conflict	Constant	β_1	β_2	Conflict
Log (Exhibition of Force)						
Coefficient (%)	5.662	-1.050	9.141	0.234***	0.718***	-2.002
Z-statistic	(1.22)	(-1.05)	(0.68)	(2.90)	(7.77)	(-0.66)
Log (Reduction of relations)						

Coefficient (%)	-7.979	1.924	18.44	0.229***	0.695***	-4.020
Z-statistic	(-0.86)	(0.95)	(0.95)	(2.77)	(6.07)	(-0.92)
Log (Coerce)						
Coefficient (%)	-23.20**	5.106**	78.67***	0.124*	0.842***	-17.37**
Z-statistic	(-1.97)	(2.04)	(3.52)	(1.91)	(14.68)	(-3.43)
Log (Assault)						
Coefficient (%)	-10.39	2.345*	4.094	0.222***	0.743***	-0.914
Z-Statistic	(-1.61)	(1.74)	(0.23)	(2.93)	(7.96)	(-0.24)
Log (Fights)						
Coefficient (%)	-16.73	3.678	-12.49	0.235***	0.718***	2.618
Z-statistic	(-1.03)	(1.08)	(-0.27)	(2.82)	(6.76)	(0.27)

Table 14:
Time-series results for expected and unexpected conflict risk different event window

This table reports the findings of equation (4): $Excess\ Return_t^{US} = \alpha + \beta_1 Expected\ Conflict_t + \beta_2 Unexpected\ Conflict_t + \varepsilon_t$, where $Excess\ Return_t^{US}$ is the monthly excess U.S. stock market return in percentages for 1st September 2001 to 31st December 2013. The $Expected\ Conflict_t$ risk is the fitted value for equation (3). Equation (3) is specified as follows: $Conflict_t = \alpha + \beta_1 Conflict_{t-1} + \varepsilon_t$, where conflict can represent any different conflict risk specification. The residuals from equation (3) are used as $Unexpected\ Conflict_t$ risk. Equation (3) is re-estimated per conflict specification. The *t*-statistics are based on heteroskedasticity-consistent standard errors.

Variables	Constant	Expected conflict risk	Unexpected conflict risk
All conflict			
Coefficient (%)	-104.1	22.43	9.969
t-Statistics	(-1.23)	(1.24)	(1.40)
Investigate			
Coefficient (%)	13.39	-2.746	0.959
t-statistic	(0.59)	(-0.56)	(0.39)
Demand			
Coefficient (%)	13.46	-2.779	1.677
t-Statistics	(0.24)	(-0.23)	(0.45)
Disapprove			
Coefficient (%)	2.215	-0.345	-3.529
t-Statistics	(0.06)	(-0.04)	(-0.59)
Reject			
Coefficient (%)	-74.49*	16.57*	1.132
t-Statistics	(-1.67)	(1.69)	(0.28)
Threaten			
Coefficient (%)	-13.97	3.096	0.604
t-Statistics	(-0.84)	(0.87)	(0.17)
Protest			
Coefficient (%)	-27.84***	6.213***	1.308
t-Statistics	(-2.76)	(2.84)	(1.15)
Exhibit Force			
Coefficient (%)	-3.601	0.914	-0.283
t-Statistics	(-0.45)	(0.53)	(-0.19)
Reduce Relations			
Coefficient (%)	-14.39	3.310	2.697
t-Statistics	(-0.50)	(0.52)	(1.21)

Coerce			
Coefficient (%)	-44.96	9.726	4.461
t-Statistics	(-1.24)	(1.26)	(1.01)
Assault			
Coefficient (%)	-9.036	2.028	3.362
t-Statistics	(-0.91)	(0.98)	(1.45)
Fight			
Coefficient (%)	17.65	-3.579	6.085
t-Statistics	(0.32)	(-0.31)	(1.62)
Mass Violence			
Coefficient (%)	7.702	-1.571	0.391
t-Statistics	(0.54)	(-0.49)	(0.79)
Severity index			
Coefficient (%)	-84.32	18.10	11.80**
T-statistic	(-1.28)	(0.29)	(2.00)

Table 15A:

Averaged risk premiums for the perceived conflict sensitivities and the 3 Fama-French factors different event window

