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The Impact of International Crisis Risk on U.S. Stock Returns

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Abstract

This paper examines the impact of perceived crisis risk on the movements in the U.S. equity market. My results suggest that news associated with conflicts in which the U.S. is directly involved plays an important role in the volatility of market returns. However, my evidence indicates that crisis risk has no significant effect on the contemporaneous U.S. market mean returns and that investors do not require a risk premium. This gives support to the idea that crisis risk is diversifiable. I also show that the market return volatility effects of crisis risk vary with the severity of the conflicts. I contribute to the existing literature by using a rich dataset that gives the opportunity to create a comprehensive measure for perceived crisis risk and to better understand what types of conflicts drive market reactions.

Keywords

International conflicts; perceived crisis risk; news analysis; stock market volatility; asset pricing

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1 Introduction

Financial markets are generally regarded as information-intensive environments and investment decisions are extensively driven by news (Dzielinski, 2011). Currently, conflicts dominate everyday news starting with disguised digs over minor clashes to full-scale wars. In this research, I attempt to provide a better understanding of the effects of perceived crisis risk on the U.S. stock market variation. Indeed, many existing studies indicate the importance of international conflicts to financial markets, but surprisingly there are only few studies investigating the link between international crises and asset pricing. The main limitation to finding universally valid evidence is the lack of a definite indicator of crisis risk. The risks associated with international conflicts are unobservable and there is no direct measure to determine such risk. Accordingly, different researchers take different approaches to proxy the risk and hence, all of the evidence presented in research today is based on various facets of crisis risk, such as political uncertainty or actual war data. This bears the problem that these studies lead to contradicting conclusions about the impact of international conflicts on the risk-return relation on capital markets. Nevertheless, understanding the reaction of the stock market to crisis risk seems to be of great importance for both research and practice purposes. The main challenges in addressing this research question are to (1) identify a suitable measure to determine investors' perception of crisis risk and (2) to investigate the link between changes in crisis risk and changes in stock market returns.

Firstly, I conduct an in-depth literature review to identify and revise already existing measures for crisis risk in asset pricing theory. I use those insights to develop my variable construction and methodology and apply them to a rich dataset providing information on international conflicts based on news events. This database, known as the GDELT (Global Data on Event, Location and Tone) Project, gives the opportunity to divide conflicts according to type, which subsequently allows for a deeper understanding of conflict characteristics and their effects. It also avoids the small sample problem occurring in research on actual wars since it does not only contain news on full-scale war events, but it also holds information on minor clashes and conflicts without violent acts. This allows me to construct crisis measures on an aggregated level as well as on sub-categories of conflicts. These measures give a good proxy for perceived crisis risk and investors' reaction is likely to align with these news events about the outlook on conflicts. Secondly, to address the gap in the literature, I attempt to empirically measure the impact of conflict-related news involving the U.S. on contemporaneous and expected U.S. equity market movements by applying the constructed proxies for international crisis risk. In particular, I assess how a change in perceived crisis risk is translated into mean excess returns and volatility of the U.S. market. Moreover, I examine whether crisis risk improves the predictability of returns on market and industry level. Through this second step I can derive conclusions about the crisis risk-return relation.

For the purpose of this article, I consider the U.S. equity market from January 02, 1979 to February 14, 2014. The results of my contemporaneous regressions suggest that perceived crisis risk associated with international conflicts involving the U.S. plays an important role in the volatility of stock market returns but no significant role in the market mean returns. I cannot find that an increase in crisis risk induces a significant decline in the mean of stock excess returns and my estimates do not indicate that investors react heavily to international conflicts. The market return volatility, however, has a significant positive relation with the intensification of perceived crisis risk. I show this pattern in the realized as well as in the implied volatility, and it is robust to changes in the assumptions of the crisis risk proxy. None of the previous analyses shows that the stock market reacts stronger to more severe conflicts than to less severe conflicts. Further tests on the predictability of stock returns are consistent with the results of the contemporaneous analyses, not showing a significant relation between perceived crisis risk and future market returns. This is also the case when looking at differences in the cross-section of industry returns. I cannot provide evidence that crisis risk is priced, indicating that it might be a diversifiable risk and hence does not affect the returns required by investors. When distinguishing in different conflict characteristics, only perceived crisis risk induced by actual wars seems to have an effect on risk premiums of industry portfolios. I find that industries with a lower sensitivity to this risk on average yield lower returns. This suggests that investors require a compensation for investments in industries that are sensitive to crisis risk induced by acts of actual wars.

My research is classified with the strand of literature, which studies the impact of different aspects of crisis risk on the behavior of stock markets, however it differs from existing literature and contributes to it in three important ways. Firstly, I combine several aspects of crisis risk by creating a comprehensive measure from conflict events. This measure makes it possible to more accurately evaluate which variations in crisis risk drive the U.S. stock market movements. Secondly, the GDELT dataset bases its information on extensive news data, which reflects investors' perception of conflicts and provides the opportunity to improve predictions about severe events. Hence, my proxy can capture investors' reactions to changes in crisis risk and is therefore better suited for asset pricing. Thirdly, I examine the importance of conflict news for industry portfolios and whether the industries' exposure to crisis risk is priced on the market. My findings are highly interesting, since a change in crisis risk induces uncertainty in the U.S. stock market. This uncertainty has a relevant impact on rational investors and, as a result of this, affects both future research and the practitioners' investment decisions. For the former, this study reveals a better explanation of the variation in the U.S. stock market volatility. Furthermore, perceived crisis risk induced by news concerning actual wars seems to be priced, which uncovers an exciting link for subsequent studies. The findings might also have implications on the latter, who react to the uncertainty resulting from international conflicts when investing in the U.S. stock markets.

The rest of this paper is structured as follows. In the next section I give insight in the existing literature about crisis risk and the hypotheses construction for this research. I proceed with the data description in section 3 and section 4 presents the empirical framework. In section 5 I report the empirical results of the effects of perceived crisis risk on the U.S. stock market. Section 6 discusses and concludes.

2 Literature review and hypotheses

This section provides a discussion about the theoretical background of the research question. Therefore relevant concepts, theories and related literature are reviewed to build a starting position for this thesis and to deduct the main hypotheses that are tested in this study. The thesis is closely related to the existing literature on the relation of international crises and asset pricing. The general intuition behind standard asset pricing models, such as the CAPM and the Fama-French three-factor model, is that investors require compensation for risk. Therefore, the CAPM uses a risk measure that compares the expected return of the asset to the market excess return, to proxy the exposure of the asset to non-diversifiable or market risk (Sharpe, 1964; Lintner, 1965; Black, 1972). The model aims to explain the risk-return relation and the risk premium investors require. The Fama-French three-factor model extends the CAPM by adding one risk factor for size and one factor for value (Fama and French, 1993). The model assumes that small-cap stocks are more risky than large-cap stocks. Furthermore it stipulates that value stocks, which are stocks with a low market value relative to their book value, incorporate more risk than growth stocks. Therefore the Fama-French three-factor model predicts that investors want to be compensated for those three risk factors. Accordingly, a high exposure to a risk factor drives up the expected returns. These standard asset pricing models are criticized for poorly describing the cross-section of industry expected returns. For example Gourio (2008a) in combination with Fama and French (1997) provides skeptical work on the CAPM and the three-factor model.

Previous studies attempt to find explanation for various major puzzles in financial economics, like the equity premium puzzle. This puzzle concerns the large differential between the historically high average return on equity and the average return on short term debt, cannot be explained with a plausible level of risk aversion, as Mehra and Prescott (1985) show. Adding crisis risk to the standard asset pricing models might solve these puzzles and offer a better explanation of the high excess rate of return in equities. But so far the assessment of the relation between international crises and asset pricing is difficult, since there is no clear-cut definition of crisis risk. According to Schneider and Troeger (2006) the lack of reliable figures on war-affected societies and their economy’s reaction characterizes the key empirical problem on this discussion. Consequentially, the existing literature does not agree on one crisis risk measure that applies uniformly. Accordingly, different researchers construct differing proxies to tackle the impact of crisis risk on capital markets. According to Berkman, Jacobsen, and Lee (2011) and Gabaix (2012) it would be useful to understand how investors perceive and estimate this risk, as Campbell and Cochrane (1999) indicate that good news for the economy seem to be followed by a decrease in risk premia. In this section, I elaborate the insights I take from different lines of research and further explain how my study distinguishes itself from previous ones.

2.1 Rare disaster models and related approaches

A common method to approach the relation between international crises and asset pricing is a rare disaster model as used by Barro (2006), Barro and Ursúa (2008, 2009). Rare disasters are low-probability events with a high-impact productivity shock, which result from economic disasters and wartime. This line of research includes data on actual crises as the probability of rare disasters to examine their impact on financial markets and whether this gives a better explanation for asset pricing puzzles. The base frame of this model is initially developed by Rietz (1988), who proposes that high equity returns can be explained as compensating investors for the risk of rare disasters. But he also raises the question whether this risk is sufficiently high and the disaster sufficiently severe to quantitatively explain the equity premium. Barro (2006) extends Rietz' original model by measuring the frequency and size of the low-probability economic disasters occurring globally during the twentieth century. Barro uses actual downward jumps in per capita GDP as a proxy for economic disasters resulting from the three major events World War I, the Great Depression, and World War II. He finds that the disasters are sufficiently frequent and large enough to support the rare disaster model as providing a good explanation for the high risk premium on equities.

Based on the Barro-Rietz model, further researchers build extended rare disaster models. For instance, Gabaix (2012) further develops the model by introducing time-varying severity of rare disasters to account for volatility as a key feature of asset markets. He finds that this time-varying disaster severity induces time-varying risk premiums, which in turn improve the predictability of asset price volatility and return based on price-dividend ratios. Unlike Gabaix, Wachter's model (2013) introduces time-varying probability of rare disasters to the Barro-Rietz model. She shows that this framework can account for the time-variation and the increase in the equity premium. Also, with her model high stock market volatility and high excess stock returns are predictable, while the volatility and return of the government bill rate remain low. Therewith she claims that the model explains the volatility puzzle. These results are in line with the findings of a similar model developed by Gourio (2008b), also accounting for time-varying probability of disaster as it varies between two discrete values. He concludes that his disaster model improves the predictability of stock returns. Veronesi (2004) takes a similar approach by creating a model with a constant small probability of being in the low state, but a time-varying subjective probability for the representative investor due to learning. This theoretical model suggests a positive bias on the mean realized returns and that high political instability leads to an increase in excess stock market volatility. Moreover, Veronesi shows that the volatility of returns varies over time. Specifically, he shows that it increases after bad news and decreases after good news. While rare disaster models focus on finding an effect of actual drops in consumption on capital markets, my study emphasizes the relation between the U.S. equity market and investors' perception of crisis risk arising from evolving tensions and conflicts between the U.S. and other countries, which becomes apparent in news articles.

A related attempt to explain the variation of stock market returns and volatility comes from Berkman et al. (2011), who consider data on changes in disaster probability as a proxy to examine how international political crisis risk affects monthly world stock market returns. Their approach is related to the rare disaster models with time-varying disaster probability. However, they use a larger sample than previously mentioned studies, as they include potential disasters in their crisis risk definition. Including this emphasizes on time-varying perceived probabilities of rare disasters, which they measure as the total number of crises. According to the authors the perceived change in the disaster probability seems to correlate with news events on which investors react. They find a negative relation between the number of starting international political crises and the world stock market returns and an increase in the volatility of world market returns. Considering future market returns, they do not identify a significant relation between crisis risk and expected market returns, but conclude from analyses on the earnings-price ratio and dividend yield that disaster risk is priced. In addition, they create a measure to distinguish crises according to their severity and find that the more severe a crisis is the stronger the effects on stock market returns are. The Berkman et al. (2011) study is connected to two studies conducted by Barro and Ursúa (2008, 2009), in which they focus on periods with actual drops in consumption. In their 2008 study, Barro and Ursúa consider the personal consumer expenditure and GDP of 21 countries to proxy the probability of an actual economic disaster. They find an estimate for disaster probability of 0.0359 per year and an average disaster size of 21.5%, assuming both parameters to be time invariant and stable across countries. The Barro and Ursúa (2009) study examines the probabilities of depressions and stock market crashes, and the covariance between them. They identify that the largest depressions are likely to be associated with stock market crashes and that this covariance between macroeconomic declines is large enough to conceive the equity premium puzzle.

My research method is closely related to that of Berkman et al. (2011), but this paper proposes two modifications. First, instead of solely testing the effect of potential disasters, I avoid the small sample problem by including news data about international conflict actions in addition to news data about disasters that may or may not eventuate. These conflict actions are defined in a broader way, so verbal conflict actions such as demands or disapproval induce a change in the perceived probability of a crisis threat. Therefore, crisis risk is defined differently in this paper, which leads to the second modification of how this measure is entered in my analysis. Instead of looking at crises as a whole and following up on them over several periods, I consider each conflict action per period as a separate observation. Hence, this paper differs from the Berkman et al. (2011) paper, as it applies a different procedure to consider news events data in a time-series analysis. This creates more variance in my analysis and enables to evaluate the results according to the driving characteristics of a conflict action in greater detail.

2.2 Political risk models

Another line of research focuses more on political instability risk. For example the analysis of Chen, Lu, and Yang (2014) does not take retrospective data on downward jumps in consumption to define crisis periods similar to the models discussed in the previous sub-section. Instead it measures the evolving political tension among countries as proxy for the ex-ante perceived global political instability by investors. The Chen et al. (2014) study combined with the Berkman et al. (2011) research indicates that taking actual crisis or war data may not offer a good parameter for international instability risk since it does not account for investors' perception of risk. Therefore Chen et al. (2014) introduce the growth of the world's aggregate militarization level, which is measures as the growth rate of global military expenditure to GDP ratio, as a new proxy for international instability risk. Their cross-country analysis results in the findings that the international instability risk is a source of systematic risk in international stock markets and therewith results in higher risk premiums and higher return volatility. With emerging markets being relatively more exposed to the risk factor than developed countries, the authors also find a higher risk premium and a higher return volatility in emerging countries, relative to developed countries. They also conduct a panel analysis which indicates a negative relation between country-level militarization and stock returns.

Chen et al. (2014), in conjunction with Fearon (1995), state that wars only occur as a result of bargaining failure and the lack of ability to reach agreements. They claim that this is due to asymmetric information about the costs and benefits that may arise from a war, or due to states being unable to credibly commit or enforce an agreement. My study takes insights from this paper and constructs conflict measures with news event analysis to account for the perceived crisis risk by investors. While the Chen et al. (2014) paper uses actual military-related data to determine the market reactions on international conflicts, my measure of international conflicts defines not only an increase in relative military expenditure as a conflict, but incorporates the bargaining period by including news reaction on an even broader set of conflict events. Therewith it enables a better understanding of which conflict characteristics drive investors' perception and thus trigger the stock market reactions.

The stream of literature which assesses the influence of political uncertainty on asset prices includes Voth (2002), as well as Pástor and Veronesi (2013). Voth (2002) defines political uncertainty through anti-government demonstrations and other indicators of political unrest or instability. His study indicates that this uncertainty substantially drives the increase in stock market volatility during the Great Depression. Pástor and Veronesi (2013) develop a theoretical model to examine the stock price and volatility effects resulting from uncertainty of government policies. This model shows that in weaker economic conditions with high political uncertainty, investors demand a larger political risk premium, while this risk premium is small in strong economic conditions. Furthermore Pástor and Veronesi (2013) find that political uncertainty also leads to more volatility and correlation of stock returns in weak economies. To support their findings empirically, they apply their model on the policy uncertainty index of Baker, Bloom, and Davis (2016). This policy uncertainty index is based on the count of newspaper articles related to economic policy uncertainty scaled by the count of all articles. Caldara and Iacoviello (2018) develop a related model of the geopolitical risk index. They define this geopolitical risk as "the risk associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations", which they measure as the frequency of articles using the same underlying method as Baker et al. (2016). The main findings of the Caldara and Iacoviello (2018) analysis include depressed economic activity, lower stock returns and a capital flow from emerging towards advanced economies as a result of higher geopolitical risk.

All these political risk studies are different from mine, since they analyze political risk provoked through government action and emphasize on political uncertainty induced by policy makers. However, I consider a broader set of conflict actions that lead to perceived crisis risk. Hence, I include conflict events involving sub-state actors such as individuals, identity groups or organizations, into the major forces that drive international politics and therefore might affect investment decisions and market dynamics. Nevertheless, I use a similar procedure to Baker et al. (2016) and Caldara and Iacoviello (2018) to construct and transform my crisis risk variable to account for a trend in the data.

2.3 Event studies and models based on actual wars

As already indicated in the previous sub-sections, many researchers including Berkman et al. (2011) and Chen et al. (2014), do not recommend taking actual crisis or war data to proxy international crisis risk, as it does not fully reflect how investors perceive the threat of a crisis. Nonetheless, there are several event studies that examine the relation between a particular conflict and financial market reactions. One of the first contributions in this line of research is made by Frey and Kucher (2000) who focus on the impact of war on financial markets in the specific case of World War II. They analyze prices of government bonds traded on the Swiss stock market and find that asset prices reflect the historical events. A, accompanying paper by Waldenström and Frey (2002) tackles the same question, but in a different market. There the impact of World War II on government bond prices listed on the Stockholm Stock exchange, where the market was unregulated, is studied. The main finding of that paper is that prices decrease when the war breaks out.

Also the Iraq War is followed by a number of research studies. For example, Rigobon and Sack (2005) measure the effect of risk associated with the war in Iraq on a number of U.S. financial market variables. Therefore they create a war risk factor that captures information on war likelihood, its expected duration and success based on news data, but without quantifying that risk. This factor allows the authors to identify that increased war risk is followed by a decline in the Treasury yield and equity prices. On top of this, they find that it explains the variance of their movements better. Another common method used to proxy war risk during the Iraq War is by observing the traded “Saddam Security”, which pays a fixed amount if Saddam Hussein is out of power by a certain date. This method captures the expectations of financial market participants about the consequences of the war. It is used by Amihud and Wohl (2004) and Wolfers and Zitzewitz (2009), and both studies find differences in the effects of the war probability between the war period and the pre-war period. In the pre-war period, a rise in the security price leads to lower stock prices, which implies the probability of a costly war breaking out. During the war, a rise in the probability of Saddam’s fall is associated with an increase in stock prices indicating a fast end of the war which involves lower costs.

Also Brune, Hens, Rieger, and Wang (2015) create a model that is based on the Iraq War in order to apply it to earlier wars and assess the effects of international conflicts on stock markets. Their model leads to similar results to Amihud and Wohl (2004) and Wolfers and Zitzewitz (2009) that market prices decrease in the pre-war phase when the likelihood of a war increases, but then market prices increase when war actually breaks out. Moreover they discover that stock market prices go down at the surprising start of a war. In their model, Brune et al. (2015) use the Saddam Security to validate their news proxy for war likelihood based on the total number of articles containing certain keywords. Also Schneider and Troeger (2006) conduct a time-series analysis of the confrontations between the Iraq and the UN, the conflict between Israel and Palestinians, and the civil wars in Ex-Yugoslavia. They use these three events to understand how international conflict events affect financial markets with a comparative analysis of three major indices. Therefore they use two main variables to proxy the severity of conflicts and to what extent the agents could anticipate these events. Their measure contains the absolute value of the sum of events per day, distinguishing between positive and negative events according to the Goldstein (1992) scale. This scale defines weights for international interaction to enable the conversion into a single conflict-cooperation measure. Schneider and Troeger (2006) show that international market developments do not generally correspond with the movements of those conflicts measures.

A problem of studies on a specific event in this setting is that the results are specific to the certain event that produces the model. Thus they cannot be easily generalized and translated into a universal statement about the influence of conflicts on the risk-return relation. My model is different from those models. Rather than using a particular conflict as a base to determine the market’s reaction to perceived crisis risk my paper assesses international conflicts of the U.S. in a time-series analysis over an extended time period. By doing so I consider several conflict events, in which the U.S. is involved. This approach ensures the cross-conflict applicability of the analysis results, increases the validity of the study, and allows to infer general statements about the U.S. market reactions to perceived crisis risk.

2.4 News event analysis approach

Moreover, it is noticeable that numerous studies use a news event analysis approach, which means that they use news data to tackle crisis risk. Amongst other aforementioned studies, this method to proxy the perceived uncertainty of a conflict is used by authors as Berkman et al. (2011), Brune et al. (2015) and Rigobon and Sack (2005). Furthermore, there are also earlier research papers including news event analysis to examine the effect of international conflicts on capital markets. For example the research that is conducted by Holsti and North (1966) uses content analysis of news to find that the rising international tensions of World War I drive the negative reaction of investors and concludes a direct relation of movements in security prices and crisis risk. Elmendorf, Hirschfeld, and Weil (1996) similarly study the relationship of world news and bond price movements by selecting a set of important news events. They identify a higher variance in returns and larger absolute returns values for weeks with important news than for weeks without such news.

I follow this trend and base my crisis risk measure on conflict news data in order to account for the investors' perception of crisis risks and the consequences of wars. This is also in line with Keynes (1919) early work, in which he emphasizes on the importance of incorporating "the subjective risk, the feeling […] in the mind of the investor", since the degree of their reaction highly depends on the information about the investment opportunity that is available to them. Accordingly, using news data analysis gives clear benefits that allow a better estimate of investors' perception of crisis risk, whilst also, stipulating breaking down the measure into different types of conflict events that underlie those news and drive the investors' reaction.

2.5 Hypotheses

The literature review reveals the problems of existent work on the relation between international crisis risk and equity market movements. The main problem in this field of research is the lack of a unifying proxy for how investors perceive crisis risk. Consequentially, several authors attempt to test the relationship by using diverging measures and thus find different results for the impact on the risk-return relation of stock markets. While some authors conclude that a high uncertainty about crisis outcomes induces a positive impact on the realized returns as compensation for the risk in crisis times, others find a negative relation between an increase in crisis risk and the market mean return. Thus, already existent crisis measures lead to different theories about the impact on equity market returns. This gives reason to develop a comprehensive measure to proxy crisis risk and to test it on its impact on the stock market.

In my approach, I incorporate the insights gained from the literature review in the variable construction and methodology to assess the impact of perceived international crisis risk on the U.S. equity market. Therefore, the examination of the rare disaster models, that use consumption and GDP as an input measure to define economic disasters, are limitedly able to answer the research question of this paper and to test the real impact of crisis risk. Their measures focus on economic activities and international tensions, which is only an aspect of crisis risk. Hence, they might not be ideal to account for the market responses to crisis risk. To be able to answer the main purpose of this thesis, I use news event data about international conflicts identified through the GDELT Project dataset. Thus, I reveal a more appropriate measure of perceived crisis risk incorporating more aspects of crisis risk. My evaluation of these effects on the U.S. stock market concentrates on how investors react to conflict news. Using this novel proxy I examine the following key hypotheses.

Financial market data often lend considerable support to a negative market reaction to crisis risk. The results tentatively suggest that crisis risk has a negative effect on stock market returns and that the volatility of market returns increases with more international conflict events. In this paper I advance the claim that perceived crisis risk induces a decrease in the stock market return. This is in line with the Berkman et al. (2011) paper, the country-level analysis conducted by Chen et al. (2014), and the results of most of the studies considering a specific war. Furthermore I expect a positive impact of perceived crisis risk on the market's expectation of future volatility. Additionally, Berkman et al. (2011) claim that world stock markets returns react stronger on more severe crises. Like these authors, I expect to find the same pattern in the relation between conflicts which imply U.S. involvement and the U.S. equity market, which is summarized in the first hypothesis of this analysis.

Hypothesis 1: The U.S. stock market return reacts negatively to an intensification of perceived crisis risk and due to the uncertainty the expected future market volatility increases. More severe conflict events have a stronger market reaction.

A further problem exposed through previous studies on crisis risk is that it is necessary to differentiate between the effects that certain components of the perceived crisis risk have on the equity market. As the rare disaster line of research demonstrates, the increased expected rare disaster risk positively affects the expected stock market excess return. Therefore distinguishing between the expected and the unexpected element of risk gives a deeper insight into what drives the variations in stock market returns. Berkman et al. (2011) claim that the negative effect of unexpected disaster risk could indirectly prove that the expected level of disaster risk explains the expected market risk premium. Therewith they follow the argumentation provided by Amihud (2002) and French, Schwert, and Stambaugh (1987) when studying other sources of risk. French et al. (1987) examine the relation between market returns and volatility, while Amihud (2002) analyzes effect of illiquitidy on returns. Both conclude that the expected market risk premium is positively related to the expected level of risk. As a result from that, the contemporaneous stock market returns are negatively related to the unexpected risk component. In my analysis I presume to find similar results in the expected U.S. equity market returns, leading to the second hypothesis.

Hypothesis 2: The expected U.S. stock market excess return is increasing with expected crisis risk, while the unexpected crisis risk has a negative impact on contemporaneous U.S. stock market returns.

Moreover, a general problem within asset pricing is shown by several authors who criticize the standard models for poorly describing the cross-section of industry expected returns. As for instance Gourio (2008a) in combination with Fama and French (1997) are skeptical about the CAPM and the three-factor model. Gourio (2008a) states that the standard measures lead to low risk and therewith do not explain cross-sectional industry expected returns well, which is why he uses an additional risk factor for the exposure to disaster. He claims that when implicating the rare disaster models in cross-sectional analysis, it should hold that assets that do better in the disaster case have lower expected returns. This prediction is in line with the model of Gabaix (2012), which proves theoretically that more resilient stocks, that perform relatively well during a disaster, have a lower ex-ante risk premium, but Gourio (2008a) does not find evidence to sufficiently support this prediction. Also Berkman et al. (2011) estimate crisis risk premiums in a cross-sectional analysis and find that on average the returns are lower for industry portfolios that do relatively good during a period of increased disaster probability. So they conclude that crisis risk is priced. Based on this extant work, I assume to find that the perceived risk resulting from international conflicts involving the U.S. is priced in the U.S. stock markets. This means that there is a positive relation between crisis sensitivity and expected returns. Beyond that it improves the forecast of equity market reactions on international conflict events. Accordingly the third hypothesis of this study is formulated.

Hypothesis 3: Industry portfolios that perform relatively well when perceived crisis risk increases yield lower returns. Accordingly, risk resulting from international conflicts is priced on the U.S. stock markets.

3 Data

The following section includes a description of the GDELT database, the construction of the proxy for international crisis risk and a summary of the stock market data. Firstly, I take insights from the literature to construct the proxy for international crisis risk by applying the identified methods to the GDELT Project dataset. Using a publicly available data source has the benefit that it ensures the replicability and creates transparency in the variable construction. Secondly, I keep the description of the U.S. stock market data short, because I use datasets that are well-known in financial research. For U.S. stock market returns I use the Fama-French Portfolios & Factors dataset and for market volatility I take the volatility index. Hence, all necessary data is available to introduce a new international crisis risk measure to better explain equity market movements.

3.1 The GDELT Project database

The GDELT (Global Data on Event, Location and Tone) open database[1], which comprises records on global events from 1979 to present, is a platform that monitors the world's news media as broadcast, print and web news including nearly every country at any point in time. It provides data about the vulnerability of populations and potential forecasts of global conflicts by quantitatively codifying news events and creating georeference records of the actors, locations, themes and emotions underlying those events. Leetaru and Schrodt (2013) give an extensive description of the data sources, an explanation of the event coding procedure and definitions of the variables. Several scientific articles revise and use the GDELT database, for instance Kwak and An (2014) assess the structure of global news coverage of disasters and its determinants on the basis of the GDELT dataset. They reveal that it aligns with variables used in previous research, which approves the usage of this dataset. The intention of GDELT is to better understand the connection between communicative discourse and global human societal-scale behavior with the use of big data. Therefore, it monitors and codifies the world's open information sources. For this purpose, the GDELT Project categorizes the events with a CAMEO code (Conflict and Mediation Event Observations). As one goes from CAMEO category 01 to 09 there is an ordinal increase in cooperation, and as one goes from CAMEO category 10 to 20 there is an ordinal increase in conflict.

I consider the GDELT 1.0 "reduced" event dataset that covers the time period from January 01, 1979 to February 17, 2014 and uses a "one a day" country-level filtering, meaning it collapses the database to a single observation per day, actor 1 (source), actor 2 (target) and the event code. This dataset includes data of 87,298,046 observations, including CAMEO code events dealing with international mediation and political conflict. Since this study tests the influence of perceived crisis risk as measures by international conflicts on equity markets, the focus is on events with CAMEO codes between 10 and 20, starting with

[1] The GDELT Project website (https://www.gdeltproject.org/) provides raw data files, real-time querying and analysis as well as a cloud-based analysis service.

the most neutral events. GDELT does not only consider news events about the highest-level decision makers of the state actors, but also includes coding for sub-state actors to create a conceptually coherent and complete ordinal coding scheme for news events. As already mentioned in the previous section, this has the benefit that my analysis is not limited to a crisis definition on policy-maker level but enables an in-depth look on conflicts that have an impact on the perceived crisis risk by investors. Accordingly, the change in the perceived risk of a crisis threat is likely to be closely aligned with news events to which investors react and therewith are followed by an adjustment of financial markets when incorporating the news. Another advantage of studying the interaction between international conflicts and financial markets is that the conflict events are likely to be exogenous (Berkman, Jacobsen, and Lee, 2011). Conflict events emphasize periods that are filled with tension, but largely independent of business fluctuations. Finally, through the assignment of CAMEO codes to each event, it is possible to distinguish the severity of a conflict. This allows me to identify which severity types of conflicts drive perceived crisis risk. This means that the perceived threat of a crisis is not inevitably triggered through an international conflict identified by material violence, but even a verbal dispute can promote investors' perception of crisis risk.

The GDELT 1.0 "reduced" event dataset comprises 17 variables per observation. Firstly, it includes descriptive variables as the specific date on a daily basis, the number of events and of articles. Secondly the dataset provides the CAMEO actor codes for the source and the target, as well as different event classifications as the CAMEO event code, the QUAD classification and the Goldstein scale. Lastly, the georeferences of the source, the target and the action itself are given. In the related GDELT 1.0 Event Database, GDELT provides detailed data on each event, the event actors and the news source, plus the website makes descriptions of the documentation of these datasets available. GDELT generates time-series data and not panel data, which means that the "one a day" observations are considered separately and independently from previous news events covering the communicative behavior between the two actors. This yields the advantage of a more detailed view on the perception of a crisis by splitting it in several independent events with their corresponding crisis potential.

Before I construct the perceived crisis risk measure for my analysis, I make two adjustments to the GDELT 1.0 "reduced" event dataset. Firstly, I am interested in risk that originates from international conflicts in which the U.S. is involved. Hence, I exclude all observations in which the U.S. is not involved and in which the U.S. is acting as both event source and event target from the analysis for the simple reason of lacking involvement of the U.S. or missing internationality of the event, respectively. Secondly, I assume that investors' attention is limited due to a shortage of cognitive resources, leading investors to only react on attention grabbing news events. Thus my analysis only includes international news events with above-daily median media coverage, measured in the number of news articles. These two adjustments leave me with a total number of 7,315,614 observations, in which the U.S. is either the source or the target of a news event. Subsequently, I construct my crisis risk variable by working around a disadvantage of the GDELT database identified by Schintler and Kulkarni's study (2014). As they analyze the potentials in big data, they find that the GDELT database suffers from temporal bias, meaning that it is skewed toward more recent years due to the rise in web-based and digital news. This makes the total number of international conflicts as a proxy for perceived crisis risk inapplicable, which is contradicting with the variable construction method used in Berkman et al. (2011). To account for this temporal bias, I use a similar method as Baker, Bloom, and Davis (2016) for their policy uncertainty index and scale the count of daily international conflict events with a CAMEO category 10 to 20 by the count of daily cooperation events with a CAMEO category 01 to 09. This method changes the interpretation of the conflict variable to the frequency of conflict events. Plus, with this method I assume that the total number of international cooperation events of the U.S. captures the trend that is induced by the increase in digital news technology.

I examine the evolution of the crisis risk measure over the period from January 01, 1979 to February 17, 2014. Fig. 1 plots the daily ratio of the total number of international conflicts to the total number of international cooperation events in which the U.S. is involved, according to the GDELT database.

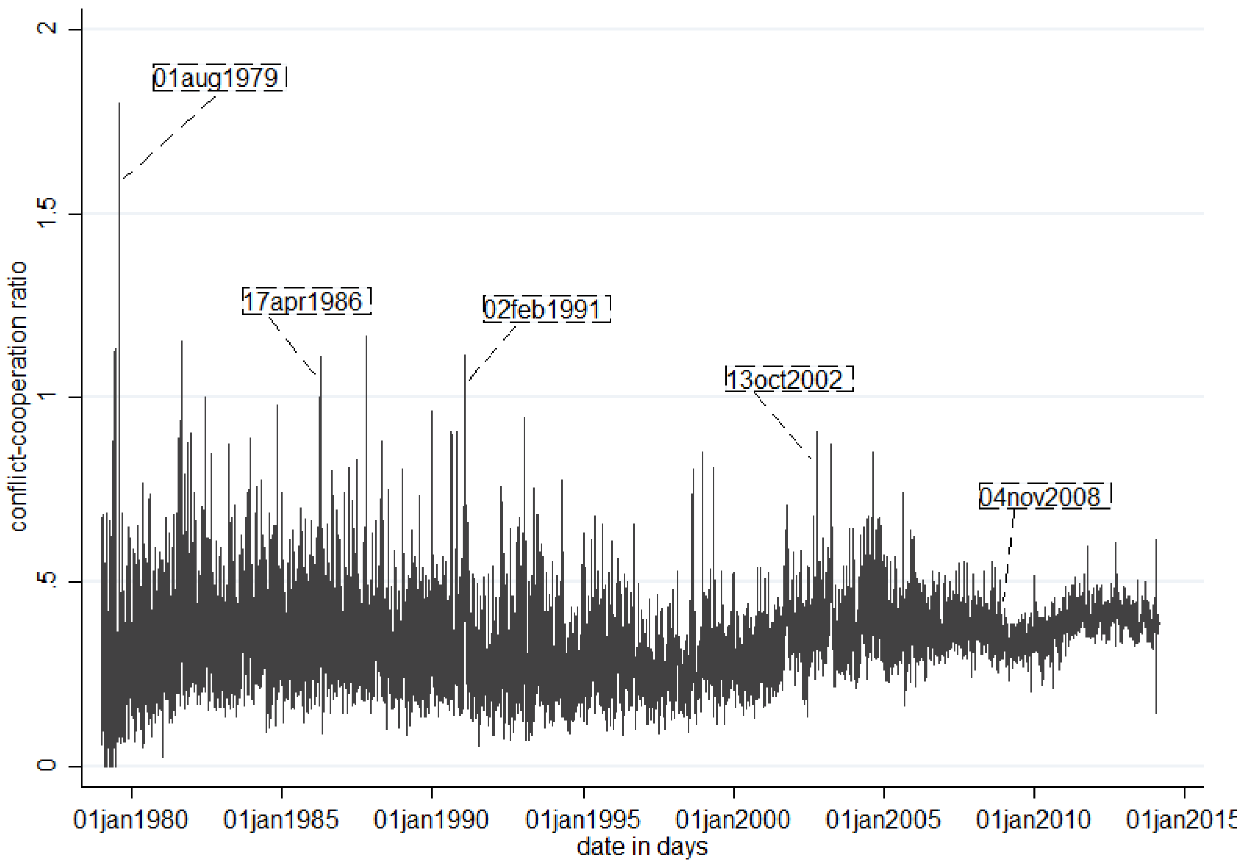

Fig. 1: The time-series of the ratio of the number of conflict events to the number of cooperation events
This figure plots the time-series of the conflict frequency, measured as the daily ratio of the number of conflict events to the number of cooperation events according to the GDELT database. The sample period is January 01, 1979 to February 17, 2014.

The daily ratio of the total number of international conflict events to the total number of international cooperation events might be a rough proxy for perceived crisis risk, but it seems to correlate well with political instability in the U.S.. Accordingly, the first peaks occur in the mid of 1979 after a period of détente in the Cold War. The year 1979 is marked by indirect conflicts between the superpowers Soviet Union and U.S. and other events including the Iranian Revolution and the Nicaraguan Revolution. Also, in the second half of 1981 political instability remains high due to major international conflicts resulting from the Iran-Iraq war and the U.S. bases in several countries. The ratio of the number of international conflict events to the number of international cooperation events peaks again around the mid of April 1986, when U.S. air and naval forces conduct bombing strikes on terrorist facilities in Libya. Also, the year 1987 until 1991 is dominated by substantial international tension due to the Iran-Iraq conflicts. This is reflected in the conflict-cooperation ratio, which exceeds a value of one on October 20, 1987 as the U.S. Navy forces attack Iranian oil platforms in the Persian Gulf and on February 02, 1991 due to further airstrikes against Iraq. After the dissolution of the Soviet Union and the end of the Cold War in December 1991, a period of relative calm follows.