This table reports findings for the monthly average risk premiums from equation (6), following a two-step Fama-Macbeth regression. $RI_{\,i,t} = \gamma_t + \gamma_{MKTRF,t}\, \beta_{i,t-1}^{MKTRF} + \gamma_{SMB,t}\, \beta_{i,t-1}^{SMB} + \gamma_{HML,t}\, \beta_{i,t-1}^{HML} + \gamma_{Conflict\,,t}\, \beta_{i,t-1}^{Conflict} + \varepsilon_{i,t}$ (6). Here $RI_{\;i,t}$ represents the excess returns for the "i" industry portfolios in month "t" for the sample period September 2001 through December 2013. Where the β`s resemble factor loadings, for respectively $MKTRF, t$, SMB, t and HML, t and $Conflict\,, t$ is obtained by re-estimating equation (5) : $RI_{\,i,\tau} = \alpha_{i,t-1} + \beta_{i,t-1}^{MKTRF} MKTRF_\tau + \beta_{i,t-1}^{SMB} SMB_\tau + \beta_{i,t-1}^{HML} HML_\tau + \beta_{i,t-1}^{Conflict} Conflict_\tau + \eta_{i,\tau}$. These time-series regressions apply over a rolling window of 60 months. The t-statistics are, based on autocorrelation-adjusted Newey-West standard errors for two lags and are presented, between the parentheses. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Variables	MKTRF	SMB	HML	Conflict
All conflict				
Coefficient	-0.101	-0.174	0.026	-0.240
t-Statistics	(-0.17)	(-0.60)	(0.10)	(-0.48)
Severity index				
Coefficient	-0.144	-0.163	0.004	-0.365
t-Statistics	(-0.24)	(-0.54)	(0.01)	(-0.79)
Investigate				
Coefficient	-0.131	-0.269	0.033	0.519
t-statistic	(-0.21)	(-1.00)	(0.13)	(1.31)
Demand				
Coefficient	0.000	-0.169	0.008	-0.297
t-Statistics	(0.00)	(-0.57)	(0.03)	(-0.66)
Disapprove				
Coefficient	-0.079	-0.099	0.087	-0.428
t-Statistics	(-0.14)	(-0.35)	(0.38)	(-0.85)
Reject				
Coefficient	-0.031	-0.069	0.024	0.253
t-Statistics	(-0.05)	(-0.25)	(0.10)	(0.45)
Threaten				
Coefficient	-0.194	-0.219	0.024	-0.104
t-Statistics	(-0.31)	(-0.75)	(0.09)	(-0.30)
Protest				
Coefficient	-0.251	-0.247	0.038	-0.275

t-Statistics	(-0.43)	(-0.87)	(0.16)	(-0.62)

Table 15B:

Averaged risk premiums for the perceived conflict sensitivities and the 3 Fama-French factors different event window

This table reports findings for the monthly average risk premiums from equation (6), following a two-step Fama and Macbeth regression. $RI_{\,i,t} = \gamma_t + \gamma_{MKTRF,t}\,\beta_{i,t-1}^{MKTRF} + \gamma_{SMB,t}\,\beta_{i,t-1}^{SMB} + \gamma_{HML,t}\,\beta_{i,t-1}^{HML} + \gamma_{Conflict\,,t}\,\beta_{i,t-1}^{Conflict} + \varepsilon_{i,t}$ (6). Here $RI_{\,i,t}$ represents the excess returns for the "i" industry portfolios in month "t" for the sample period September 2001 through December 2013. Where the β`s resemble factor loadings, for respectively $MKTRF, t$, SMB, t and HML, t and $Conflict\,, t$ is obtained by re-estimating equation (5) : $RI_{\,i,\tau} = \alpha_{i,t-1} + \beta_{i,t-1}^{MKTRF} MKTRF_\tau + \beta_{i,t-1}^{SMB} SMB_\tau + \beta_{i,t-1}^{HML} HML_\tau + \beta_{i,t-1}^{Conflict} Conflict_\tau + \eta_{i,\tau}$. These time-series regressions apply over a rolling window of 60 months. The t-statistics are, based on autocorrelation-adjusted Newey-West standard errors for two lags and are presented, between the parentheses. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Variables	MKTRF	SMB	HML	Conflict
Exhibit Force				
Coefficient	-0.437	-0.201	0.015	0.264
t-Statistics	(0.71)	(-0.66)	(0.06)	(0.65)
Reduce Relations				
Coefficient	-0.101	-0.160	0.137	0.374
t-Statistics	(-0.16)	(-0.53)	(0.52)	(0.87)
Coerce				
Coefficient	-0.041	-0.176	0.180	-0.060
t-Statistics	(-0.07)	(-0.63)	(0.69)	(-0.13)
Assault				
Coefficient	-0.131	-0.172	-0.006	0.085
t-Statistics	(-0.21)	(-0.58)	(-0.02)	(0.24)
Fight				
Coefficient	0.009	-0.069	-0.003	-0.736*
t-Statistics	(0.01)	(-0.23)	(-0.01)	(-1.68)
Mass Violence				
Coefficient	-0.355	-0.270	-0.026	0.006
t-Statistics	(-0.56)	(-0.89)	(-0.10)	(0.01)

Appendix C

Appendix C: Robustness check 2 reports the results for one-month lagged conflict risk variables and represent the second robustness check.

Table 16:

Effects of lagged perceived conflict risk on international U.S. equities

Results for equation (1) through $Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t$. where $Excess\ Return_t^{US}$ is the monthly excess return on U.S. stock markets for 1st January 1979 to 31st December 2013. $Conflict_t$ represents each one-month lagged conflict variable and is constructed by the number of events in month *t*. For category, the variable scaled by the total event count for that month *t*, standardized by their sample standard deviation. A natural logarithm transformation applies to every conflict risk variable. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level. The *t*-statistics are based on heteroskedasticity-consistent standard errors.

	Constant	Conflict
Log (All Conflicts)		
Coefficient (%)	2.246	-0.348
T-statistic	(0.21)	(-0.15)
Log (Investigate)		
Coefficient (%)	0.955	-0.068
T-statistic	(0.19)	(-0.06)
Log (Demand)		
Coefficient (%)	3.384	-0.597
T-statistic	(0.52)	(-0.43)
Log (Disapprove)		
Coefficient (%)	2.770	-0.463
T-statistic	(0.36)	(-0.27)
Log (Reject)		
Coefficient (%)	-11.310	2.602
T-statistic	(-1.34)	(1.42)
Log (Threaten)		
Coefficient (%)	0.870	-3.337
T-statistic	(0.94)	(-0.79)
Log (Protest)		
Coefficient (%)	-2.998	0.802
T-statistic	(-1.15)	(1.41)
Log (Exhibit force)		
Coefficient (%)	1.510	-0.193
T-statistic	(0.80)	(-0.46)
Log (Reduce relations)		
Coefficient (%)	3.398	-0.602
T-statistic	(-0.67)	(0.83)
Log (Coerce)		
Coefficient (%)	-1.345	0.433
T-statistic	(-0.23)	(0.34)
Log (Assault)		
Coefficient (%)	3.27	-0.578

T-statistic	(1.22)	(-0.98)
Log (Fights)		
Coefficient (%)	6.22	-1.221
T-statistic	(1.67)	(-1.51)
Log(Use of Mass Violence)		
Coefficient (%)	0.474	0.033
T-statistic	(0.033)	(0.1)
Log (Severity Index)		
Coefficient (%)	5.192	-0.989
T-statistic	(0.63)	(-0.55)

Table 17A:

Regression results for the effect of lagged perceived conflict risk variables on the realized U.S. stock market volatility

This table reports the GARCH (1,1) model results following equation (2). $Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 Conflict_t + \varepsilon_t$ (2). where excess return is the excess stock return for U.S. equity markets from January 1979 to December 2013. For every $Conflict_t$, the one-month lagged variable scaled by the total event count for that month t is standardized by their sample standard deviation, and a natural logarithm transformation applies to each conflict risk variable. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Mean		Volatility			
	constant	conflict	constant	β_1	β_2	Conflict
Log (All conflicts)						
Coefficient (%)	2.761	-0.446	21.31*	0.113***	0.860***	-4.729*
Z-statistic	(0.30)	(-0.22)	(1.87)	(3.87)	(30.15)	(-1.83)
Log (Severity Index)						
Coefficient (%)	4.560	-0.835	17.31**	0.113***	0.859***	-3.857**
Z-statistic	(0.61)	(-0.52)	(2.13)	(3.83)	(28.25)	(-2.07)
Log (Investigate)						
Coefficient (%)	0.741	-0.0110	8.988	0.116***	0.855***	-2.039
Z-statistic	(0.17)	(-0.01)	(1.59)	(3.73)	(27.08)	(-1.56)
Log (Demand)						
Coefficient (%)	4.499	-0.828	16.51**	0.099***	0.869***	-3.694**
Z-statistic	(0.80)	(-0.68)	(2.23)	(3.92)	(30.63)	(-2.21)
Log (Disapprove)						
Coefficient (%)	4.243	-0.770	3.549	0.113***	0.860***	-0.844
Z-statistic	(0.56)	(-0.47)	(0.36)	(3.58)	(25.94)	(-0.38)
Log (Reject)						
Coefficient (%)	-12.67**	2.928**	-22.6***	0.123***	0.828***	4.902***
Z-statistic	(-2.14)	(2.26)	(-3.01)	(3.67)	(16.83)	(3.14)
Log (Threaten)						

	Mean		Volatility			
Coefficient (%)	-2.432	0.685	11.11**	0.115***	0.846***	-2.481**
Z-statistic	(-0.65)	(0.84)	(2.48)	(3.83)	(24.77)	(-2.41)
Log (Protest)						
Coefficient (%)	-5.702**	1.453**	4.641***	0.183***	-0.180	-0.358*
Z-statistic	(-2.07)	(2.45)	(5.42)	(2.67)	(-1.45)	(-1.81)

Table 17B:
Regression results for the effect of lagged perceived conflict risk variables on the realized U.S. stock market volatility

This table reports the GARCH (1,1) model results following equation (2). $Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 Conflict_t + \varepsilon_t$ (2), where excess return is the excess stock return for U.S. equity markets from January 1979 to December 2013. . For every $Conflict_t$, the one-month lagged variable scaled by the total event count for that month t is standardized by their sample standard deviation, and a natural logarithm transformation applies to each conflict risk variable. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Mean		Volatility			
	Constant	Conflict	Constant	β_1	β_2	Conflict
Log (Exhibition of Force)						
Coefficient (%)	2.467	-0.387	3.946*	0.111***	0.849***	-0.914*
Z-statistic	(1.27)	(-0.90)	(1.85)	(3.59)	(25.89)	(-1.72)
Log (Reduction of relations)						
Coefficient (%)	4.297	-0.782	-30.8***	0.121***	0.866***	6.363***
Z-statistic	(1.05)	(-0.88)	(-2.84)	(4.71)	(34.57)	(2.96)
Log (Coerce)						
Coefficient (%)	-2.384	0.673	12.32**	0.114***	0.853***	-2.756**
Z-statistic	(-0.48)	(0.63)	(2.41)	(3.46)	(25.36)	(-2.31)
Log (Assault)						
Coefficient (%)	2.903	-0.484	8.149**	0.112***	0.873***	-1.992**
Z-Statistic	(0.98)	(-0.75)	(2.06)	(4.21)	(34.26)	(-1.98)
Log (Fights)						
Coefficient (%)	5.645	-1.068	8.456***	0.112***	0.852***	-1.903**
Z-statistic	(1.42)	(-1.25)	(2.71)	(3.96)	(27.08)	(-2.47)
Log (Use of mass violence)						
Coefficient (%)	-1.697	0.540*	-2.087	0.263***	0.682***	0.493
Z-statistic	(-1.22)	(1.86)	(-0.56)	(2.98)	(6.60)	(0.71)