Conflicts flare up in the end of 2001, when the U.S. launches the military campaign War on Terror and invades Afghanistan. The continuing political distemper is reflected in another peak in the conflict-cooperation ratio in October 2002, when the U.S. Congress passes the Iraq resolution authorizing military action against Iraq leading to the Iraq War, which begins with the U.S. invasion in March 2003. However, during the George W. Bush presidency from 2001 until 2009 the U.S. is involved in several major international conflict events as the Second Liberian Civil War in 2003 and within the War on Terror campaign in Georgia, Kenya, and Yemen amongst others. This is also reflected in the ratio of the total number of international conflict events to the total number of international cooperation events, which is relatively high in this period and declines noticeably with the presidential election on November 04, 2008, when Barack Obama is elected. Nevertheless, some conflicts emerge also during that period, which can be traced back to the Gulf War and responses to actions by Al Qaeda terrorists as the killing of Osama Bin Laden by U.S. military forces in May 2011. In this study, I investigate whether the total number of international conflict events to the total number of international cooperation events as a measure of perceived crisis risk has the potential to affect the U.S. stock market.

3.2 Crisis risk variables

To understand and assess the influence of international conflict events on the U.S. equity market, the main variable I use is the ratio of the total number of international conflict events to the total number of international cooperation events implying U.S. involvement on day t according to the GDELT database: *All Conflicts*$_t$. Furthermore the GDELT dataset covers several aspects of conflicts displayed in the event classifications through the CAMEO event code. Therewith it allows to distinguish this general variable according to the severity of the conflict and to test whether different conflict characteristics have different effects on the equity market. This distinction is necessary to test the first hypothesis of this study that more severe conflicts increase the perceived crisis risk, which in turn leads to a stronger market reaction. Therefore I use dummy variables for each of the CAMEO event codes between 10 and 20 to account for the severity of the conflict event and break the conflicts into eleven sub-samples: whether there is a verbal conflict as actors demand something, disapprove, reject, threaten or protest on each other or whether the conflict is material as actors exhibit military posture, reduce relations, coerce, assault, that there is a fight or actors engage in unconventional mass violence. The numbers of events in these sub-samples also suffer from the trend due to digitalization, which is why I apply the same method as previously and account for the trend in the variable construction by taking the ratio of the count of the conflict events in the sub-category to the count of daily cooperation events with U.S. involvement. The variables are then scaled by the daily number of cooperation events, thus measure the frequency of the events in the sub-category.

Considering verbal conflicts, the GDELT database includes a CAMEO event code whether the conflict event characterizes a demand of an actor. The *Demand* variable contains the scaled number of conflicts related to a demand or order. *Disapprove* is the frequency variable for conflicts in which actors express disapproval, objections or complaints. Conflicts in the sub-group *Reject* are all rejection and refusal events scaled by the cooperation events. The CAMEO event code for *Threaten* defines the scaled conflict event variable of threats, coercive or forceful warnings with serious potential repercussions. For my analysis, I also consider the subset *Protest* which includes the ratio of all civilian demonstrations and other collective actions carried out as protests against the target actor to all cooperation events. With this sub-category it becomes more obvious that the GDELT database does not only include events initiated by the highest-level decision makers of the state actors, but also sub-state actors.

Further I also separate the material conflicts. The (*Exhibit) Military Posture* variable contains the scaled events in which military posture or police power is exhibited but falls short of actual use of force and therewith dissociates from the last three sub-samples. The sub-sample *Reduce Relations* comprises the number of conflicts in which normal or cooperative relations are reduced relative to the number of cooperation events. The *Coerce* conflict variable is the scaled conflict events number in which repression, violence against civilians, their rights or properties is present. Additionally, the sub-sample *Assault* considers the ratio of the usage of unconventional forms of violence, which do not require high levels of organization or conventional weaponry as for example a hijacking or suicide bombing, to the number of cooperation events. The sub-category *Fight* considers the scaled event number, which includes conflicts in which conventional force is used and acts of war typically by organized armed groups. To distinguish the frequency of conflicts including uses of unconventional force that is meant to cause mass destruction, casualties, and suffering the (*Engage In Unconventional) Mass Violence* variable is constructed.

Each of the eleven sub-samples above enables the analysis of these conflict characteristics separately. Furthermore, it may be worthwhile to look at the combined effect of all characteristics, so I summarize them by constructing a *Severity Index*. This index is measured as the scaled numbers of events in the sub-samples weighted by its CAMEO event codes, which range from CAMEO category 10 to 20 in an ordinal scale increasing in conflict severity. The *Severity Index* variable is highly correlated with the ratio of the total number of international conflict events to the total number of international cooperation events *All Conflicts*$_t$ (correlation coefficient of 0.99), which is why I do not include a separate figure plotting the movements of the *Severity index* over time.

Table 1 provides the descriptive statistics of the perceived crisis risk variables from January 01, 1979 to February 17, 2014 leading to 12,832 days in the sample. Panel A shows the average ratio of conflict events to cooperation events over the entire period is 0.34 per day, which is deducted from the total number of 1,987,845 conflicts and 5,327,769 cooperation events which imply U.S. involvement during that period (not reported in the table). This means that on average 155 conflicts and 415 cooperation events take place on any given day. The descriptive statistics of the sub-sample means provides several interesting observations that the frequency of conflicts varies between the sub-samples and their specific conflict characteristics. More frequent conflicts include conflicts in which disapprovals or complaints are expressed, conflicts concerning coercions or violence against civilians and conflicts in the fight sub-category in which conventional force or acts of war are used being on average 0.09, 0.05 and 0.06 as frequent as cooperation events respectively. In comparison, the conflict frequencies concerning protests or civilian demonstrations (conflict-cooperation ratios of 0.011), conflicts in which military or police power are exhibited (0.008), in the case of reductions of relations (0.019), assaults including conflicts with unconventional forms of force or violence (0.017) and conflicts in which unconventional violence is used to cause mass destruction (<0.001) are on average lower. The mean of the *Severity index* is 4.95.

The highest frequency of all conflict events on a day is 1.8 and occurs on August 01, 1979. On that day the U.S. was involved in a total number of nine conflicts, while they engaged in five cooperation events. The conflict events relate to fights with Austria and other civilian parties and the U.S. threatens Nigeria on that day. Apart from these fights Africa, China and political oppositions express disapproval with the U.S. and its military. The lowest conflict-cooperation ratio of zero, which means that there is no conflict event on that day, is rare. There are precisely six days out of the 12,832 days in the sample without any conflicts, all occurring in the first half of 1979. This could be due to lower media coverage before digitalization. The last column ρ(1) displays the first-order autocorrelations, which show a significant positive relation between the conflict frequency of the previous day and the conflict frequency on the day. The correlations are very low, so that I do not expect a bias in my results.

Table 1, Panel B presents the correlation between the crisis risk variables, which are mostly positive and significant. For example, the correlations between the conflict frequencies of disapprovals, coercions and fights, which I identified as more frequent conflict events, are slightly higher. Not surprisingly, they are also highly correlated with the broad variables of *All conflicts* and the *Severity index*.

Table 1: Descriptive statistics and correlation table of crisis risk variables

*Panel A presents the descriptive statistics of the crisis risk variables including the mean, standard deviation, minimum, median, maximum, and the first-order autocorrelation of the time-series capturing the time period from January 01, 1979 to February 17, 2014. All conflicts denotes the number of conflict events scaled by the number of cooperation events on any day, in which the U.S. is either a source or a target actor. This variable is split into the following sub-samples: Demand, Disapprove, Reject, Threaten, Protest, (Exhibit) Military Posture, Reduce Relations, Coerce, Assault, Fight and (Engage In Unconventional) Mass Violence. Their CAMEO event code is denoted in square brackets. The reported values give the number of international conflict events in the respective sub-sample scaled by the number of cooperation events. The Severity index denotes a combined measure of the conflict frequency in the sub-samples weighted by its CAMEO classification. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level. All variables are created with the use of the GDELT 1.0 "reduced" event dataset.*

Panel B reports the correlation coefficients among the crisis risk variables.

Panel A: Descriptive statistics of crisis risk variables

Variables	Mean	Std. dev.	Min	Median	Max	ρ(1)
All conflicts	0.3442	0.1106	0.0000	0.3420	1.8000	0.4352***
Demand [10]	0.0203	0.0148	0.0000	0.0191	0.1579	0.0888***
Disapprove [11]	0.0933	0.0412	0.0000	0.0917	0.8000	0.2715***
Reject [12]	0.0383	0.0246	0.0000	0.0357	0.6667	0.1687***
Threaten [13]	0.0227	0.0182	0.0000	0.0210	0.4667	0.2059***
Protest [14]	0.0111	0.0141	0.0000	0.0084	0.1935	0.2935***
Military Posture [15]	0.0078	0.0113	0.0000	0.0046	0.3077	0.1617***
Reduce Relations [16]	0.0191	0.0166	0.0000	0.0162	0.2683	0.1649***
Coerce [17]	0.0495	0.0286	0.0000	0.0478	0.5000	0.2814***
Assault [18]	0.0171	0.0161	0.0000	0.0152	0.3750	0.2641***
Fight [19]	0.0645	0.0421	0.0000	0.0615	0.6000	0.4778***
Mass Violence [20]	0.0003	0.0017	0.0000	0.0000	0.0333	0.0973***
Severity index	4.9463	1.6603	0.0000	4.9073	25.2000	0.4587***

Panel B: Correlation coefficients between crisis risk variables

	All	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	Index
All conflicts	1												
Demand [10]	0.29***	1											
Disapprove [11]	0.69***	0.12***	1										
Reject [12]	0.39***	0.07***	0.15***	1									
Threaten [13]	0.44***	0.07***	0.24***	0.12***	1								
Protest [14]	0.32***	0.08***	0.18***	0.08***	0.08***	1							
Military Posture [15]	0.20***	0.06***	0.06***	0.04***	0.08***	0.05***	1						
Reduce Relations [16]	0.24***	0.06***	0.08***	0.07***	0.06***	0.05**	0.02*	1					
Coerce [17]	0.49***	0.07***	0.19***	0.08***	0.06***	0.09***	-0.01	0.04***	1				
Assault [18]	0.39***	0.05***	0.15***	0.01	0.08***	0.06***	0.03***	0.02***	0.19***	1			
Fight [19]	0.69***	0.08***	0.31***	0.08***	0.25***	0.12***	0.09***	0.02***	0.21***	0.27***	1		
Mass Violence [20]	0.04***	-0.00	0.02***	-0.00	0.01	0.01	0.01	-0.01	0.00	-0.00	0.04***	1	
Severity index	0.99***	0.24***	0.62***	0.33***	0.42***	0.31***	0.19***	0.24***	0.53***	0.43***	0.76***	0.05***	1

3.3 Stock market data

In this sub-section, I provide key features about the U.S. equity market. I abstain from an extensive description of the datasets, because they are well-known in financial research, and proceed with the description of the relevant variables for my analysis. Table 2, Panel A reports the descriptive statistics of the stock market return variables, which includes the U.S. stock market excess returns, the risk-free returns and the Fama-French size and value factor premiums. These are taken from the Fama-French Portfolios & Factors dataset available on WRDS, which is based on the dataset from Kenneth French's Data Library at Dartmouth. *MKTRF* denotes the daily excess return of the value-weighted portfolio of all NYSE, AMEX and NASDAQ firms available on CRSP over the risk-free return *RF*, which simply is the daily rate that over the number of trading days in the month compounds to the Ibbotson and Associates Inc. one-month Treasury-bill rate. *SMB* and *HML* are the Fama-French factors capturing the size and value effect in stock returns respectively, obtained through six double-sorted portfolios into two size groups and three book-to-market ratio groups. SMB is the difference between the average return on the three Small-firm portfolios and the average return on the three Big-firm portfolios. HML is the difference between the average return on the two High book-to-market equity portfolios and the average return on the two Low book-to-market equity portfolios. All returns are daily returns from January 02, 1979 until February 14, 2014 including 8,861 business day observations. For the cross-sectional analysis to test the third hypothesis, I take the Fama-French 49 Industry Portfolio dataset available on Kenneth French's Data Library at Dartmouth. This dataset contains the value-weighted returns for the 49 industry portfolios (not reported in the table) over the same period starting in January 02, 1979 until February 14, 2014. The advantage of using the Fama-French 49 Industry Portfolio dataset for the cross-sectional analysis is that a narrow distinction of the industries reduces the unobserved heterogeneity within the industry groups, as indicated by Gormley and Matsa (2014). Also it is beneficial that the dataset includes the same individual stocks than the market level dataset.

Table 2, Panel B presents the descriptive statistics of the volatility index *VIX* of the CBOE (Chicago Board Options Exchange), which is retrieved from Yahoo Finance. The VIX index is an implied measure of the stock market's expectation of volatility based on S&P 500 stock index option prices. I use the daily adjusted closing price, which adjusts for both dividends and splits. According to several authors as Park (2016) and Chow, Jiang, and Li (2014), the VIX has a positively skewed distribution. This asymmetry comes from investors reacting differently to good and bad news. Thus, I also report the logarithm of the VIX *lnVIX*, which I use as a dependent variable for my analysis to account for the positive skewness as suggested by Engle and Gallo (2006). The logarithmic transformation also simplifies the interpretation of the coefficients in my analysis. The sample of the VIX begins on January 02, 1990 until February 14, 2014 due to limited data availability, yielding to 6,080 business day observations.

Table 2: Descriptive statistics of return and volatility variables

Panel A presents the descriptive statistics of the return variables including the mean, standard deviation, minimum, median, maximum, and the number of observations from January 02, 1979 to February 14, 2014. MKTRF denotes the excess return of the value-weighted portfolio of all NYSE, AMEX and NASDAQ firms on CRSP over RF. RF is the daily rate that over the number of trading days in the month compounds to the Ibbotson and Associates Inc. one month Treasury-bill rate. SMB is the size premium, which is the difference in the average return of small-firm portfolios and the average return of big-firm portfolios. HML is the value premium, which is the difference in the average return of high book-to-market firm portfolios and the average return of low book-to-market firm portfolios. All variables are obtained from the Fama-French Portfolios & Factors dataset available on WRDS.

Panel B reports the descriptive statistics of CBOE's volatility index VIX available on Yahoo Finance and the natural logarithm of the VIX including the mean, standard deviation, minimum, median, maximum, and the number of observations from January 02, 1990 until February 14, 2014.

Panel A: Descriptive statistics of return variables						
Variables	Mean (in %)	Std. dev. (in %)	Min (in %)	Median (in %)	Max (in %)	# Obs.
MKTRF	0.0317	1.0873	-17.4400	0.0600	11.3500	8,861
RF	0.0192	0.0139	0.0000	0.0190	0.0610	8,861
SMB	0.0049	0.5809	-11.5800	0.0300	6.2000	8,861
HML	0.0160	0.5561	-4.2200	0.0100	4.8300	8,861
Panel B: Descriptive statistics of volatility variables						
Variables	Mean (in USD)	Std. dev. (in USD)	Min (in USD)	Median (in USD)	Max (in USD)	# Obs.
VIX	20.1631	8.0552	9.3100	18.4700	80.8600	6,080
lnVIX	2.9394	0.3469	2.2311	2.9161	4.3927	6,080

The Fama-French Portfolios & Factors dataset is a well-known dataset in financial research, which is why I do not extend the data description. The average market premium over the entire time period is 0.0317% per day, or approximately 8.25% annual compounding, with a high volatility indicated by the standard deviation of 1.0873% per day. The most negative return on a day of -17.44% occurred on October 19, 1987, which is known as Black Monday. On October 13, 2008, the most positive return on a day of 11.35% was obtained during the volatile period resulting from the financial crisis in 2008. The average daily risk-free return is 0.0192%, or 4.92% annually. The size premium as well as the value premium is on average positive. Small-firm portfolios outperform the Big-firm portfolios with 0.0049% per day, or 1.23% annually, while the High book-to-market firm portfolios outperform the Low ones with 0.0160% per day, or 4.08% annually.

The VIX index has an average adjusted closing price of 20.1631 USD in the entire period from January 02, 1990 until February 14, 2014, but is very volatile with a standard deviation of 8.0552. The highest price occurred on November 20, 2008, during the highly volatile period resulting from the financial crisis in 2008 with a lnVIX of 4.3927. The lowest adjusted closing price occurred on December 22, 1993 during a historically low period with a lnVIX of 2.2311.

4 Empirical framework

In this chapter, I elaborate the methodologies used to tackle the research question whether the conflict events in which the U.S. are entangled explain a part of the variation in the U.S. stock market. In the previous sections, I use the insights from my literature review to construct a new measure for perceived crisis risk. On the basis of this measure I examine whether a link exists between changes in this risk measure and stock market movements. First, the methods to test contemporaneous effects of crisis risk are described. Then, an explanation of the predictive analysis follows. Mostly, my methods are closely related to those of Berkman, Jacobsen, and Lee (2011), to ensure the comparability of my work. I describe these methods in this section and go deeper into when my methods deviate from theirs and explain why I choose for certain ways of analyzing.

4.1 Contemporaneous models

To test the first part of Hypothesis 1 whether the U.S. stock market return depends on perceived international crisis risk, I measure the impact of the frequency of conflicts on any given day t on stock returns according to the model:

$$MKTRF_t = \mu + \alpha_1 Crisis_t + \varepsilon_t, \qquad (1)$$

where $MKTRF_t$ denotes the daily excess return of the value-weighted portfolio of all NYSE, AMEX and NASDAQ firms over the risk-free return. This simple OLS regression is performed for the main variable *All Conflicts*, which is the ratio of the total number of international conflict events to the total number of international cooperation events concerning the U.S. on day t, but also for the specific conflict characteristics and the *Severity index*. This is necessary to test the first part of the first hypothesis, whether the U.S. stock market return reacts negatively to an increase in crisis risk and whether more severe conflict events have a stronger market reaction. For this distinction I restrict the number of conflicts to the number of conflicts in one of the following sub-categories: *Demand*, *Disapprove*, *Reject*, *Threaten*, *Protest*, (*Exhibit) Military Posture*, *Reduce Relations*, *Coerce*, *Assault*, *Fight* and (*Engage In Unconventional) Mass Violence*. Then I divide the respective number of conflicts by the total number of cooperation events and perform regression model (1) for each of these ratios as proxies for crisis risk. Plus, I investigate with the *Severity Index* variable whether there is a combined effect of the conflicts in the sub-categories. I deviate from the Berkman et al. (2011) paper by considering each conflict event separately, and not following up on a crisis over time, to have a deeper insight in the effects of certain conflict characteristics on the U.S. equity market return.