Table 18
Time-series results for expected and unexpected lagged conflict risk

This table reports the findings of equation (4): $Excess\ Return_t^{US} = \alpha + \beta_1 Expected\ Conflict_t + \beta_2 Unexpected\ Conflict_t + \varepsilon_t$, where $Excess\ Return_t^{US}$ is the monthly excess U.S. stock market return in percentages for 1st January 1979 to 31st December 2013. The $Expected\ Conflict_t$ risk is the fitted value for equation (3). Equation (3) is specified as follows: $Conflict_t = \alpha + \beta_1 Conflict_{t-1} + \varepsilon_t$, where $Conflict_t$ can represent any different conflict risk specification. The residuals from equation (3) are used as $Unexpected\ Conflict_t$ risk. Equation (3) is re-estimated per conflict specification. The *t*-statistics are based on heteroskedasticity-consistent standard errors.

Variables	Constant	Expected conflict risk	Unexpected conflict risk
All conflict			
Coefficient (%)	4.482	-0.909	-0.094
t-Statistics	(0.3)	(-0.26)	(-0.03)
Investigate			
Coefficient (%)	-3.111	0.821	-0.312
t-statistic	(-0.28)	(0.34)	(-0.26)
Demand			
Coefficient (%)	44.972	-9.623	-0.176
t-Statistics	(0.46)	(-1.48)	(-0.12)
Disapprove			
Coefficient (%)	14.337	-2.976	-0.254
t-Statistics	(0.69)	(-0.66)	(-0.14)
Reject			
Coefficient (%)	-3.91	3.166	0.994
t-Statistics	(-0.18)	(1.63)	(0.21)
Threaten			
Coefficient (%)	5.33	-1.023	1.159
t-Statistics	(0.48)	(-0.42)	(1.14)
Protest			
Coefficient (%)	3.588	-0.647	1.013*
t-Statistics	(0.47)	(-0.38)	(1.66)
Exhibit Force			
Coefficient (%)	0.103	0.122	-0.332
t-Statistics	(0.03)	(0.15)	(-0.73)
Reduce Relations			
Coefficient (%)	6.63	-1.306	-0.64
t-Statistics	(0.39)	(-0.35)	(-0.69)
Coerce			
Coefficient (%)	-5.184	1.273	0.133
t-Statistics	(-0.57)	(0.65)	(0.09)
Assault			
Coefficient (%)	2.720	-0.454	-0.241
t-Statistics	(0.53)	(-0.41)	(-0.31)
Fight			
Coefficient (%)	0.261	0.086	-2.286**
t-Statistics	(0.04)	(0.07)	(-2.37)
Mass Violence			
Coefficient (%)	2.776	-0.461	-0.041
t-Statistics	(0.36)	(-0.28)	(-0.11)
Severity index			
Coefficient (%)	1.975	-0.287	-1.533
T-statistic	(0.18)	(-0.12)	(-0.64)

Table 19A:

Averaged risk premiums for the lagged perceived conflict sensitivities and the 3 Fama-French factors

This table reports findings for the monthly average risk premiums from equation (6), following a two-step Fama and Macbeth regression. $RI_{\ i,t} = \gamma_t + \gamma_{MKTRF,t}\ \beta_{i,t-1}^{MKTRF} + \gamma_{SMB,t}\ \beta_{i,t-1}^{SMB} + \gamma_{HML,t}\ \beta_{i,t-1}^{HML} + \gamma_{Conflict\ ,t}\ \beta_{i,t-1}^{Conflict} + \varepsilon_{i,t}$ (6). Here $RI_{\ i,t}$ represents the excess returns for the "i" industry portfolios in month "t" for the sample period February 1979 through December 2013. Where the β`s resemble factor loadings, for respectively $MKTRF, t$, SMB, t and HML, t and $Conflict\ , t$ is obtained by re-estimating equation (5) : $RI_{i,\tau} = \alpha_{i,t-1} + \beta_{i,t-1}^{MKTRF} MKTRF_\tau + \beta_{i,t-1}^{SMB} SMB_\tau + \beta_{i,t-1}^{HML} HML_\tau + \beta_{i,t-1}^{Conflict} Conflict_\tau + \eta_{i,\tau}$. These time-series regressions apply over a rolling window of 60 months. The *t*-statistics are, based on autocorrelation-adjusted Newey-West standard errors for two lags and are presented, between the parentheses. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Variables	MKTRF	SMB	HML	Conflict
All conflict				
Coefficient	-0.139	0.027	0.261	0.024
t-Statistics	(-0.39)	(0.14)	(1.35)	(0.18)
Severity index				
Coefficient	-0.117	0.023	0.246	0.106
t-Statistics	(-0.33)	(0.12)	(1.29)	(0.81)
Investigate				
Coefficient	-0.096	0.102	0.197	0.239
t-statistic	(-0.27)	(0.54)	(1.01)	(1.52)
Demand				
Coefficient	-0.215	0.066	0.168	0.137
t-Statistics	(-0.61)	(0.35)	(0.87)	(0.92)
Disapprove				
Coefficient	-0.196	0.017	0.239	-0.128
t-Statistics	(-0.56)	(0.09)	(1.23)	(-0.81)
Reject				
Coefficient	-0.261	0.156	0.183	-0.168
t-Statistics	(-0.74)	(0.83)	(0.94)	(-1.15)
Threaten				
Coefficient	-0.059	0.050	0.184	-0.061
t-Statistics	(-0.16)	(0.26)	(0.95)	(-0.35)
Protest				
Coefficient	-0.101	0.017	0.199	0.082
t-Statistics	(-0.29)	(0.10)	(1.05)	(0.54)