To test the second part of Hypothesis 1, whether the U.S. stock market volatility increases due to uncertainty originating from an increase in perceived crisis risk, I take two daily aggregate stock market volatility measures into account, as Pástor and Veronesi (2013) recommend: the realized and the implied volatility. Firstly, for the realized volatility I estimate a GARCH(1,1) model with an exogenous variable, similar to the model of Berkman et al. (2011) in combination with Engle (2002). Secondly, the implied volatility is measured as the natural logarithm of the daily adjusted closing price of the CBOE's VIX index.

The realized volatility is computed on the daily U.S. market excess returns by a GARCH model with an exogenous variable, which is a multi-step regression to capture the volatility effects as the conditional variance of the error term, controlling for the effect crisis risk has on the mean excess return. Hence, the conditional variance of the error term depends on the most recent squared residual, the most recent conditional variance and the contemporaneous crisis risk:

$$MKTRF_t = \mu + \alpha_1 Crisis_t + \varepsilon_t,$$
$$\varepsilon_t \sim N(0, \sigma_t^2),$$
$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 Crisis_t + \eta_t, \qquad (2)$$

where $MKTRF_t$ denotes the daily U.S. market excess return. The conflict frequency of *All Conflicts*, the same sub-categories as in the previous regression and the *Severity index* are used as the exogenous variable. ε_t is the error term and σ_t^2 the conditional variance of the error term.

While the GARCH model is a retrospective model computing historical volatility, the VIX index reflects the implied volatility using S&P500 stock index option prices to calculate the stock market's expectation of volatility. Accordingly, it is a supplement to the GARCH model, which is why I use a VIX model additional to the Berkman et al. (2011) methodology. To investigate whether an increase in the expected future market volatility is driven by the fear of crisis risk, I test the relation between the natural logarithm of the VIX and the crisis risk measure through the following simple OLS model:

$$lnVIX_t = \mu + \alpha_1 Crisis_t + \varepsilon_t. \qquad (3)$$

$lnVIX_t$ denotes the natural logarithm of the VIX adjusted closing price on any given day t, which is regressed on the main variable *All Conflict*$_t$, the conflict sub-category variables *Demand*, *Disapprove*, *Reject*, *Threaten*, *Protest*, (*Exhibit) Military Posture*, *Reduce Relations*, *Coerce*, *Assault*, *Fight* and (*Engage In Unconventional) Mass Violence* and the *Severity index* variable.

4.2 Predictive analysis

Similar to the work of Berkman et al. (2011), I examine the explanatory power of perceived crisis risk on the expected stock returns in the U.S. stock market with the aid of two models. The first model looks at the time-series of the expected aggregate U.S. market excess return in it's entirely, while the second model considers the cross-sectional movements in the expected industry excess returns.

As Amihud (2002), Berkman et al. (2011) and French, Schwert, and Stambaugh (1987) argue, I expect that the U.S. excess returns can be better explained when including contemporaneous unexpected changes in crisis risk into the regression, plus that the coefficient on the unpredicted component of crisis risk bears indirect evidence about the effects of predictable crisis risk on ex ante risk premiums. Thus, it is important to include unexpected crisis risk into the analysis on the U.S. stock market excess returns. In order to test Hypothesis 2, whether higher expected crisis risk leads to a higher expected U.S. stock market excess return and whether the contemporaneous U.S. stock market return is decreasing with unexpected crisis risk, I apply a two-step regression. Firstly, I estimate the expected and unexpected crisis risk by following the methodology used in previous papers as Amihud (2002), Berkman et al. (2011) and French et al. (1987). This estimation procedure assumes that investors determine the expected crisis risk for any day based on the information available on the previous day, and then require an expected return based on this predicted crisis risk. Accordingly, crisis risk is assumed to follow the AR(1) model:

$$Crisis_t = \alpha + \beta_1 Crisis_{t-1} + \varepsilon_t, \qquad (4)$$

where $Crisis_t$ as the frequency of conflict events on day t is regressed on the frequency of conflict events on day t-1, $Crisis_{t-1}$. With the aid of a supremum Wald test I check whether the estimates are stable over time. Secondly, investors determine the expected crisis risk at day t based on the fitted value from model (4) estimated over the entire period and the unexpected crisis risk is denoted by the residual ε_t of the model. To examine the second hypothesis of this thesis, the daily U.S. market excess return, $MKTRF_t$, is regressed on the expected and unexpected component of perceived crisis risk:

$$MKTRF_t = \alpha + \beta_1 Expected\ Crisis\ Risk_t + \beta_2 Unexpected\ Crisis\ Risk_t + \varepsilon_t. \qquad (5)$$

I apply the above described method on each of the alternative crisis risk measures including the conflict frequency of *All Conflicts*, of the same sub-categories as in previous regressions and the *Severity index* to estimate the predicted and the unpredicted component of crisis risk.

Lastly, I conduct a cross-sectional analysis of perceived crisis risk to test Hypothesis 3 of this thesis and to get a deeper understanding of the variation in expected returns across industries. The cross-sectional implication of perceived crisis risk would mean that assets in an industry with low crisis risk sensitivity yield to a lower expected return, which means in return that the crisis risk factor is priced. To examine the relationship between the crisis risk sensitivity and the one-month-ahead return, the Fama and MacBeth (1973) two-step approach is used and applied on the Fama-French 49 Industry Portfolio returns. In the first step, I extend the Fama-French (1993) three-factor model and incorporate an additional factor for perceived crisis risk. This extended asset pricing model is used to estimate the risk sensitivities through a multiple time-series regression of excess returns for an industry portfolio on the contemporaneous Fama-French factors and the crisis risk factor. This first step is implemented on overlapping 250-day windows through the sample period, which is equivalent to the previous year in business days, to obtain estimates of the industry's risk loadings with respect to the four factors in the following model:

$$RIRF_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKTRF} MKTRF_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{Crisis} Crisis_t + \varepsilon_{i,t}. \qquad (6)$$

$RIRF_{i,t}$ is the excess return on the value-weighted industry portfolio i on day t; $MKTRF_t$, SMB_t and HML_t are the Fama-French factors for the market, size and value premium respectively on day t. $Crisis_t$ is the perceived crisis risk factor, measured as the unexpected crisis risk as obtained from model (4), on day t using the main variable *All Conflicts*, the conflict sub-category variables and the *Severity index* variable.

Before I run the second-stage cross-sectional regression, I imply modifications to the standard Fama and MacBeth (1973) analysis. The initial procedure focuses on the regression on the day following the estimation period, but I use the set of betas of the last day of the month as explanatory variables for the next month following the estimation period. Therefore, it is necessary to transform the daily excess returns on the industry portfolios into monthly compounded portfolio excess returns. Furthermore, Berkman et al. (2011) propose a transformation of the beta for crisis risk sensitivity to make the results more robust to estimation errors in the first step and to simplify the interpretation of the coefficient in the second step of the analysis. Thus, I convert the crisis risk sensitivities $\beta_{i,t}^{Crisis}$ into decile ranks on the last day of each month and rescale their values that they range from zero to one. Then I run the second-stage cross-sectional regression in each month following the estimation period of the Fama-French factor betas and the rescaled decile ranks of the crisis risk factor at the last day of the previous month:

$$RIRF_{i,m} = \gamma_m + \gamma_m^{MKTRF} \beta_{i,m-1}^{MKTRF} + \gamma_m^{SMB} \beta_{i,m-1}^{SMB} + \gamma_m^{HML} \beta_{i,m-1}^{HML} + \gamma_m^{Crisis} \beta_{i,m-1}^{Crisis} + \varepsilon_{i,m}. \qquad (7)$$

where $RIRF_{i,m}$ denotes the excess return on industry portfolio i in month m; $\beta_{i,m-1}^{MKTRF}$, $\beta_{i,m-1}^{SMB}$, $\beta_{i,m-1}^{HML}$ and $\beta_{i,m-1}^{Crisis}$ denote the estimated factor loadings, or respectively the rescaled decile rank of the factor loading, for each industry portfolio i on the last day of month m-1. Finally, the monthly estimates are averaged over the sample period and tested for statistical significance.

5 Empirical results

This section comprises the main results from the empirical analysis that are obtained when the models from the previous section are applied to the datasets described in section 3. First, the results from the contemporaneous analysis are presented. Then the outcomes from the predictive tests are shown. Enclosed, the robustness of these results is checked.

5.1 International crisis risk and stock market mean returns

The effect of perceived international crisis risk on the stock returns is measured through a simple regression analysis, with the daily U.S. market excess return as the dependent variable, as specified in model (1). The regression coefficients and t-statistics based on heteroskedasticity-robust standard errors are presented in Table 3. To examine whether crisis risk has a negative effect on the excess returns, I look at the crisis risk coefficient. The first row in Table 3 gives the results, where *All conflicts* are used to proxy crisis risk. The following rows contain the estimations of the crisis risk proxy of the specific conflict sub-samples *Demand*, *Disapprove*, *Reject*, *Threaten*, *Protest*, (*Exhibit) Military Posture*, *Reduce Relations*, *Coerce*, *Assault*, *Fight* and (*Engage In Unconventional) Mass Violence*. This allows testing whether investors react stronger to more severe crises with certain conflict characteristics. The last row in Table 3 reports the combined effect of all conflicts weighted by the severity, based on the *Severity index* measure.

The coefficient of the first specification, using *All conflicts* to proxy crisis risk, is not significantly different from zero at a 10% significance level, with a t-statistic of -0.13. Hence, I cannot reject the null-hypothesis of the crisis risk coefficient being equal to zero and it is not meaningful to interpret the sign as well as the magnitude of the regression coefficient. Accordingly, I do not find that the variation in the conflict frequency of all conflicts explains movements in the market mean excess returns in the U.S. equity market. The analysis of perceived crisis risk based on conflicts in the certain sub-categories leads to similar results. None of the eleven crisis coefficients appears to be significant at the level of 10%. Thus, the results provide no evidence that there is a relation between the number of conflicts in the respective sub-category conflicts scaled by the number of cooperation events and the variation in the contemporaneous U.S. stock market excess return. Also, the sign of the crisis coefficients do not indicate a direction of the relation, let alone a stronger reaction of investors in the case of more severe conflicts. Besides looking at the variables separately, it is important to account for a potential combined effect of all conflicts weighted by their severity. However, I also find no significant estimation coefficient at the 10% significance level for the *Severity index*, with a t-statistic of -0.23.

Overall, the results are self-consistent. I cannot find that an increase in perceived crisis risk resulting from conflicts in which the U.S. is involved has a significant effect on the contemporaneous U.S. stock market excess returns. As a consequence, my dataset does not support the first part of Hypothesis 1. A possible explanation for this result is that, on average, the crisis risk-return relation is non-linear, meaning that investors might react differently to crisis risk when being in the tails of the distribution than when there is a low level of perceived crisis risk.

Table 3: Regression results for the effect of perceived crisis risk on the contemporaneous U.S. stock market returns

*In this table the regression results for model (1) are reported: $MKTRF_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, where $MKTRF_t$ is the daily U.S. stock market excess return (in %) from January 02, 1979 until February 14, 2014 including 8,861 business day observations and $Crisis_t$ is the conflict frequency constructed as the ratio of the total number of international conflict events to the total number of international cooperation events concerning the U.S. on day t. I report the estimates for the crisis risk variable including All conflicts, the variables of the conflicts in the sub-samples and the variable of the Severity index. The t-statistics, which are based on heteroskedasticity-robust standard errors, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Crisis
All conflicts		
Coefficient (%)	0.0366	-0.0143
t-Statistics	(0.93)	(-0.13)
Demand [10]		
Coefficient (%)	0.0234	0.4100
t-Statistics	(1.30)	(0.61)
Disapprove [11]		
Coefficient (%)	0.0170	0.1565
t-Statistics	(0.68)	(0.66)
Reject [12]		
Coefficient (%)	0.0413**	-0.2473
t-Statistics	(1.98)	(-0.58)
Threaten [13]		
Coefficient (%)	0.0431**	-0.5072
t-Statistics	(2.14)	(-0.61)
Protest [14]		
Coefficient (%)	0.0193	1.1551
t-Statistics	(1.35)	(1.35)
Military Posture [15]		
Coefficient (%)	0.0391***	-0.9574
t-Statistics	(2.79)	(-0.86)
Reduce Relations [16]		
Coefficient (%)	0.0377**	-0.3147
t-Statistics	(2.17)	(-0.52)
Coerce [17]		
Coefficient (%)	0.0210	0.2135
t-Statistics	(1.01)	(0.60)
Assault [18]		
Coefficient (%)	0.0455***	-0.8215
t-Statistics	(3.01)	(-1.32)
Fight [19]		
Coefficient (%)	0.0399*	-0.1319
t-Statistics	(1.81)	(-0.38)
Mass Violence [20]		
Coefficient (%)	0.0311***	1.8469
t-Statistics	(2.65)	(0.30)
Severity index		
Coefficient (%)	0.0404	-0.0018
t-Statistics	(1.05)	(-0.23)

5.2 International crisis risk and stock market volatility effects

I now address the second part of Hypothesis 1, whether perceived crisis risk affects the volatility of the U.S. stock market returns. To estimate the effects of my explanatory variable, I use two approaches to measure the market volatility. The first model is a GARCH model, which assesses the effect of crisis risk on the realized volatility. The second model is a linear regression model to investigate the relation between crisis risk and the implied volatility of market returns. The results of both approaches are presented in this sub-section.

5.2.1 Realized volatility effects

In order to be consistent with the Berkman, Jacobsen and Lee (2011) paper, I use a GARCH(1,1) model with an exogenous variable to examine the realized volatility effects of crisis risk as elucidated in equation (2). The model allows perceived international crisis risk to affect the market volatility, while controlling for the effects it has on the daily market mean returns of all NYSE, AMEX and NASDAQ firms. Therewith the GARCH model pursues a retrospective approach. Table 4 shows the result for the estimators of the GARCH model on the general crisis risk variable considering all international conflicts in the first row. It also presents the results of similar models, in which perceived crisis risk is approximated by using the conflicts in the sub-categories depending on the characteristics of the conflict.[2] Lastly, the results for the estimators of the *Severity index* are given.

The GARCH model reveals the following three main findings. The results of the first-step regression on the market excess return of the GARCH model are computed in the first two columns. The first finding is that the results are in line with the outputs in Table 3, showing no significant effect of perceived crisis risk on the mean excess return, at the level of 10% significance. Furthermore, the second-step regression outputs on the variance of the error term are reported in the last four columns, which show that these estimates capture some effects. Both the coefficients β_1 of the lagged squared error term and β_2 of the lagged variance are highly statistically significant of at least a level of 5% for all different crisis definitions, excluding the conflicts in the sub-category *Demand*. This leads to the following second implication that there is conditional heteroskedasticity in the regression of daily U.S. stock market excess returns. In turn, the estimators of the first-step regression might be biased and inconsistent, so the inference of these regressions is not reliable.

However, the main interest is the effect of perceived crisis risk on the market volatility, which is estimated by the crisis coefficient in the last column of Table 4. When considering the coefficients of the broad crisis measures, based on *All conflicts* and the *Severity index* in the first and the last row, I find that they are highly significant at the level of 1%, with t-statistics of 8.66 and 10.41 respectively, and have a

[2] Results for the GARCH(1,1) model are only given for seven crisis definitions based on the conflict severity. The crisis risk measures on *Disapprove* and *Coerce* conflicts do not produce an outcome due to flat log likelihood. The models for crisis risk measures on *Reject* and *Military Posture* conflicts cannot be defined, because the GARCH model is not suitable for these measures.

positive sign. This means that an increase in perceived crisis risk induces an increase in the daily variance of the error term. Accordingly, there is a positive relation between the market volatility and the crisis risk induced by the conflict measures on an aggregated level.

Table 4: Regression results for the effect of perceived crisis risk on the realized U.S. stock market volatility

*This table contains the estimation results for the GARCH model as expressed in equation (2): $MKTRF_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1\varepsilon_{t-1}^2 + \beta_2\sigma_{t-1}^2 + \beta_3 Crisis_t + \eta_t$. $MKTRF_t$ is the daily U.S. stock market excess return (in %) from January 02, 1979 until February 14, 2014 including 8,861 business day observations and $Crisis_t$ denotes the conflict frequency on day t. The estimates are reported for All conflicts, for the conflicts in the sub-samples and the Severity index as proxy for crisis risk. The t-statistics are based on heteroskedasticity-robust standard errors and are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Mean		Volatility			
	Constant	Crisis	Constant	β_1	β_2	Crisis
All conflicts						
Coefficient (%)	0.0716**	-0.0523	-3.9304***	0.2503***	0.6591***	3.8545***
t-Statistics	(2.00)	(-0.51)	(-10.71)	(22.13)	(32.02)	(8.66)
Demand [10]						
Coefficient (%)	0.0219	0.4911	0.7176***	-0.0000	-0.6330***	-1.6205***
t-Statistics	(0.92)	(0.50)	(6.60)	(-0.05)	(-3.29)	(-2.80)
Threaten [13]						
Coefficient (%)	0.0698***	-0.6480	-3.3962***	0.2401***	0.6709***	30.0108***
t-Statistics	(4.14)	(-0.95)	(-9.95)	(23.41)	(32.97)	(9.70)
Protest [14]						
Coefficient (%)	0.0472***	0.6453	-4.0287***	0.2359***	0.7223***	18.3353
t-Statistics	(3.68)	(0.79)	(-4.26)	(22.46)	(31.38)	(1.54)
Reduce Relations [16]						
Coefficient (%)	0.0639***	-0.4950	-2.2589***	0.2490***	0.6705***	-26.6220***
t-Statistics	(4.12)	(-0.77)	(-10.92)	(21.45)	(25.83)	(-2.64)
Assault [18]						
Coefficient (%)	0.0707***	-0.9919	-4.1230***	0.2355***	0.7256***	9.3442
t-Statistics	(4.78)	(-1.52)	(-3.55)	(21.79)	(28.99)	(0.89)
Fight [19]						
Coefficient (%)	0.0661***	-0.2100	-2.9180***	0.2525***	0.6294***	10.2359***
t-Statistics	(3.22)	(-0.69)	(-14.06)	(21.85)	(30.39)	(12.96)
Mass Violence [20]						
Coefficient (%)	0.0314**	2.1504	0.7671***	-0.0005**	-0.7853***	11.7799***
t-Statistics	(2.51)	(0.22)	(7.73)	(-2.09)	(-4.37)	(2.97)
Severity index						
Coefficient (%)	0.0720**	-0.0038	-4.0638***	0.2492***	0.6601***	0.2913***
t-Statistics	(2.09)	(-0.56)	(-11.92)	(22.45)	(34.42)	(10.41)

When taking a closer look into differences within the sub-categories, this effect is not as clear. While the coefficients for *Threaten*, *Fight* and *Mass Violence* are highly significant at a 1% significance level and positive, the coefficients of *Demand* and *Reduce Relations* are also highly significant, but negative. This implies that different conflict characteristics affect the variance of the error term differently. On the one hand, a significant positive coefficient means that an increase in this sub-category of perceived crisis risk is related to higher volatility of the U.S. stock market returns. This seems reasonable, because an increase of the following crisis measures *All conflicts*, *Threaten*, *Fight*, *Mass Violence* and the *Severity* *index* might introduces more uncertainty to the U.S. stock market. On the other hand, the significant negative coefficients for the *Demand* and *Reduce Relations* sub-categories can be interpreted as a reduction of U.S. stock market volatility if those measures increase. This could be due to reaching clarification about market perspectives.