Table 19B:
Averaged risk premiums for the lagged perceived conflict sensitivities and the 3 Fama-French factors

This table reports findings for the monthly average risk premiums from equation (6), following a two-step Fama and Macbeth regression. $RI_{\ i,t} = \gamma_t + \gamma_{MKTRF,t}\ \beta_{i,t-1}^{MKTRF} + \gamma_{SMB,t}\ \beta_{i,t-1}^{SMB} + \gamma_{HML,t}\ \beta_{i,t-1}^{HML} + \gamma_{Conflict\ ,t}\ \beta_{i,t-1}^{Conflict} + \varepsilon_{i,t}$ (6). Here $RI_{\ i,t}$ represents the excess returns for the "i" industry portfolios in month "t" for the sample period February 1979 through December 2013. Where the β`s resemble factor loadings, for respectively $MKTRF, t$, SMB, t and HML, t and $Conflict\ , t$ is obtained by re-estimating equation (5) : $RI_{i,\tau} = \alpha_{i,t-1} + \beta_{i,t-1}^{MKTRF} MKTRF_\tau + \beta_{i,t-1}^{SMB} SMB_\tau + \beta_{i,t-1}^{HML} HML_\tau + \beta_{i,t-1}^{Conflict} Conflict_\tau + \eta_{i,\tau}$. These time-series regressions apply over a rolling window of 60 months. The *t*-statistics are, based on autocorrelation-adjusted Newey-West standard errors for two lags and are presented, between the parentheses. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Variables	MKTRF	SMB	HML	Conflict
Exhibit Force				
Coefficient	-0.065	0.028	0.241	-0.096
t-Statistics	(-0.19)	(0.15)	(1.24)	(-0.64)
Reduce Relations				
Coefficient	-0.024	0.0496	0.201	-0.028
t-Statistics	(-0.07)	(0.27)	(1.05)	(-0.18)

Coerce				
Coefficient	-0.121	0.112	0.209	0.036
t-Statistics	(-0.35)	(0.59)	(1.07)	(0.26)
Assault				
Coefficient	-0.112	0.014	0.250	0.162
t-Statistics	(-0.32)	(0.08)	(1.31)	(1.05)
Fight				
Coefficient	-0.060	0.019	0.227	0.082
t-Statistics	(-0.17)	(0.10)	(1.19)	(0.57)
Mass Violence				
Coefficient	0.033	0.389	0.394	-0.035
t-Statistics	(0.08)	(1.44)	(1.42)	(-0.17)

Appendix D:

Appendix D reports on only events with U.S. involvement where the United States is a source for event that takes place and is included in this sample.

Table 20:

Descriptive statistics for all conflict variables for outgoing events only

Table 20 reports the descriptive statistics of conflict variables. Panel A reports the mean, standard deviation, minimum and maximum. The sample period for these descriptive statistics is January 1979 to December 2013. This is a total of 420 monthly observations. All conflict denotes the number of conflict-based events that take place scaled by the total number of events monthly. These descriptive statistics represent all events that involve U.S. involvement and exclude domestic events. The variables that are reported on are the following: investigate, demand, disapprove, reject, threaten, protest, exhibit force posture, reduction of relations, coerce, assault, fight and use of mass violence. The severity index is a weighted index of all conflict events weighted by their severity. The critical value at the 1% level for the Dickey Fuller –GLS test are statistics for a test with a null-hypothesis of a unit root equal to -2.57. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Panel A: Descriptive statistics

VARIABLES	Mean	Std. Dev.	Min	Max	DF-GLS
All Conflicts	0.2823	0.0295	0.1853	0.3862	-9.217***
Investigate	0.0177	0.0042	0.0048	0.0353	-9.804***
Demand	0.0714	0.0101	0.0441	0.0983	-16.038***
Disapprove	0.0312	0.0058	0.0124	0.0543	-16.000***
Reject	0.0166	0.0047	0.0036	0.0370	-15.286 ***
Threaten	0.0075	0.0034	0.0010	0.0183	-15.340***
Protest	0.0055	0.0031	0.0002	0.0205	-13.585***
Exhibit Force	0.0149	0.0043	0.0010	0.0389	-14.039***
Reduce Relations	0.0437	0.0085	0.0157	0.0718	-15.352***
Coerce	0.0152	0.0057	0.0036	0.0300	-12.658***
Assault	0.0488	0.0146	0.0097	0.1177	-9.727***
Fights	0.0004	0.0006	0.0000	0.0037	-13.177***
Mass Violence	0.0177	0.0042	0.0048	0.0353	-15.455***
Severity index	1.9357	0.2686	1.0893	3.0546	--9.217***

Table 21:

The correlation matrix for all outgoing conflict variables

Table 21 reports correlation coefficients between the different conflict risk variables. The correlation coefficient is stated for every conflict risk variable. These correlation coefficients are representative for the sample period of January 1979 to December 2013. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	AC	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	Severity index
All Conflicts	1.00													
Investigate (9)	0.35 *	1.00												
Demand (10)	0.20 ***	0.03 ***	1.00											
Disapprove (11)	0.59 ***	0.14 **	0.19 **	1.00										
Reject (12)	0.37 ***	0.02	-0.06	0.02 ***	1.00									
Threaten (13)	0.37 ***	-0.05	0.08	0.20 ***	-0.11 *	1.00								
Protest (14)	0.18 ***	-0.07	-0.08	0.04	0.10 *	0.00	1.00							
Exhibit of Force (15)	0.31 ***	-0.03	0.03	0.09	0.00	0.2 ***	-0.07	1.00						
Reduce Relations (16)	0.15 **	-0.11 *	0.10 *	0.01	0.04	0.03	0.11 *	0.05	1.00					
Coerce (17)	0.57 ***	0.31	0.02	0.20 **	0	0.14 **	0.02 *	-0.03	-0.01	1.00				
Assault (18)	0.52 ***	0.13 **	-0.05	0.19 **	-0.11 *	0.19 *	0.26 *	-0.01	-0.05	0.38 **	1.00			
Fights (19)	0.70 ***	0.14	-0.10	0.17 **	-0.11 *	0.12 *	-0.02	0.33*	-0.02	0.27*	0.27 ***	1.00		
Use Mass Violence (20)	0.10 *	0.10 *	-0.05	0.01	-0.05	0.07	-0.04	0.01	0.01	-0.07	0.05	0.16 *	1.00	
Severity Index	0.95 ***	0.26 ***	0.10 *	0.4 ***	-0.03	0.31 ***	0.08	0.32 ***	0.11 *	0.59 ***	0.56 ***	0.85 ***	0.13 **	1.00

Table 22:

Effects of perceived conflict risk on international U.S. equities

Results for equation (1) through $Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t$. where $Excess\ Return_t^{US}$ is the monthly excess return on U.S. stock markets for 1st January 1979 to 31st December 2013. $Conflict_t$ represents each conflict variable and is constructed by the number of events in month t. For category, the variable scaled by the total event count for that month t, standardized by their sample standard deviation. A natural logarithm transformation applies to every conflict risk variable. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level. The t-statistics are based on heteroskedasticity-consistent standard errors.

	Constant	Conflict
Log (All Conflicts)		
Coefficient (%)	-0.546	0.260
T-statistic	(-0.06)	(0.13)
Log (Investigate)		
Coefficient (%)	-1.185	0.402
T-statistic	(-0.31)	(0.49)
Log (Demand)		
Coefficient (%)	-3.240	0.850
T-statistic	(-0.63)	(0.76)
Log (Disapprove)		
Coefficient (%)	4.924	-0.930
T-statistic	(0.76)	(-0.66)
Log (Reject)		
Coefficient (%)	1.742	-0.238
T-statistic	(0.29)	(-0.18)
Log (Threaten)		
Coefficient (%)	1.337	-0.150
T-statistic	(0.49)	(-0.25)
Log (Protest)		
Coefficient (%)	-1.509	0.481
T-statistic	(-0.79)	(1.13)
Log (Exhibit force)		
Coefficient (%)	2.741*	-0.471
T-statistic	(1.73)	(-1.34)
Log (Reduce relations)		
Coefficient (%)	-3.742	0.963
T-statistic	(-0.86)	((1.01)
Log (Coerce)		
Coefficient (%)	-3.401	0.884
T-statistic	(-0.85)	(1.01)
Log (Assault)		
Coefficient (%)	0.763	-0.024
T-statistic	(0.33)	(-0.05)
Log (Fights)		
Coefficient (%)	1.180	-0.116
T-statistic	(0.37)	(-0.05)
Log(Use of Mass Violence)		
Coefficient (%)	1.854	-0.274
T-statistic	(1.15)	(-0.85)

Log (Severity Index)		
Coefficient (%)	1.261	-0.133
T-statistic	(0.18)	(-0.09)

Table 23A:

Regression results for the effect of perceived conflict risk variables on the realized U.S. stock market volatility

This table reports the GARCH (1,1) model results following equation (2). $Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 Conflict_t + \varepsilon_t$ (2). where excess return is the excess stock return for U.S. equity markets from January 1979 to December 2013. For every $Conflict_t$, the variable scaled by the total event count for that month *t* is standardized by their sample standard deviation, and a natural logarithm transformation applies to each conflict risk variable. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Mean		Volatility			
	Constant	Conflict	Constant	β_1	β_2	Conflict
Log (All conflicts)						
Coefficient (%)	-6.240	1.509	21.20**	0.111***	0.851***	-4.651**
Z-statistic	(-0.65)	(0.72)	(2.19)	(3.82)	(25.51)	(-2.13)
Log (Severity Index)						
Coefficient (%)	-4.398	1.111	17.17**	0.112***	0.849***	-3.778**
Z-statistic	(-0.60)	(0.69)	(2.41)	(2.68)	(25.39)	(-2.33)
Log (Investigate)						
Coefficient (%)	0.104	0.860	3.771	0.118***	0.856***	-0.907
Z-statistic	(0.03)	(1.03)	(0.71)	(3.68)	(26.04)	(-0.75)
Log (Demand)						
Coefficient (%)	5.360	0.133	12.670***	0.107***	0.836***	-2.750***
Z-statistic	(0.81)	(0.15)	(3.50)	(3.57)	(18.87)	(-3.24)
Log (Disapprove)						
Coefficient (%)	18.51	-1.010	9.330	0.114***	0.849***	-2.057
Z-statistic	(0.93)	(-0.70)	(1.06)	(3.57)	(22.75)	(-1.06)
Log (Reject)						
Coefficient (%)	-2.045	0.599	-15.65	0.112***	0.855***	3.334
Z-statistic	(-0.38)	(0.51)	(-1.47)	(3.60)	(22.19)	(1.47)
Log (Threaten)						
Coefficient (%)	-3.042	0.822	4.578	0.111***	0.859***	-1.075
Z-statistic	(-0.30)	(0.39)	(1.14)	(3.66)	(26.63)	(-1.19)
Log (Protest)						
Coefficient (%)	-9.396*	2.239*	-2.499	0.112***	0.848***	0.548
Z-statistic	(-1.71)	(1.87)	(-1.01)	(3.35)	(18.89)	(0.95)

Table 23B:

Regression results for the effect of perceived conflict risk variables on the realized U.S. stock market volatility

This table reports the GARCH (1,1) model results following equation (2). $Excess\ Return_t^{US} = \mu + \alpha_1 Conflict_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 Conflict_t + \varepsilon_t$ (2), where excess return is the excess stock return for U.S. equity markets from January 1979 to December 2013. For every $Conflict_t$, the variable scaled by the total event count for that month *t* is standardized by their sample standard deviation, and a natural logarithm transformation applies to each conflict risk variable. *** denotes 1% significance level, ** denotes 5% significance level and *denotes 10% significance level.

	Mean		Volatility			
	Constant	Conflict	Constant	β_1	β_2	Conflict
Log (Exhibition of Force)						
Coefficient (%)	1.860	-0.259	2.479	0.105***	0.858***	-0.600
Z-statistic	(1.14)	(-0.71)	(0.99)	(3.41)	(23.12)	(-1.04)
Log (Reduction of relations)						
Coefficient (%)	-3.822	0.990	5.430***	0.110***	0.852***	-1.23***
Z-statistic	(-1.26)	(1.48)	(2.78)	(3.52)	(23.93)	(-2.67)
Log (Coerce)						
Coefficient (%)	-5.296	1.310	11.29***	0.115***	0.841***	-2.485**
Z-statistic	(-0.94)	(1.08)	(2.59)	(3.57)	(20.56)	(-2.49)
Log (Assault)						
Coefficient (%)	-1.861	0.563	6.847*	0.113***	0.864***	-1.656*
Z-Statistic	(-0.69)	(0.96)	(1.76)	(3.99)	(28.30)	(-1.77)
Log (Fights)						
Coefficient (%)	-0.861	0.348	7.290**	0.111***	0.852***	-1.651**
Z-statistic	(-0.26)	(0.48)	(2.51)	(3.91)	(26.95)	(-2.31)
Log (UMV)						
Coefficients (%)	0.992	-0.0416	5.009**	0.268***	0.655***	-1.022*
Z-statistic	(0.56)	(-0.12)	(2.55)	(2.73)	(5.37)	(-1.70)

Table 24:
Time-series results for expected and unexpected outgoing conflict risk

This table reports the findings of equation (4): $Excess\ Return_t^{US} = \alpha + \beta_1 Expected\ Conflict_t + \beta_2 Unexpected\ Conflict_t + \varepsilon_t$, where $Excess\ Return_t^{US}$ is the monthly excess U.S. stock market return in percentages for 1st January 1979 to 31st December 2013. The $Expected\ Conflict_t$ risk is the fitted value for equation (3). Equation (3) is specified as follows: $Conflict_t = \alpha + \beta_1 Conflict_{t-1} + \varepsilon_t$, where conflict can represent any different conflict risk specification. The residuals from equation (3) are used as $Unexpected\ Conflict_t$ risk. Equation (3) is re-estimated per conflict specification. The *t*-statistics are based on heteroskedasticity-consistent standard errors.

Variables	Constant	Expected conflict risk	Unexpected conflict risk
All conflict			
Coefficient (%)	16.24	-3.390	2.697
t-Statistics	(1.04)	(-1.00)	(1.11)
Investigate			
Coefficient (%)	3.142	-0.546	0.474
t-statistic	(0.22)	(-0.18)	(0.58)
Demand			
Coefficient (%)	-25.55	5.718	0.522
t-Statistics	(-1.48)	(1.52)	(0.44)

Disapprove			
Coefficient (%)	17.90	-3.754	-0.560
t-Statistics	(0.76)	(-0.73)	(-0.38)
Reject			
Coefficient (%)	-6.103	1.470	-0.441
t-Statistics	(-0.23)	(0.25)	(-0.33)
Threaten			
Coefficient (%)	3.051	-0.528	-0.119
t-Statistics	(0.28)	(-0.22)	(-0.19)
Protest			
Coefficient (%)	-4.063	1.048	0.398
t-Statistics	(-0.76)	(0.88)	(0.85)
Exhibit Force			
Coefficient (%)	7.880*	-1.629*	-0.280
t-Statistics	(1.94)	(-1.77)	(-0.70)
Reduce Relations			
Coefficient (%)	7.184	-1.434	1.269
t-Statistics	(0.72)	(-0.65)	(1.32)
Coerce			
Coefficient (%)	-1.563	0.481	0.955
t-Statistics	(-0.13)	(0.18)	(0.94)
Assault			
Coefficient (%)	1.929	-0.284	0.0951
t-Statistics	(0.42)	(-0.28)	(0.16)
Fight			
Coefficient (%)	13.48**	-2.816*	0.717
t-Statistics	(2.00)	(-1.90)	(0.96)
Mass Violence			
Coefficient (%)	-7.700	1.687	-0.511
t-Statistics	(-1.11)	(1.19)	(-1.20)
Severity index			
Coefficient (%)	17.03	-3.567	2.782
T-Statistic	(1.49)	(-1.43)	(1.39)