As a result, the GARCH model does not lead to an unambiguous inference, but by tendency offers support for the second part of Hypothesis 1 that international crisis risk on an aggregated level increases the volatility on the U.S. stock market.

5.2.2 Implied volatility effects

In comparison to the regression framework of the GARCH model, the VIX model provides a forward-looking way to assess the relation between perceived crisis risk and market volatility. The daily VIX index is based on S&P 500 stock index option prices and therewith comprises the stock market's expectation of volatility. To estimate the effects of my explanatory variable, I use a linear regression model on the natural logarithm of the VIX adjusted closing price as specified in equation (3). Table 5 shows the estimates of the coefficients and t-statistics based on heteroskedasticity-robust standard errors for the perceived crisis risk.

The first rows of Table 5 report the impact of the crisis risk measure approximated by the ratio of *All conflict* events to cooperation events in which the U.S. is involved on a day. I find a positive coefficient for crisis risk of 0.1648 which is highly significant at the level of 1%, with a t-statistic of 3.63. This can be interpreted that an increase of 0.1 in the conflict-cooperation ratio leads to a 1.6% increase in the VIX price. Taking a closer look at the crisis risk definitions on conflicts in the sub-categories, I observe that the effects come from both conflict characteristics that increase and conflict characteristics that decrease the implied market volatility, rather than driving volatility purely up. With that said, the following rows show ambiguous effects of the crisis risk measures for each of the sub-categories of conflicts. The results for *Demand*, *Disapprove*, *Reject*, *Threaten*, *Protest*, *Military Posture* and *Fight* indicate a significant positive effect, at least at the 10% significance level. In contrast, the crisis measures on *Reduce Relations*, *Coerce* and *Assault* conflicts are negative and highly significant at a level of 1%. This finding suggests that the changes in the expectations about volatility depend on the crisis risk definition. While most conflict events increase the market volatility investors expect, some others decrease the stock market's expectation of volatility. When the independent variable is based on the *Severity index*, I again find a positive and significant relation between the implied volatility and the crisis risk measure, at a level of 1%. An increase of the *Severity index* variable of 0.1 induces a higher volatility of 0.08%. This result is shown in the last rows of Table 5.

Table 5: Regression results for the effect of perceived crisis risk on the contemporaneous VIX index price

*This table shows the results of the regression model (3): $lnVIX_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, where the dependent variable is the natural logarithm of the adjusted closing price of the VIX index from January 02, 1990 until February 14, 2014 including 6,080 business day observations regressed on $Crisis_t$, which is the conflict frequency on day t. I use All conflicts, the conflicts in the sub-samples and the Severity index, respectively, to construct the proxy for crisis risk. The t-statistics, which are based on heteroskedasticity-robust standard errors, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Crisis
All conflicts		
Coefficient	2.8838***	0.1648***
t-Statistics	(185.27)	(3.63)
Demand [10]		
Coefficient	2.9248***	0.7145*
t-Statistics	(334.79)	(1.90)
Disapprove [11]		
Coefficient	2.8687***	0.7771***
t-Statistics	(220.26)	(5.65)
Reject [12]		
Coefficient	2.9235***	0.4273*
t-Statistics	(278.38)	(1.69)
Threaten [13]		
Coefficient	2.8673***	3.0862***
t-Statistics	(342.85)	(9.48)
Protest [14]		
Coefficient	2.9121***	2.7682***
t-Statistics	(488.66)	(7.11)
Military Posture [15]		
Coefficient	2.9288***	1.4554***
t-Statistics	(490.65)	(2.57)
Reduce Relations [16]		
Coefficient	2.9574***	-0.9524***
t-Statistics	(382.45)	(-2.96)
Coerce [17]		
Coefficient	2.9765***	-0.7445***
t-Statistics	(304.26)	(-4.15)
Assault [18]		
Coefficient	2.9678***	-1.7358***
t-Statistics	(417.84)	(-5.18)
Fight [19]		
Coefficient	2.9250***	0.2288*
t-Statistics	(357.15)	(1.91)
Mass Violence [20]		
Coefficient	2.9402***	-1.9908
t-Statistics	(639.65)	(-0.82)
Severity index		
Coefficient	2.9025***	0.0076***
t-Statistics	(198.51)	(2.57)

To summarize, I find that an increase in the two broad crisis risk measures, based on *All conflicts* or the *Severity index*, positively affects the implied volatility. However, these effects are not the same for all sub-categories of conflicts. Consequently, these empirical findings are consistent with the results from the GARCH model in the previous sub-section. Perceived crisis risk that considers conflicts on an aggregated level seems to have a positive relation with the market volatility so that these crisis risk measures lead to more uncertainty on the stock market. Moreover, I find in both models that the effect of perceived crisis risk differs among the sub-categories of conflict events. The results of the models correspond for the following sub-categories: They show a positive effect of *Threaten* and *Fight* conflict events and a negative effect of *Reduce Relations* conflict events on the volatility of the stock market. The results of the VIX model, combined with the findings of the GARCH model, are indicating that an increase in the market volatility is due to uncertainty induced by certain conflict events, while other conflict events create certainty about the stock market outlook by making a clear statement.

5.3 International crisis risk and expected returns

Besides the regressions to assess the contemporaneous effects of perceived crisis risk, it is important to account for the effects of perceived crisis risk on expected returns. To distinguish between Hypothesis 2 and Hypothesis 3, I first test whether the return predictability on market level is driven by the expectations that investors have about crisis risk and hence affect the return they require. In the second step, I examine the effects of perceived crisis risk on industry level with the aid of a cross-sectional analysis. There I observe whether the return predictability is dependent on the industries' sensitivity to crisis risk.

5.3.1 Time-series regression

In this sub-section I present my results for the assessment of Hypothesis 2, whether an increase in expected crisis risk drives up the expected U.S. stock market excess returns. This assessment is divided into two steps. To firstly get a deeper understanding of what affects the variation in excess returns, I determine the expected and the unexpected crisis risk components by applying the AR(1) model described in equation (4). The regression for the *All conflicts* variable produces an estimate of the intercept of 0.1944 (t-statistic of 42.60) and an estimated slope coefficient of 0.4352 (t-statistic of 32.26). I conduct a supremum of Wald's structural break test with the null hypothesis that the estimates are constant over the entire sample period. The null hypothesis can be rejected at a 1% significance level, thus it is likely that there is a break in the estimates. The test suggests September 08, 2001 as the break date. This would mean that investors' estimation of expected crisis risk is not stable over time. Consequentially, I perform additional tests on a later sub-period, which are outlined in sub-section 5.4. Based on the estimate results from equation (4) over the entire sample period, I obtain the expected crisis risk being the fitted value and the unexpected crisis risk being the residual from the AR(1) model.

Secondly, a multiple regression model of the expected and unexpected components on the daily U.S. market excess return, as described in equation (5), is performed to enable to derive implications about

Hypothesis 2. Table 6 provides the outcomes of the regression estimates and t-statistics based on heteroskedasticity-robust standard errors.

Table 6: Regression results for the effect of perceived crisis risk on the expected stock market returns

*Table 6 presents the estimation results for model (5): $MKTRF_t = \alpha + \beta_1 Expected\ Crisis\ Risk_t + \beta_2 Unexpected\ Crisis\ Risk_t + \varepsilon_t$, where $MKTRF_t$ is the daily U.S. stock market excess return (in %) from January 02, 1979 until February 14, 2014 including 8,861 business day observations, Expected Crisis Risk is the fitted value of model (4) and the unexpected risk component is the residual from the following AR model (4): $Crisis_t = \alpha + \beta_1 Crisis_{t-1} + \varepsilon_t$. $Crisis_t$ denotes the frequency of international conflict events on day t. For each crisis risk proxy, as including All conflicts, only the conflicts in the sub-samples or the Severity index, the expected and unexpected crisis risk has to be re-estimated with model (4). The t-statistics are based on heteroskedasticity-robust standard errors and are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Expected	Unexpected
All conflicts			
Coefficient (%)	-0.0261	0.1686	-0.0590
t-Statistics	(-0.28)	(0.62)	(-0.49)
Demand [10]			
Coefficient (%)	-0.1222	7.5946	0.3390
t-Statistics	(-0.78)	(0.99)	(0.50)
Disapprove [11]			
Coefficient (%)	0.0294	0.0235	0.1672
t-Statistics	(0.29)	(0.02)	(0.69)
Reject [12]			
Coefficient (%)	-0.0214	1.3930	-0.3074
t-Statistics	(-0.23)	(0.58)	(-0.71)
Threaten [13]			
Coefficient (%)	-0.0062	1.6638	-0.6170
t-Statistics	(-0.08)	(0.50)	(-0.73)
Protest [14]			
Coefficient (%)	-0.0214	4.8433*	0.8069
t-Statistics	(-0.72)	(1.95)	(0.92)
Military Posture [15]			
Coefficient (%)	0.0177	1.7918	-1.0411
t-Statistics	(0.41)	(0.34)	(-0.91)
Reduce Relations [16]			
Coefficient (%)	0.0455	-0.7204	-0.3028
t-Statistics	(0.66)	(-0.21)	(-0.50)
Coerce [17]			
Coefficient (%)	-0.0081	0.8065	0.1565
t-Statistics	(-0.13)	(0.64)	(0.42)
Assault [18]			
Coefficient (%)	0.0568	-1.4844	-0.7712
t-Statistics	(1.28)	(-0.58)	(-1.22)
Fight [19]			
Coefficient (%)	0.0224	0.1374	-0.2187
t-Statistics	(0.53)	(0.20)	(-0.65)
Mass Violence [20]			
Coefficient (%)	0.0207	31.7014	1.5112
t-Statistics	(0.87)	(0.53)	(0.24)
Severity index			
Coefficient (%)	-0.0164	0.0098	-0.0050
t-Statistics	(-0.20)	(0.57)	(-0.60)

The estimates for the expected crisis risk measure, with the exception of the *Protest* coefficient, and the estimates for the unexpected crisis risk measure are mostly not significantly different from zero at a 10% level. Hence it is not meaningful to interpret the sign as well as the magnitude of these regression coefficients. This means that predominantly I do not find evidence in favor of the second hypothesis that expected crisis risk increases the expected U.S. stock market excess return and that unexpected crisis risk has a negative effect on contemporaneous excess returns. However, the coefficient of expected crisis risk induced by *Protest* conflicts has a significant positive effect on the expected U.S. market excess return, at a significance level of 10%. This could mean that the excess return is an increasing function of expected risk due to conflicts in the *Protest* sub-category and that investors require compensation when that risk increases. Still, this implication has to be regarded with caution, because the frequency of *Protest* conflicts is, on average, very low.

Overall, the results from the predictive regression in Table 6 provide very little support for Hypothesis 2, which is consistent with my finding in Table 3. There seems to be neither a positive effect of expected crisis risk on the expected U.S. stock market excess return nor that the contemporaneous stock market excess return is a decreasing function of unexpected crisis risk. Thus, this model does not give a good explanation of the variation in expected returns considering the expected and unexpected component of perceived crisis risk. Therewith it does not improve the predictability of U.S. stock market excess returns. Similar to the results in sub-section 5.1 this could be due to a non-linear crisis risk-expected return relation. Furthermore, the second-stage regression output might suffer from an error-in-variables problem, since the dependent variables are estimates instead of true observations. This is also indicated by the break test that shows that it is unlikely that the estimates are stable over the entire period. Consequentially, the results of the second regression analysis could be biased. Therefore, for a robustness check, I repeat the same experiment for a different time horizon starting after the identified structural break point. The results are elaborated in sub-section 5.4 and the outputs can be found in Appendix A1.6.

5.3.2 Cross-sectional analysis

For the cross-sectional analysis I conduct the two-stage method of Fama and MacBeth (1973), as explained in sub-section 4.2, with excess returns of the 49 industry portfolios as the dependent variable. In the first stage, the sensitivity of each industry portfolio return to the Fama-French factors and to perceived crisis risk is estimated on each day according to model (6). The sensitivities to crisis risk are transformed into decile ranks and scaled back to values between 0 and 1, before the second-stage analysis is conducted. For each month, I regress the industry excess returns on the sensitivities to the three Fama-French factors and to the scaled decile value of crisis risk of the last day of the previous month, as elucidated in equation (7). Table 7 reports the time-series averages of each estimated regression coefficient and the t-statistics based on standard errors adjusted for autocorrelation using the Newey and

West (1986) correction with three lags. Given that I use a 250-day rolling window to estimate the sensitivities and removing data on February 2014, as the last month entered into, my sample consists of 409 monthly observations from December 1980 to January 2014.

In the first three columns of Table 7 the estimated risk premiums for the Fama-French factors are given. All the factors are statistically insignificant in my sample, plus they do not uniformly have a positive sign contrary to expectations. Accordingly, this means that these factors do not offer a good description of the cross-section of the 49 industry portfolios. This finding, however, may not be surprising given that I consider industry portfolios instead of portfolios sorted on size or book-to-market.

With the cross-sectional analysis I address Hypothesis 3, whether perceived international crisis risk is priced on the U.S. stock markets. Therefore, I consider the risk premiums for crisis sensitivity in the remaining column of Table 7. In the case that the risk is priced, the time-series average of the risk premium would be negative. This implies that industry portfolios that do relatively well during a period of high conflict frequency, on average, yield lower returns. In my dataset, this only applies to perceived crisis risk approximated by the frequency of conflicts in the *Fight* sub-category with a time-series average of monthly estimates of the crisis risk premium of -0.2295, statistically significant at the 10% level (t-statistic of -1.80). This means that the least sensitive industry decile is significantly outperformed by the most sensitive industry decile. Also this finding suggests that investors require a compensation for investments in industries that are sensitive to perceived crisis risk induced by acts of actual wars. Moreover, the estimate for the crisis sensitivity measure of *Mass violence* conflicts is significant at a significance level of 10%, but positive. This, in turn, would mean that industries that are relatively less sensitive to a high frequency of mass violence events yield a higher excess return, on average. However, the interpretation might be conditional to the very low frequency of *Mass violence* conflicts though and thus is unreliable.

Considering the other models, the risk premiums for the two broad crisis measures *All conflicts* and the *Severity index* are statistically insignificant. The results for crisis risk induced by the conflicts in the remaining sub-categories yield similar results. While the coefficients of the risk premiums for the two broad crisis measures are negative and indicating in the direction of the third hypothesis, the coefficients of the risk premium for most conflict sub-categories are positive. Nevertheless, their results cannot be reliably interpreted due to their low significance.

From these results I can see that my dataset provides not enough evidence to accept Hypothesis 3. Hence, I cannot find that perceived crisis risk is priced on the U.S. equity market, with the exception of crisis risk induced by conflicts in the *Fight* sub-category.

Table 7: Estimated risk premiums for the Fama-French factors and crisis sensitivity

In this table the averages of the risk premiums for each month from the second-stage cross-sectional regression (7) are reported: $RIRF_{i,m} = \gamma_m + \gamma_m^{MKTRF}\beta_{i,m-1}^{MKTRF} + \gamma_m^{SMB}\beta_{i,m-1}^{SMB} + \gamma_m^{HML}\beta_{i,m-1}^{HML} + \gamma_m^{Crisis}\beta_{i,m-1}^{Crisis} + \varepsilon_{i,m}$. $RIRF_{i,m}$ *is the monthly excess return (in %) of the 49 Fama-French industry portfolios i in month m from January 1980 until January 2014 including 409 monthly observations.* $\beta_{i,m-1}^{MKTRF}$, $\beta_{i,m-1}^{SMB}$, $\beta_{i,m-1}^{HML}$ *and* $\beta_{i,m-1}^{Crisis}$ *are the factor loadings, or respectively the rescaled decile rank of the factor loading, for each industry portfolio i on the last day of month m-1. The factor loadings are estimated from first-stage time-series regression (6) using an overlapping 250-day window:* $RIRF_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKTRF}MKTRF_t + \beta_{i,t}^{SMB}SMB_t + \beta_{i,t}^{HML}HML_t + \beta_{i,t}^{Crisis}Crisis_t + \varepsilon_{i,t}$. *Note that the first-stage regression is applied on daily data.* $RIRF_{i,t}$ *is the daily excess return (in %) of the industry portfolio i on day t,* $MKTRF_t$, SMB_t *and* HML_t *are the Fama-French factors for market, size and value on day t and* $Crisis_t$ *is the unexpected perceived crisis risk as obtained from model (4) on day t. The estimates are reported for All conflicts, for the conflicts in the sub-samples and the Severity index. The t-statistics, which are based on autocorrelation-adjusted standard errors using the Newey and West (1986) correction with three lags, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	MKTRF	SMB	HML	Crisis
All conflicts				
Coefficient (%)	0.2870	0.0031	0.0361	-0.0669
t-Statistics	(0.89)	(0.02)	(0.23)	(-0.50)
Demand [10]				
Coefficient (%)	0.2873	-0.0172	0.0387	0.0823
t-Statistics	(0.90)	(-0.10)	(0.25)	(0.64)
Disapprove [11]				
Coefficient (%)	0.3299	-0.0200	0.0230	0.0037
t-Statistics	(1.04)	(-0.12)	(0.15)	(0.03)
Reject [12]				
Coefficient (%)	0.2855	-0.0634	0.0367	0.0418
t-Statistics	(0.88)	(-0.36)	(0.24)	(0.30)
Threaten [13]				
Coefficient (%)	0.3331	-0.0184	0.0384	0.1495
t-Statistics	(1.05)	(-0.11)	(0.25)	(0.99)
Protest [14]				
Coefficient (%)	0.2895	-0.0546	0.0317	0.0220
t-Statistics	(0.89)	(-0.32)	(0.21)	(0.17)
Military Posture [15]				
Coefficient (%)	0.2720	-0.0333	0.0434	-0.1548
t-Statistics	(0.83)	(-0.20)	(0.28)	(-1.09)
Reduce Relations [16]				
Coefficient (%)	0.2205	0.0072	0.0138	0.1881
t-Statistics	(0.67)	(0.04)	(0.09)	(1.52)
Coerce [17]				
Coefficient (%)	0.2946	-0.0079	0.0325	0.0450
t-Statistics	(0.92)	(-0.05)	(0.21)	(0.38)
Assault [18]				
Coefficient (%)	0.3186	-0.0364	0.0261	0.0888
t-Statistics	(0.99)	(-0.21)	(0.17)	(0.62)
Fight [19]				
Coefficient (%)	0.2911	0.0029	0.0188	-0.2295*
t-Statistics	(0.91)	(0.02)	(0.12)	(-1.80)
Mass Violence [20]				
Coefficient (%)	0.2657	-0.0581	0.0179	0.2411*
t-Statistics	(0.82)	(-0.33)	(0.12)	(1.78)
Severity index				
Coefficient (%)	0.2854	0.0081	0.0300	-0.0913
t-Statistics	(0.88)	(0.05)	(0.19)	(-0.69)

The insignificance of the coefficients could be due to several reasons. Firstly, it could support the idea that perceived crisis risk is diversifiable. Secondly, there might be unobservable heterogeneity in the industry portfolios and hence, the risk factors offer a poor explanation of the cross-section of industry portfolio returns. Lastly, there is some criticism about the Fama and MacBeth (1973) methodology that could cause these results. The betas, which are used as independent variables in the second-step regression, are estimated so that they have some uncertainty themselves. This error-in-variables might make the standard errors of the second stage too high, as Basher and Sadorsky (2006) explain, leading to biases that could explain these outcomes.

5.4 Robustness tests

To assess the stability of the relation between perceived international crisis risk and the U.S. stock returns, I conduct several robustness checks. In particular, I examine whether the results presented in this chapter are dependent on the event window used and whether they are sensitive to the assumptions made to proxy crisis risk. The estimation results for the robustness checks are found in the Appendix A1 to A4.

As already laid out in the description of the GDELT database the news event approach leads to a temporal bias in the dataset due to digitalization. In my main analysis I assume that the number of cooperation events captures this trend, which is why I scale the number of conflict events by the number of cooperation events on a specific day in order to remove the trend. Still, there seems to be a structural break on September 08, 2001, as pronounced in sub-section 5.3.1 and also roughly indicated by the GDELT creators Leetaru and Schrodt (2013). With the objective to alleviate the concern that my results are not stable throughout the time window used in the main analysis, I re-estimate all models for the period September 08, 2001 until February 14, 2014. The results of the later time period are reported in Appendix A1. The descriptive statistics in Appendix A1.1 shows that the average of the *All conflicts* variable and the *Severity index* increase in the sub-period, indicating that conflict events become more frequent and the severity increases. Furthermore, Appendix A1.2 reports a lower U.S. market excess return and a higher implied volatility. The tests partly confirm the results of my main analysis. They coincide that perceived crisis risk has no significant effect on the U.S. market mean return and that it does neither increase the predictability of the market returns nor the returns on industry portfolios. Albeit, the regressions of perceived crisis risk on both realized and implied volatility do not give evidence in favor of my findings, but even show a contradictory relation (Appendix A1.4 and Appendix A1.5). The effect of perceived crisis risk on the volatility does not seem to be robust to a modification in the event window and the pattern is not consistent throughout the entire period. Hence, I cannot verify the time consistency of the effects I find in the previous sub-section and they seem to be specific for the time sample I use.

In the main specification I use the ratio of the number of conflict events to the number of cooperation events on a day. To establish whether my results are robust to the assumption that the number of cooperation events on a day captures the trend in the dataset, I introduce an alternative method to de-trend the GDELT dataset by assuming instead that the number of all events accounts for the trend. Accordingly, I scale the number of conflict events by the number of all conflict and cooperation events occurring on a day to obtain a relative conflict measure as proxy for perceived crisis risk. The description and results for this alternative variable are found in Appendix A2. As evident in the Appendix A2.3 and A2.4, the effects of perceived crisis risk on volatility and the significance of the results change only slightly. The coefficients for crisis risk on the U.S. market mean excess return, as well as for the return predictability remain insignificant. Therefore, the assumption about the trend in the GDELT dataset is unlikely to impact the inferences made about the relation between perceived crisis risk and the U.S. market movements. The volatility effects appear to be robust to the assumption about the trend in the GDELT dataset.

Finally, I also test the robustness to the conjecture made in my tests so far that investors react to the conflict events that happen on a specific day. Investors may perceive conflicts later than indicated in the GDELT database. To make sure that the news about conflict events are publicly available to the investors I repeat all five methods for the one-day lagged ratio of conflict events to cooperation events as well as the one-day lagged ratio of conflict events to all conflict and cooperation events as perceived crisis risk proxies. This variation changes the conjecture and implies that investors react to the news events from the previous day. The regression outcomes are presented in Appendix A3 and A4, respectively. However, I find that the adjustments leave the initial outcomes largely unaffected. The additional analyses support the results from the main specifications, validating the effect of perceived crisis risk on the U.S. market volatility. In addition, they also show that crisis risk based on conflicts in the *Fight* sub-category is priced on the equity market.

Overall, my findings about the effect of perceived crisis risk are robust to changes in the assumption on the trend in the data, but seem to depend on the certain time period used in the main analysis.

6 Discussion and conclusions

This study investigates the link between U.S. stock market movements and crisis risk. By combining insights and methods from asset pricing literature with the available information about news events from the GDELT database, I construct a novel proxy that measures perceived crisis risk. I find that changes in this measure of perceived crisis risk do not have an impact on the mean of the contemporaneous U.S. stock market excess returns, but on the volatility. However, I neither find a relation between expected crisis risk and expected excess returns nor evidence of crisis risk premiums for industries with relatively high risk loadings.

To begin with, I construct a comprehensive proxy for perceived crisis risk using the GDELT Project database. This database contains extensive data on global events identified through news media. It is likely that investors react to these news events and, accordingly, these news events reflect investors' perception of crisis risk. Following this argumentation, it seems intuitive that financial markets react to news about conflict events and hence it is a suitable measure for asset pricing. Moreover, my proxy for perceived international crisis risk aligns with political instability in the U.S.. Furthermore, my proxy allows for looking deeper into what conflict characteristics drive investors' perception of risk, as it comprises several facets of crisis risk. Therewith I can thoroughly assess the relation between perceived crisis risk and U.S. market reactions.

The weak result on the market mean excess return might be due to non-linearity in the relation of crisis risk and returns, so that investors only react to crisis risk when exceeding a certain threshold. Nevertheless this finding is surprising because most existing literature concludes that international crises have a negative effect on contemporaneous stock returns on country level. Consequently, my research leads to a diverging conclusion than the individual country analysis of Berkman, Jacobsen and Lee (2011) on perceived disaster risk, Rigobon and Sack's analysis (2005) of the impact of war risk on the U.S. financial markets and other time-varying disaster probability models. There are two possible explanations why my results differ from existing literature. On the one hand, the difference in results might come from the nature and the timeframe of the data I consider. I use a broader definition of perceived crisis risk with the intention to expose which conflict characteristics drive market reactions. Due to digitalization there is a rise in media coverage, while globalization enlarges the involvement in conflict events. Both increases the number of news events that are reported, including also minor clashes. Thereby, I end up with a large quantity of news events. In the whole sample period occur, on average, 155 conflicts and 415 cooperation events on a day. Hence, it is likely that there is an overload in news flows that investors do not factor in due to limited attention capacity. Following this, it might be that the the amount of news events dilutes the effect of crisis risk on the mean of the market returns. It could be useful to further narrow down the quantity of events, according to their importance to reveal the true effect. Another limitation originating from the nature of the dataset and the CAMEO code categorization is that the conflicts are sub-divided by their type. At the same time, the extent of the conflict and the outlook about its aftermath are disregarded, even though these elements could likewise affect investors' reaction. On the other hand, not finding an effect of perceived crisis risk on the market mean return could also come from a recent change in investors' behavior. I observe a more recent time period than previous papers, which comes with a stronger effect of digitalization associated with an increase in the conflict frequency. This means that investors are regularly exposed to news about conflict events and they might act irrationally by reducing their efforts and elude their decision about asset allocations, as Agnew and Szykman (2010) find.

Moreover, I show that changes in perceived crisis risk have a significant impact on the U.S. market volatility. A higher frequency of international conflicts is associated with an increase in both the realized and the implied volatility of U.S. market returns. However, I find that this market reaction is internally inconsistent in the conflict sub-categories. While the frequencies of conflict events considering threats or actual wars have a positive relation with the return volatility, a reduction of cooperative relations seems to have a negative effect on the volatility of the stock market. A positive effect could be due to more uncertainty about the stock market outlook induced by the conflict events. If there is a negative relation this could mean that those conflict events might provide clarification of stock market prospects by making a clear statement.

So I cannot conclude that more severe conflict events lead to a stronger market reaction. Also, I cannot affirm that this effect is stable over time. When considering a more recent time period, I find that the overall result is driven by contradicting effects. But these features appear in a short period of time, thus they should not be over-interpreted. Still, they might give reason for further research and should be kept under review. Therefore, my overall conclusion remains that the regression outputs provide evidence of a positive effect of perceived crisis risk on the market volatility. With this support for the idea that crisis risk provides some explanatory power of the movements in return volatility, I amplify extant research from Beaulieu, Cosset, and Essaddam (2005), Pástor and Veronesi (2013) and Voth (2002) establishing a relation between political instability and stock market return volatility. This is also in line with the findings on time-varying disaster models on the link between disaster risk and volatility.

Furthermore, I study the explanatory power of expected crisis risk on expected excess returns by replicating the approach of Berkman et al. (2011). Through the predictive analysis I do not find that perceived crisis risk is a good predictor of future U.S. stock market returns. In my dataset neither expected crisis risk has an effect on expected stock market excess returns, nor does unexpected crisis risk significantly affect contemporaneous market returns. This conjecture is confirmed in Appendix A1 to A4, which presents the robustness of the results. In these modifications of the considered timeframe and assumptions about the trend in the data, the estimated coefficients on expected and unexpected crisis risk continue to be insignificant. Hence, I can conclude as Berkman et al. (2011) that there is no direct evidence that expected stock market excess returns are increasing with expected crisis risk. The reason for this might be similar to the insignificant coefficients for contemporaneous returns. A non-linear relation might explain the insignificance of the regression outputs, implied through investor's asymmetric reaction to good and bad news as Gaa (2009) finds. Another explanation might be the overload of news events as illustrated previously.

Last, to explain differences of the return predictions in the cross-section of industry portfolios, I employ Fama and MacBeth (1973) regressions. I find little evidence in favor of an association between the cross-sectional return predictability and the sensitivities to the Fama-French factors or the sensitivity to perceived crisis risk. When I compare these results with existing literature, finding insignificant coefficients for the Fama-French factors is not surprising. This is in line with Gourio (2008a) and Fama and French (1997), who claim that the factors do not describe the cross-section of industry returns well. Also Core, Guay and Verdi (2008) argue that insignificant coefficients are typical for tests on realized returns. I also observe insignificant coefficients for crisis risk sensitivity from conflicts on an aggregated level. Again, there are several possible explanations for the insignificance of this relation. The first explanation assumes that the results might offer a good estimation of the prediction of industry portfolio returns. This indicates that perceived crisis risk is not priced on the U.S. equity market and that this risk can be diversified away. Secondly, the insignificance of the coefficients from the cross-sectional analysis could be explained with remaining unobservable heterogeneity within the industry groups. Therewith, effects that might occur on a stock level may be distorted. The breakdown of the crisis sensitivity deciles over industries shows that heterogeneity appears to be present within industries. Crisis risk sensitivity does not seem to be an industry characteristic, as it strongly varies for each industry over time. Accordingly, there might be a relation between crisis risk and asset prices, but not on an industry level. Following this, the role of perceived crisis risk as a firm-specific attribute provides an interesting area for future research. Building homogeneous portfolios sorted by crisis risk sensibilities might possibly improve establishing a link between crisis risk and investment decisions. The last explanation is a general criticism on the two-step Fama and MacBeth (1973) approach. The approach neglects the estimation error in the first-stage regression. This error-in-variables result in too high standard errors in the coefficients of the second stage regression and the estimates might be inconsistent. Moreover, considering the crisis risk induced by the sub-categories of conflicts, the Fama and MacBeth (1973) regressions mostly report insignificant coefficients for crisis risk sensitivity, except for the conflict sub-category considering actual wars. This indicates that this aspect of crisis risk might be a source of systematic risk, which is in line with previous findings in the asset pricing literature. For instance, Chen, Lu, and Yang (2014) discover a relation between the exposure to the risk factor, which is based on military expenditure, and stock returns. The important insight to be taken from this set of analyses is that, if any, investors are more concerned with their exposure to the risk associated with U.S.'s direct involvement in actual war conflicts relative to their exposure to crisis risk ensuing from minor clashes when investing in the U.S. stock market.

Taken together, the evidence in my sample seems to be consistent in itself, but the perceived crisis risk effects differ from the findings in previous research. This might be due to the more recent time period

I consider, but could also reduce the power of my tests. Nevertheless, there are several limitations that might give reasons for future research. For instance, there remains some doubt whether my proxy for perceived crisis risk is consistent over time. It seems to correlate well with historical conflict affairs which imply U.S. involvement, but it might need further transformation to improve statements about the crisis risk-return relation. Possibly a quadratic or discontinuous model describes the relationship better. A general problem in asset pricing is that analyses of the models in fact test two hypotheses. First, whether the model is right and second, whether the proxy is a good choice. This limits the power of my results. Furthermore, it is natural to raise the concern that the estimated effects might be biased due to omitted variables. The frequency of conflict events, for example, might contain information about expected consumption next to the information regarding crisis risk. This study reveals a linear relation between crisis risk and the stock market volatility, but to make a statement about causal effects further investigation is required.

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Appendices

A1 Robustness tests with later event window

A1.1 Descriptive statistics for crisis risk variables in later sub-period

Table 8: Descriptive statistics and correlation table of crisis risk variables

*Panel A presents the descriptive statistics of the crisis risk variables including the mean, standard deviation, minimum, median, maximum, and the first-order autocorrelation of the time-series capturing the time period from September 08, 2001 to February 17, 2014. In this sample, All conflicts denotes the number of conflict events scaled by the number of cooperation events that take place on any day and in which the U.S. is either a source or a target actor. This variable is split into the following sub-samples: Demand, Disapprove, Reject, Threaten, Protest, (Exhibit) Military Posture, Reduce Relations, Coerce, Assault, Fight and (Engage In Unconventional) Mass Violence. Their CAMEO event code is denoted in square brackets. The reported values give the number of international conflict events in the respective sub-sample scaled by the number of cooperation events. The Severity index denotes a combined measure of the conflict frequency in the sub-samples weighted by its CAMEO classification. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level. All variables are created with the use of the GDELT 1.0 "reduced" event dataset.*

Panel B reports the correlation coefficients among the crisis risk variables.

Panel A: Descriptive statistics of crisis risk variables

Variables	Mean	Std. dev.	Min	Median	Max	ρ(1)
All conflicts	0.3858	0.0681	0.1376	0.3824	0.9068	0.5385***
Demand [10]	0.0216	0.0081	0.0000	0.0207	0.0763	0.2050***
Disapprove [11]	0.1010	0.0236	0.0214	0.0875	0.2736	0.4058***
Reject [12]	0.0369	0.0118	0.0000	0.0364	0.1636	0.2817***
Threaten [13]	0.0265	0.0119	0.0000	0.0244	0.1102	0.4558***
Protest [14]	0.0109	0.0097	0.0000	0.0093	0.1553	0.5346***
Military Posture [15]	0.0072	0.0062	0.0000	0.0056	0.0678	0.4228***
Reduce Relations [16]	0.0175	0.0089	0.0000	0.0161	0.0993	0.3254***
Coerce [17]	0.0585	0.0182	0.0000	0.0587	0.1806	0.4692***
Assault [18]	0.0214	0.0103	0.0000	0.0208	0.1081	0.4242***
Fight [19]	0.0840	0.0269	0.0088	0.0808	0.2876	0.4673***
Mass Violence [20]	0.0004	0.0011	0.0000	0.0000	0.0189	0.2145***
Severity index	5.6361	1.0353	2.1223	5.5849	13.2549	0.5425***

Panel B: Correlation coefficients between crisis risk variables

	All	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	Index
All conflicts	1												
Demand [10]	0.29***	1											
Disapprove [11]	0.71***	0.18***	1										
Reject [12]	0.35***	0.11***	0.20***	1									
Threaten [13]	0.47***	0.12***	0.35***	0.15***	1								
Protest [14]	0.42***	0.08***	0.27***	0.13***	0.23***	1							
Military Posture [15]	0.26***	0.08***	0.18***	0.10***	0.27***	0.15***	1						
Reduce Relations [16]	0.28***	0.12***	0.13***	0.05***	0.13***	0.08***	0.12***	1					
Coerce [17]	0.43***	-0.01	0.14***	0.09***	-0.05***	0.05**	-0.17***	0.00	1				
Assault [18]	0.45***	0.00	0.14***	0.03**	0.02	0.08***	-0.07***	0.04***	0.30***	1			
Fight [19]	0.69***	0.08***	0.29***	0.00	0.18***	0.17***	0.14***	0.08***	0.17***	0.37***	1		
Mass Violence [20]	0.15***	0.01	0.12***	-0.00	0.08***	0.03**	0.04**	0.01	0.03*	0.08***	0.13***	1	
Severity index	0.9974***	0.23***	0.63***	0.29***	0.42***	0.39***	0.24***	0.28***	0.47***	0.51***	0.76***	0.16***	1

A1.2 Descriptive statistics for stock market variables in later event window

Table 9: Descriptive statistics of return and volatility variables

Panel A presents the descriptive statistics of the return variables including the mean, standard deviation, minimum, median, maximum, and the number of observations from September 08, 2001 to February 14, 2014. MKTRF is the excess return of the value-weighted portfolio of all NYSE, AMEX and NASDAQ firms on CRSP over RF. RF is the daily rate that over the number of trading days in the month compounds to the Ibbotson and Associates Inc. one month Treasury-bill rate. SMB is the size premium, which is the difference in the average return of small-firm portfolios and the average return of big-firm portfolios. HML is the value premium, which is the difference in the average return of high book-to-market firm portfolios and the average return of low book-to-market firm portfolios. All variables are obtained from the Fama-French Portfolios & Factors dataset available on WRDS.