Table 25A:

Averaged risk premiums for the perceived conflict sensitivities and the 3 Fama-French factors

This table reports findings for the monthly average risk premiums from equation (6), following a two-step Fama and Macbeth regression. $RI_{i,t} = \gamma_t + \gamma_{MKTRF,t}\,\beta_{i,t-1}^{MKTRF} + \gamma_{SMB,t}\,\beta_{i,t-1}^{SMB} + \gamma_{HML,t}\,\beta_{i,t-1}^{HML} + \gamma_{Conflict,t}\,\beta_{i,t-1}^{Conflict} + \varepsilon_{i,t}$ (6). Here $RI_{i,t}$ represents the excess returns for the "i" industry portfolios in month "t" for the sample period February 1979 through December 2013. Where the β`s resemble factor loadings, for respectively $MKTRF, t$, SMB, t and HML, t and $Conflict\ , t$ is obtained by re-estimating equation (5) : $RI_{i,\tau} = \alpha_{i,t-1} + \beta_{i,t-1}^{MKTRF} MKTRF_\tau + \beta_{i,t-1}^{SMB} SMB_\tau + \beta_{i,t-1}^{HML} HML_\tau + \beta_{i,t-1}^{Conflict} Conflict_\tau + \eta_{i,\tau}$. These time-series regressions apply over a rolling window of 60 months. The t-statistics are, based on autocorrelation-adjusted Newey-West standard errors for two lags and are presented, between the parentheses. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Variables	MKTRF	SMB	HML	Conflict
All conflict				
Coefficient	0.018	0.172	0.212	0.159
t-Statistics	(0.05)	(0.88)	(1.11)	(0.93)
Severity index				
Coefficient	-0.029	0.205	0.196	0.067
t-Statistics	(-0.24)	(-0.54)	(0.01)	(-0.79)

Investigate				
Coefficient	0.054	0.070	0.237	0.234
t-statistic	(0.15)	(0.38)	(1.23)	(1.38)
Demand				
Coefficient	-0.116	0.106	0.217	-0.074
t-Statistics	(-0.33)	(0.55)	(1.12)	(-0.47)
Disapprove				
Coefficient	-0.150	0.101	0.214	0.250
t-Statistics	(-0.44)	(0.54)	(1.11)	(1.63)
Reject				
Coefficient	-0.093	0.072	0.277	0.077
t-Statistics	(-0.27)	(0.38)	(1.48)	(0.53)
Threaten				
Coefficient	-0.044	0.082	0.230	0.023
t-Statistics	(-0.12)	(0.43)	(1.20)	(0.15)
Protest				
Coefficient	-0.061	0.139	0.132	0.206
t-Statistics	(-0.18)	(0.73)	(0.67)	(1.54)

Table 25B:
Averaged risk premiums for the perceived conflict sensitivities and the 3 Fama-French factors

This table reports findings for the monthly average risk premiums from equation (6), following a two-step Fama and Macbeth regression. $RI_{\,i,t} = \gamma_t + \gamma_{MKTRF,t}\, \beta_{i,t-1}^{MKTRF} + \gamma_{SMB,t}\, \beta_{i,t-1}^{SMB} + \gamma_{HML,t}\, \beta_{i,t-1}^{HML} + \gamma_{Conflict\,,t}\, \beta_{i,t-1}^{Conflict} + \varepsilon_{i,t}$ (6). Here $RI_{\,i,t}$ represents the excess returns for the "i" industry portfolios in month "t" for the sample period February 1979 through December 2013. Where the β`s resemble factor loadings, for respectively $MKTRF, t$, SMB, t and HML, t and $Conflict\,, t$ is obtained by re-estimating equation (5) : $RI_{\,i,\tau} = \alpha_{i,t-1} + \beta_{i,t-1}^{MKTRF} MKTRF_\tau + \beta_{i,t-1}^{SMB} SMB_\tau + \beta_{i,t-1}^{HML} HML_\tau + \beta_{i,t-1}^{Conflict} Conflict_\tau + \eta_{i,\tau}$. These time-series regressions apply over a rolling window of 60 months. The t-statistics are, based on autocorrelation-adjusted Newey-West standard errors for two lags and are presented, between the parentheses. *denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Variables	MKTRF	SMB	HML	Conflict
Exhibit Force				
Coefficient	-0.100	0.102	0.260	0.052
t-Statistics	(-0.27)	(0.54)	(1.30)	(0.35)
Reduce Relations				
Coefficient	-0.112	0.101	0.223	0.218
t-Statistics	(-0.32)	(0.53)	(1.16)	(1.32)
Coerce				
Coefficient	-0.005	0.106	0.223	0.173
t-Statistics	(-0.01)	(0.56)	(1.15)	(1.36)
Assault				
Coefficient	-0.127	0.060	0.273	0.293**
t-Statistics	(-0.37)	(0.32)	(1.42)	(2.16)
Fight				
Coefficient	-0.101	0.0903	0.248	-0.155
t-Statistics	(-0.28)	(0.47)	(1.27)	(1.00)
Mass Violence				
Coefficient	-0.539	0.263	0.231	-0.445*
t-Statistics	(-1.03)	(-0.84)	(0.65)	(-1.71)