Panel B reports the descriptive statistics of CBOE's volatility index VIX available on Yahoo Finance and the natural logarithm of the VIX including the mean, standard deviation, minimum, median, maximum, and the number of observations from September 08, 2001 until February 14, 2014.

Panel A: Descriptive statistics of return variables						
Variables	Mean (in %)	Std. dev. (in %)	Min (in %)	Median (in %)	Max (in %)	# Obs.
MKTRF	0.0307	1.2972	-8.9500	0.0800	11.3500	3,127
RF	0.0060	0.0066	0.0000	0.0040	0.0220	3,127
SMB	0.0161	0.5897	-3.7500	0.0300	3.8300	3,127
HML	0.0070	0.6389	-4.2200	0.0100	4.8300	3,127
Panel B: Descriptive statistics of volatility variables						
Variables	Mean (in USD)	Std. dev. (in USD)	Min (in USD)	Median (in USD)	Max (in USD)	# Obs.
VIX	21.0576	9.5666	9.8900	18.4400	80.8600	3,127
lnVIX	2.9666	0.3844	2.2915	2.9145	4.3927	3,127

A1.3 Stock market mean returns with later event window

Table 10: Regression results for the effect of perceived crisis risk on the contemporaneous U.S. stock market returns

*In this table the regression results for model (1) are reported: $MKTRF_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, where $MKTRF_t$ is the daily U.S. stock market excess return (in %) from September 08, 2001 until February 14, 2014 including 3,127 business day observations and $Crisis_t$ is the conflict frequency on day t. I report the estimates for the crisis risk variable including All conflicts, the variables on the conflicts in the sub-samples and the variable of the Severity index. The t-statistics, which are based on heteroskedasticity-robust standard errors, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Crisis
All conflicts		
Coefficient (%)	-0.1548	0.4879
t-Statistics	(-1.05)	(1.30)
Demand [10]		
Coefficient (%)	0.0192	0.5321
t-Statistics	(0.30)	(0.20)
Disapprove [11]		
Coefficient (%)	-0.0291	0.5911
t-Statistics	(-0.26)	(0.57)
Reject [12]		
Coefficient (%)	0.0012	0.7870
t-Statistics	(0.01)	(0.38)
Threaten [13]		
Coefficient (%)	0.0502	-0.7438
t-Statistics	(0.80)	(-0.33)
Protest [14]		
Coefficient (%)	-0.0075	3.7782
t-Statistics	(-0.20)	(1.29)
Military Posture [15]		
Coefficient (%)	0.0096	3.0136
t-Statistics	(0.26)	(0.80)
Reduce Relations [16]		
Coefficient (%)	-0.0316	3.6129
t-Statistics	(-0.63)	(1.49)
Coerce [17]		
Coefficient (%)	-0.0397	1.1833
t-Statistics	(-0.51)	(0.98)
Assault [18]		
Coefficient (%)	-0.0250	2.6820
t-Statistics	(-0.47)	(1.25)
Fight [19]		
Coefficient (%)	-0.0253	0.7122
t-Statistics	(-0.30)	(0.70)
Mass Violence [20]		
Coefficient (%)	0.0322	-3.8724
t-Statistics	(1.32)	(-0.20)
Severity index		
Coefficient (%)	-0.2697	0.0543
t-Statistics	(-0.81)	(0.90)

A1.4 Realized stock market volatility effects with later event window

Table 11: Regression results for the effect of perceived crisis risk on the realized U.S. stock market volatility[3]

*This table contains the estimation results for the GARCH model as expressed in equation (2): $MKTRF_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1\varepsilon_{t-1}^2 + \beta_2\sigma_{t-1}^2 + \beta_3 Crisis_t + \eta_t$. $MKTRF_t$ is the daily U.S. stock market excess return (in %) from September 08, 2001 until February 14, 2014 including 3,127 business day observations and $Crisis_t$ denotes the conflict frequency on day t as crisis risk proxy. The estimates are reported for All conflicts, for the conflicts in the sub-samples and the Severity index. The t-statistics are based on heteroskedasticity-robust standard errors and are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Mean		Volatility			
	Constant	Crisis	Constant	β_1	β_2	Crisis
All conflicts						
Coefficient (%)	-0.0183	0.2133	1.5673	0.2836***	0.6822***	-16.2287
t-Statistics	(-0.17)	(0.75)	(0.46)	(15.64)	(31.20)	(-1.20)
Reject [12]						
Coefficient (%)	0.0765	-0.3982	-18.4983	0.2816***	0.6934***	158.6346
t-Statistics	(1.14)	(-0.23)	(-0.20)	(15.76)	(53.65)	(0.21)
Threaten [13]						
Coefficient (%)	0.1250**	-2.4579	-6.5643**	0.2844***	0.6826***	70.6805*
t-Statistics	(2.56)	(-1.38)	(-2.16)	(15.48)	(34.78)	(1.75)
Reduce Relations [16]						
Coefficient (%)	0.0517	0.6361	-1.9876***	0.2872***	0.6685***	-99.3637
t-Statistics	(1.18)	(0.27)	(-3.13)	(13.96)	(18.33)	(-0.87)
Coerce [17]						
Coefficient (%)	0.0122	0.8280	-5.7143	0.2829***	0.6930***	-37.8937
t-Statistics	(0.19)	(0.79)	(-0.07)	(14.64)	(18.91)	(-0.01)
Assault [18]						
Coefficient (%)	0.0529	0.4471	-4.4143	0.2827***	0.6907***	-60.0755
t-Statistics	(1.15)	(0.21)	(-0.62)	(13.87)	(15.75)	(-0.07)
Mass Violence [20]						
Coefficient (%)	0.0605***	4.9697	-51.2877***	0.2827***	0.6934***	-3901.4280***
t-Statistics	(3.21)	(0.26)	(-78.40)	(15.55)	(53.39)	(-17.68)
Severity index						
Coefficient (%)	-0.0273	0.0162	1.4028	0.2836***	0.6829***	-1.1035
t-Statistics	(-0.26)	(0.85)	(0.41)	(15.64)	(31.70)	(-1.14)

[3] Results for the GARCH(1,1) model are only given for seven crisis definitions based on the conflict severity. The models for crisis risk measures on *Demand*, *Disapprove*, *Protest*, *Military Posture* and *Fight* conflicts cannot be defined, because the GARCH model is not suitable for these measures.

A1.5 Implied stock market volatility effects with later event window

Table 12: Regression results for the effect of perceived crisis risk on the contemporaneous VIX index price

*This table shows the results of the regression model (3): $lnVIX_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, where the dependent variable is the natural logarithm of the adjusted closing price of the VIX index from September 08, 2001 until February 14, 2014 including 3,127 business day observations regressed on $Crisis_t$, which is the conflict frequency on day t. I use All conflicts, the conflicts in the sub-samples and the Severity index, respectively, to construct the proxy for crisis risk. The t-statistics, which are based on heteroskedasticity-robust standard errors, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Crisis
All conflicts		
Coefficient	3.1155***	-0.3915***
t-Statistics	(67.36)	(-3.31)
Demand [10]		
Coefficient	3.0097***	-1.9893**
t-Statistics	(147.16)	(-2.25)
Disapprove [11]		
Coefficient	2.9930***	-0.2612
t-Statistics	(84.09)	(-0.77)
Reject [12]		
Coefficient	2.9555***	0.2969
t-Statistics	(116.41)	(0.46)
Threaten [13]		
Coefficient	2.8412***	4.7876***
t-Statistics	(162.95)	(8.04)
Protest [14]		
Coefficient	2.9439***	2.2436***
t-Statistics	(262.60)	(2.65)
Military Posture [15]		
Coefficient	2.9377***	4.1422***
t-Statistics	(270.45)	(3.49)
Reduce Relations [16]		
Coefficient	3.0340***	-3.9100***
t-Statistics	(196.63)	(-5.04)
Coerce [17]		
Coefficient	3.0992***	-2.2292***
t-Statistics	(130.35)	(-6.11)
Assault [18]		
Coefficient	3.1394***	-8.3127***
t-Statistics	(193.74)	(-13.05)
Fight [19]		
Coefficient	3.0339***	-0.8544***
t-Statistics	(116.39)	(-2.74)
Mass Violence [20]		
Coefficient	2.9729***	-16.7164***
t-Statistics	(404.90)	(-2.76)
Severity index		
Coefficient	3.1480***	-0.0328***
t-Statistics	(71.90)	(-4.28)

A1.6 Time-series predictive regression with later event window

Table 13: Regression results for the effect of perceived crisis risk on the expected stock market returns

*Table 13 presents the estimation results for model (5) : $MKTRF_t = \alpha + \beta_1 Expected\ Crisis\ Risk_t + \beta_2 Unexpected\ Crisis\ Risk_t + \varepsilon_t$, where $MKTRF_t$ is the daily U.S. stock market excess return (in %) from September 08, 2001 until February 14, 2014 including 3,127 business day observations, Expected Crisis Risk is the fitted value of model (4) and the unexpected risk component is the residual from the following AR model (4): $Crisis_t = \alpha + \beta_1 Crisis_{t-1} + \varepsilon_t$, $Crisis_t$ denotes the frequency of international conflict events on day t. For each crisis risk proxy, as including All conflicts, only the conflicts in the sub-samples or the Severity index, the expected and unexpected crisis risk has to be re-estimated with model (4). The t-statistics are based on heteroskedasticity-robust standard errors and are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Expected	Unexpected
All conflicts			
Coefficient (%)	-0.1194	0.3958	0.5312
t-Statistics	(-0.43)	(0.56)	(1.34)
Demand [10]			
Coefficient (%)	0.1391	-5.0087	0.7844
t-Statistics	(0.50)	(-0.40)	(0.29)
Disapprove [11]			
Coefficient (%)	0.2613	-2.2958	1.2691
t-Statistics	(1.00)	(-0.90)	(1.21)
Reject [12]			
Coefficient (%)	0.0857	-1.5111	0.9968
t-Statistics	(0.31)	(-0.20)	(0.48)
Threaten [13]			
Coefficient (%)	0.0204	0.3772	-1.0827
t-Statistics	(0.16)	(0.08)	(-0.47)
Protest [14]			
Coefficient (%)	-0.0468	7.4026	2.2649
t-Statistics	(-0.76)	(1.39)	(0.71)
Military Posture [15]			
Coefficient (%)	-0.0364	9.4657	1.4992
t-Statistics	(-0.55)	(1.10)	(0.36)
Reduce Relations [16]			
Coefficient (%)	-0.1318	9.3626	2.9051
t-Statistics	(-0.98)	(1.26)	(1.09)
Coerce [17]			
Coefficient (%)	-0.2032	4.0153	0.3095
t-Statistics	(-1.25)	(1.49)	(0.22)
Assault [18]			
Coefficient (%)	0.1057	-3.4191	4.1891*
t-Statistics	(0.97)	(-0.71)	(1.76)
Fight [19]			
Coefficient (%)	-0.0743	1.2885	0.5003
t-Statistics	(-0.46)	(0.66)	(0.46)
Mass Violence [20]			
Coefficient (%)	-0.0073	97.5713	-9.2437
t-Statistics	(-0.18)	(1.15)	(-0.46)
Severity index			
Coefficient (%)	-0.1622	0.0349	0.0334
t-Statistics	(-0.62)	(0.76)	(1.27)

A1.7 Cross-sectional model for later event window

Table 14: Estimated risk premiums for the Fama-French factors and crisis sensitivity

In this table the averages of the risk premiums for each month from the second-stage cross-sectional regression equation (7) are reported: $RIRF_{i,m} = \gamma_m + \gamma_m^{MKTRF}\beta_{i,m-1}^{MKTRF} + \gamma_m^{SMB}\beta_{i,m-1}^{SMB} + \gamma_m^{HML}\beta_{i,m-1}^{HML} + \gamma_m^{Crisis}\beta_{i,m-1}^{Crisis} + \varepsilon_{i,m}$. $RIRF_{i,m}$ *is the monthly excess return (in %) of the 49 Fama-French industry portfolios i in month m from October 2002 until January 2014 including 137 monthly observations.* $\beta_{i,m-1}^{MKTRF}$, $\beta_{i,m-1}^{SMB}$, $\beta_{i,m-1}^{HML}$ *and* $\beta_{i,m-1}^{Crisis}$ *are the factor loadings, or respectively the rescaled decile rank of the factor loading, for each industry portfolio i on the last day of month m-1. The factor loadings are estimated from first-stage time-series regression (6) using an overlapping 250-day window:* $RIRF_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKTRF}MKTRF_t + \beta_{i,t}^{SMB}SMB_t + \beta_{i,t}^{HML}HML_t + \beta_{i,t}^{Crisis}Crisis_t + \varepsilon_{i,t}$. *Note that the first-stage regression is applied on daily data.* $RIRF_{i,t}$ *is the daily excess return (in %) of the industry portfolio i on day t,* $MKTRF_t$, SMB_t *and* HML_t *are the Fama-French factors for market, size and value on day t and* $Crisis_t$ *is the unexpected perceived crisis risk as obtained rom model (4) on day t. The estimates are reported for All conflicts, for the conflicts in the sub-samples and the Severity index. The t-statistics, which are based on autocorrelation-adjusted standard errors using the Newey and West (1986) correction with three lags, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	MKTRF	SMB	HML	Crisis
All conflicts				
Coefficient (%)	0.3356	0.3415	-0.0561	0.0826
t-Statistics	(0.55)	(1.05)	(-0.22)	(0.43)
Demand [10]				
Coefficient (%)	0.3648	0.3661	-0.0621	0.1532
t-Statistics	(0.61)	(1.11)	(-0.25)	(0.65)
Disapprove [11]				
Coefficient (%)	0.3330	0.3356	-0.0822	0.0654
t-Statistics	(0.55)	(1.02)	(-0.34)	(0.27)
Reject [12]				
Coefficient (%)	0.3606	0.2791	-0.0795	0.6139***
t-Statistics	(0.59)	(0.84)	(-0.31)	(2.72)
Threaten [13]				
Coefficient (%)	0.3467	0.3203	-0.0024	0.4018
t-Statistics	(0.58)	(0.99)	(-0.01)	(1.61)
Protest [14]				
Coefficient (%)	0.3870	0.2605	-0.0606	-0.0061
t-Statistics	(0.63)	(0.79)	(-0.23)	(-0.03)
Military Posture [15]				
Coefficient (%)	0.4011	0.3699	-0.0667	-0.2676
t-Statistics	(0.64)	(1.14)	(-0.25)	(-1.16)
Reduce Relations [16]				
Coefficient (%)	0.2132	0.3607	-0.0280	0.2030
t-Statistics	(0.34)	(1.09)	(-0.11)	(0.97)
Coerce [17]				
Coefficient (%)	0.3019	0.3444	-0.0550	0.0978
t-Statistics	(0.51)	(1.04)	(-0.22)	(0.54)
Assault [18]				
Coefficient (%)	0.4676	0.3233	-0.0527	-0.1239
t-Statistics	(0.77)	(1.01)	(-0.20)	(-0.47)
Fight [19]				
Coefficient (%)	0.3853	0.3245	-0.0644	-0.1030
t-Statistics	(0.64)	(1.01)	(-0.25)	(-0.49)
Mass Violence [20]				
Coefficient (%)	0.3213	0.2723	-0.0609	-0.0691
t-Statistics	(0.52)	(0.81)	(-0.24)	(-0.29)
Severity index				
Coefficient (%)	0.3400	0.3457	-0.0618	0.0375
t-Statistics	(0.55)	(1.07)	(-0.24)	(0.20)

A2 Robustness tests with relative conflict measure

A2.1 Descriptive statistics for crisis risk variables with relative conflict measure

Table 15: Descriptive statistics and correlation table of crisis risk variables

*Panel A presents the descriptive statistics of the crisis risk variables including the mean, standard deviation, minimum, median, maximum, and the first-order autocorrelation of the time-series from January 01, 1979 to February 17, 2014 including 8,861 business day observations. In the whole sample, All conflicts denotes the number of conflict events scaled by the number of all conflict and cooperation events that take place on any day and in which the U.S. is either a source or a target actor. This variable is split into the following sub-samples: Demand, Disapprove, Reject, Threaten, Protest, (Exhibit) Military Posture, Reduce Relations, Coerce, Assault, Fight and (Engage In Unconventional) Mass Violence. Their CAMEO event code is denoted in square brackets. The reported values give the number of international conflict events in the respective sub-sample scaled by the number of all conflict and cooperation events. The Severity index denotes a combined measure of the conflict frequency in the sub-samples weighted by its CAMEO classification. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level. All variables are created with the use of the GDELT 1.0 "reduced" event dataset.*
Panel B reports the correlation coefficients among the crisis risk variables.

Panel A: Descriptive statistics of crisis risk variables

Variables	Mean	Std. dev.	Min	Median	Max	ρ(1)
All conflicts	0.2513	0.0592	0.0000	0.2548	0.6429	0.4417***
Demand [10]	0.0149	0.0106	0.0000	0.0141	0.1071	0.0787***
Disapprove [11]	0.0682	0.0261	0.0000	0.0678	0.2857	0.2349***
Reject [12]	0.0281	0.0168	0.0000	0.0263	0.3125	0.1637***
Threaten [13]	0.0166	0.0123	0.0000	0.0156	0.2188	0.1798***
Protest [14]	0.0081	0.0097	0.0000	0.0063	0.1111	0.2496***
Military Posture [15]	0.0057	0.0080	0.0000	0.0034	0.1739	0.1594***
Reduce Relations [16]	0.0141	0.0119	0.0000	0.0120	0.1429	0.1590***
Coerce [17]	0.0362	0.0196	0.0000	0.0357	0.3077	0.2730***
Assault [18]	0.0124	0.0112	0.0000	0.0112	0.1765	0.2531***
Fight [19]	0.0466	0.0273	0.0000	0.0459	0.2327	0.4660***
Mass Violence [20]	0.0003	0.0013	0.0000	0.0000	0.0286	0.0959***
Severity index	3.6075	0.9063	0.0000	3.6588	9.0000	0.4720***

Panel B: Correlation coefficients between crisis risk variables

	All	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	Index
All conflicts	1												
Demand [10]	0.20***	1											
Disapprove [11]	0.57***	0.02**	1										
Reject [12]	0.26***	0.01	0.02**	1									
Threaten [13]	0.33***	0.02**	0.11***	0.01	1								
Protest [14]	0.24***	0.01	0.09***	0.02**	0.02**	1							
Military Posture [15]	0.13***	0.02**	-0.01	-0.00	0.03***	0.02**	1						
Reduce Relations [16]	0.15***	0.01	-0.02**	0.01	0.01	-0.00	-0.02**	1					
Coerce [17]	0.42***	-0.00	0.06***	-0.01	-0.02**	0.03***	-0.06***	-0.02***	1				
Assault [18]	0.33***	-0.00	0.05***	-0.06***	0.02*	0.01	-0.02**	-0.03***	0.13***	1			
Fight [19]	0.60***	-0.01	0.13***	-0.05***	0.14***	0.04***	0.03***	-0.06***	0.11***	0.20***	1		
Mass Violence [20]	0.03	-0.01	0.01	-0.01	0.00	0.01	0.00	-0.01	-0.01	-0.01	0.02**	1	
Severity index	0.98***	0.13***	0.46***	0.19***	0.30***	0.22***	0.13***	0.16***	0.46***	0.38***	0.71***	0.03***	1

A2.2 Stock market mean returns with relative conflict measure

Table 16: Regression results for the effect of perceived crisis risk on the contemporaneous U.S. stock market returns

*In this table the regression results for model (1) are reported: $MKTRF_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, where $MKTRF_t$ is the daily U.S. stock market excess return (in %) from January 02, 1979 until February 14, 2014 including 8,861 business day observations and $Crisis_t$ is the conflict frequency constructed as the ratio of the total number of international conflict events to the total number of all international conflict and cooperation events concerning the U.S. on day t. I report the estimates for the crisis risk variable including All conflicts, the variables on the conflicts in the sub-samples and the variable of the Severity index. The t-statistics, which are based on heteroskedasticity-robust standard errors, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Crisis
All conflicts		
Coefficient (%)	0.0345	-0.0111
t-Statistics	(0.68)	(-0.05)
Demand [10]		
Coefficient (%)	0.0251	0.4444
t-Statistics	(1.36)	(0.47)
Disapprove [11]		
Coefficient (%)	0.0077	0.3497
t-Statistics	(0.27)	(0.94)
Reject [12]		
Coefficient (%)	0.0399*	-0.2853
t-Statistics	(1.81)	(-0.46)
Threaten [13]		
Coefficient (%)	0.0424**	-0.6524
t-Statistics	(2.17)	(-0.60)
Protest [14]		
Coefficient (%)	0.0189	1.6366
t-Statistics	(1.31)	(1.39)
Military Posture [15]		
Coefficient (%)	0.0398***	-1.4173
t-Statistics	(2.84)	(-0.95)
Reduce Relations [16]		
Coefficient (%)	0.0399**	-0.5776
t-Statistics	(2.24)	(-0.68)
Coerce [17]		
Coefficient (%)	0.0176	0.3845
t-Statistics	(0.81)	(0.76)
Assault [18]		
Coefficient (%)	0.0466***	-1.2162
t-Statistics	(2.99)	(-1.35)
Fight [19]		
Coefficient (%)	0.0404*	-0.1932
t-Statistics	(1.77)	(-0.38)
Mass Violence [20]		
Coefficient (%)	0.0311***	2.4591
t-Statistics	(2.66)	(0.29)
Severity index		
Coefficient (%)	0.0417	-0.0028
t-Statistics	(0.85)	(-0.20)

A2.3 Realized stock market volatility effects with relative conflict measure

Table 17: Regression results for the effect of perceived crisis risk on the realized U.S. stock market volatility[4]

*This table contains the estimation results for the GARCH model as expressed in equation (2): $MKTRF_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1\varepsilon_{t-1}^2 + \beta_2\sigma_{t-1}^2 + \beta_3 Crisis_t + \eta_t$. $MKTRF_t$ is the daily U.S. stock market excess return (in %) from January 02, 1979 until February 14, 2014 including 8,861 business day observations and $Crisis_t$ denotes the conflict frequency on day t as crisis risk proxy. The estimates are reported for All conflicts, for the conflicts in the sub-samples and the Severity index. The t-statistics are based on heteroskedasticity-robust standard errors and are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Mean		Volatility			
	Constant	Crisis	Constant	β_1	β_2	Crisis
All conflicts						
Coefficient (%)	0.0724	-0.0749	-5.5783***	0.2456***	0.6777***	10.6102***
t-Statistics	(1.55)	(-0.41)	(-9.60)	(22.69)	(37.05)	(8.18)
Disapprove [11]						
Coefficient (%)	0.0193	0.1698	0.9010***	-0.0001	-0.7945***	-1.7853***
t-Statistics	(0.53)	(0.35)	(24.07)	(-0.32)	(-8.65)	(-5.82)
Threaten [13]						
Coefficient (%)	0.0701***	-0.9199	-3.2106***	0.2441***	0.6641***	36.0299***
t-Statistics	(4.05)	(-0.97)	(-8.36)	(21.58)	(26.50)	(6.58)
Protest [14]						
Coefficient (%)	0.0463***	0.9997	-4.5843***	0.2328***	0.7333***	26.9332
t-Statistics	(3.56)	(0.88)	(-2.70)	(22.52)	(31.16)	(0.82)
Military Posture [15]						
Coefficient (%)	0.0656***	-2.0618	-9.8116	0.2291***	0.7484***	11.9384
t-Statistics	(5.44)	(-1.50)	(-0.03)	(20.17)	(27.75)	(0.00)
Reduce Relations [16]						
Coefficient (%)	0.0658***	-0.7976	-2.1836***	0.2503***	0.6654***	-36.8864***
t-Statistics	(4.16)	(-0.88)	(-11.44)	(21.45)	(25.75)	(-2.86)
Coerce [17]						
Coefficient (%)	0.0174	0.3905	0.7905***	-0.0004**	-0.7672***	-0.7926**
t-Statistics	(0.57)	(0.52)	(7.58)	(-1.97)	(-3.82)	(-2.50)
Assault [18]						
Coefficient (%)	0.0716***	-1.4301	-4.1281***	0.2364***	0.7235***	18.6230
t-Statistics	(4.67)	(-1.50)	(-3.57)	(21.91)	(28.97)	(1.09)
Fight [19]						
Coefficient (%)	0.0651***	-0.2634	-3.0969***	0.2510***	0.6361***	16.6678***
t-Statistics	(3.00)	(-0.59)	(-12.31)	(21.50)	(29.44)	(10.22)
Mass Violence [20]						
Coefficient (%)	0.0538***	1.6007	-6.6138	0.2292***	0.7468***	260.9655
t-Statistics	(5.57)	(0.17)	(-0.85)	(25.50)	(50.24)	(0.53)
Severity index						
Coefficient (%)	0.0747*	-0.0061	-6.7283***	0.2402***	0.6956***	0.9455***
t-Statistics	(1.70)	(-0.50)	(-12.32)	(24.02)	(51.96)	(11.46)

[4] Results for the GARCH(1,1) model are only given for nine crisis definitions based on the conflict severity. The crisis risk measure on *Demand* conflicts does not produce an outcome due to flat log likelihood. The model for the crisis risk measure on *Reject* conflicts cannot be defined, because the GARCH model is not suitable for this measure.

A2.4 Implied stock market volatility effects with relative conflict measure

Table 18: Regression results for the effect of perceived crisis risk on the contemporaneous VIX index price

*This table shows the results of the regression model (3): $lnVIX_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, where the dependent variable is the natural logarithm of the adjusted closing price of the VIX index from January 02, 1990 until February 14, 2014 including 6,080 business day observations regressed on $Crisis_t$, which is the conflict frequency on day t. I use All conflicts, the conflicts in the sub-samples and the Severity index, respectively, to construct the proxy for crisis risk. The t-statistics, which are based on heteroskedasticity-robust standard errors, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Crisis
All conflicts		
Coefficient	2.8589***	0.3235***
t-Statistics	(141.91)	(4.00)
Demand [10]		
Coefficient	2.9254***	0.9183*
t-Statistics	(330.36)	(1.79)
Disapprove [11]		
Coefficient	2.8526***	1.2919***
t-Statistics	(193.13)	(6.05)
Reject [12]		
Coefficient	2.9249***	0.5240
t-Statistics	(272.06)	(1.51)
Threaten [13]		
Coefficient	2.8632***	4.4304***
t-Statistics	(325.44)	(9.36)
Protest [14]		
Coefficient	2.9122***	3.7597***
t-Statistics	(472.35)	(6.57)
Military Posture [15]		
Coefficient	2.9304***	1.6670**
t-Statistics	(487.91)	(2.16)
Reduce Relations [16]		
Coefficient	2.9600***	-1.4655***
t-Statistics	(379.17)	(-3.38)
Coerce [17]		
Coefficient	2.9821***	-1.1629***
t-Statistics	(287.37)	(-4.45)
Assault [18]		
Coefficient	2.9705***	-2.5901***
t-Statistics	(408.85)	(-5.47)
Fight [19]		
Coefficient	2.9251***	0.3088*
t-Statistics	(328.95)	(1.69)
Mass Violence [20]		
Coefficient	2.9403***	-2.9160
t-Statistics	(639.79)	(-0.90)
Severity index		
Coefficient	2.8918***	0.0133***
t-Statistics	(156.40)	(2.58)

A2.5 Time-series predictive regression with relative conflict measure

Table 19: Regression results for the effect of perceived crisis risk on the expected stock market returns

*Table 19 presents the estimation results for model (5) : $MKTRF_t = \alpha + \beta_1 Expected\ Crisis\ Risk_t + \beta_2 Unexpected\ Crisis\ Risk_t + \varepsilon_t$, where $MKTRF_t$ is the daily U.S. stock market excess return (in %) from January 02, 1979 until February 14, 2014 including 8,861 business day observations, Expected Crisis Risk is the fitted value of model (4) and the unexpected risk component is the residual from the following AR model (4): $Crisis_t = \alpha + \beta_1 Crisis_{t-1} + \varepsilon_t$, $Crisis_t$ denotes the frequency of international conflict events on day t. For each crisis risk proxy, as including All conflicts, only the conflicts in the sub-samples or the Severity index, the expected and unexpected crisis risk has to be re-estimated with model (4). The t-statistics are based on heteroskedasticity-robust standard errors and are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Expected	Unexpected
All conflicts			
Coefficient (%)	-0.0292	0.2434	-0.0761
t-Statistics	(-0.26)	(0.54)	(-0.36)
Demand [10]			
Coefficient (%)	-0.1212	10.2510	0.3675
t-Statistics	(-0.69)	(0.87)	(0.39)
Disapprove [11]			
Coefficient (%)	0.0469	-0.2264	0.3840
t-Statistics	(0.39)	(-0.13)	(1.02)
Reject [12]			
Coefficient (%)	-0.0407	2.5833	-0.3811
t-Statistics	(-0.40)	(0.73)	(-0.60)
Threaten [13]			
Coefficient (%)	-0.0016	2.0019	-0.7508
t-Statistics	(-0.02)	(0.39)	(-0.69)
Protest [14]			
Coefficient (%)	-0.0332	8.1301**	1.2014
t-Statistics	(-0.94)	(1.96)	(1.00)
Military Posture [15]			
Coefficient (%)	0.0220	1.7003	-1.5112
t-Statistics	(0.48)	(0.23)	(-0.99)
Reduce Relations [16]			
Coefficient (%)	0.0618	-2.1385	-0.5344
t-Statistics	(0.83)	(-0.41)	(-0.63)
Coerce [17]			
Coefficient (%)	-0.0090	1.1254	0.3176
t-Statistics	(-0.13)	(0.60)	(0.60)
Assault [18]			
Coefficient (%)	0.0701	-3.1064	-1.0831
t-Statistics	(1.57)	(-0.88)	(-1.18)
Fight [19]			
Coefficient (%)	0.0348	-0.0738	-0.2295
t-Statistics	(0.77)	(-0.07)	(-0.47)
Mass Violence [20]			
Coefficient (%)	0.0238	30.7588	2.1451
t-Statistics	(0.98)	(0.37)	(0.25)
Severity index			
Coefficient (%)	-0.0100	0.0116	-0.0071
t-Statistics	(-0.10)	(0.42)	(-0.50)

A2.6 Cross-sectional model with relative conflict measure

Table 20: Estimated risk premiums for the Fama-French factors and crisis sensitivity

In this table the averages of the risk premiums for each month from the second-stage cross-sectional regression equation (7) are reported: $RIRF_{i,m} = \gamma_m + \gamma_m^{MKTRF}\beta_{i,m-1}^{MKTRF} + \gamma_m^{SMB}\beta_{i,m-1}^{SMB} + \gamma_m^{HML}\beta_{i,m-1}^{HML} + \gamma_m^{Crisis}\beta_{i,m-1}^{Crisis} + \varepsilon_{i,m}$. *$RIRF_{i,m}$ is the monthly excess return (in %) of the 49 Fama-French industry portfolios i in month m from January 1980 until January 2014 including 409 monthly observations. $\beta_{i,m-1}^{MKTRF}$, $\beta_{i,m-1}^{SMB}$, $\beta_{i,m-1}^{HML}$ and $\beta_{i,m-1}^{Crisis}$ are the factor loadings, or respectively the rescaled decile rank of the factor loading, for each industry portfolio i on the last day of month m-1. The factor loadings are estimated from first-stage time-series regression (6) using an overlapping 250-day window:* $RIRF_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKTRF}MKTRF_t + \beta_{i,t}^{SMB}SMB_t + \beta_{i,t}^{HML}HML_t + \beta_{i,t}^{Crisis}Crisis_t + \varepsilon_{i,t}$. *Note that the first-stage regression is applied on daily data. $RIRF_{i,t}$ is the daily excess return (in %) of the industry portfolio i on day t, $MKTRF_t$, SMB_t and HML_t are the Fama-French factors for market, size and value on day t and $Crisis_t$ denotes the unexpected perceived crisis risk as obtained from model (4) on day t. The estimates are reported for All conflicts, for the conflicts in the sub-samples and the Severity index. The t-statistics, which are based on autocorrelation-adjusted standard errors using the Newey and West (1986) correction with three lags, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	MKTRF	SMB	HML	Crisis
All conflicts				
Coefficient (%)	0.2888	-0.0043	0.0398	-0.0282
t-Statistics	(0.90)	(-0.03)	(0.26)	(-0.21)
Demand [10]				
Coefficient (%)	0.2892	-0.0141	0.0339	0.0868
t-Statistics	(0.90)	(-0.08)	(0.22)	(0.69)
Disapprove [11]				
Coefficient (%)	0.3134	-0.0241	0.0280	0.0636
t-Statistics	(0.99)	(-0.14)	(0.18)	(0.49)
Reject [12]				
Coefficient (%)	0.2934	-0.0612	0.0344	0.0493
t-Statistics	(0.90)	(-0.35)	(0.22)	(0.37)
Threaten [13]				
Coefficient (%)	0.3319	-0.0141	0.0317	0.1747
t-Statistics	(1.05)	(-0.08)	(0.20)	(1.16)
Protest [14]				
Coefficient (%)	0.2804	-0.0636	0.0334	0.0481
t-Statistics	(0.87)	(-0.37)	(0.22)	(0.37)
Military Posture [15]				
Coefficient (%)	0.2714	-0.0363	0.0427	-0.1548
t-Statistics	(0.83)	(-0.21)	(0.27)	(-1.12)
Reduce Relations [16]				
Coefficient (%)	0.2331	-0.0012	0.0126	0.1960
t-Statistics	(0.71)	(-0.01)	(0.08)	(1.61)
Coerce [17]				
Coefficient (%)	0.3028	-0.0158	0.0310	0.0649
t-Statistics	(0.95)	(-0.09)	(0.20)	(0.56)
Assault [18]				
Coefficient (%)	0.3175	-0.0357	0.0294	0.0752
t-Statistics	(0.99)	(-0.21)	(0.19)	(0.54)
Fight [19]				
Coefficient (%)	0.3000	-0.0032	0.0184	-0.2146
t-Statistics	(0.93)	(-0.02)	(0.12)	(-1.64)
Mass Violence [20]				
Coefficient (%)	0.2629	-0.0531	0.0192	0.2480*
t-Statistics	(0.81)	(-0.31)	(0.12)	(1.86)
Severity index				
Coefficient (%)	0.2860	0.0071	0.0289	-0.0486
t-Statistics	(0.88)	(0.04)	(0.19)	(-0.37)

A3 Robustness tests with one-day lagged ratio conflict measure

A3.1 Stock market mean returns with lagged ratio conflict measure

Table 21: Regression results for the effect of perceived crisis risk on the contemporaneous U.S. stock market returns

*In this table the regression results for model (1) are reported: $MKTRF_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, where $MKTRF_t$ is the daily U.S. stock market excess return (in %) from January 02, 1979 until February 14, 2014 including 8,861 business day observations and $Crisis_t$ is the onde-day lagged conflict frequency constructed as the ratio of the total number of international conflict events to the total number of international cooperation events concerning the U.S. on day t-1 according to the GDELT database. I report the estimates for the crisis risk variable including All conflicts, the variables on the conflicts in the sub-samples and the variable of the Severity index. The t-statistics, which are based on heteroskedasticity-robust standard errors, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Crisis
All conflicts		
Coefficient (%)	0.0066	0.0738
t-Statistics	(0.16)	(0.63)
Demand [10]		
Coefficient (%)	0.0180	0.6786
t-Statistics	(1.02)	(0.99)
Disapprove [11]		
Coefficient (%)	0.0313	0.0047
t-Statistics	(1.10)	(0.02)
Reject [12]		
Coefficient (%)	0.0229	0.2310
t-Statistics	(1.18)	(0.57)
Threaten [13]		
Coefficient (%)	0.0239	0.3467
t-Statistics	(1.31)	(0.51)
Protest [14]		
Coefficient (%)	0.0166	1.4139*
t-Statistics	(1.18)	(1.93)
Military Posture [15]		
Coefficient (%)	0.0296**	0.2796
t-Statistics	(2.18)	(0.33)
Reduce Relations [16]		
Coefficient (%)	0.0340**	-0.1196
t-Statistics	(2.04)	(-0.21)
Coerce [17]		
Coefficient (%)	0.0205	0.2314
t-Statistics	(1.02)	(0.65)
Assault [18]		
Coefficient (%)	0.0382**	-0.3782
t-Statistics	(2.43)	(-0.55)
Fight [19]		
Coefficient (%)	0.0270	0.0737
t-Statistics	(1.28)	(0.23)
Mass Violence [20]		
Coefficient (%)	0.0306***	3.1034
t-Statistics	(2.61)	(0.54)
Severity index		
Coefficient (%)	0.0096	0.0045
t-Statistics	(0.25)	(0.58)

A3.2 Realized stock market volatility effects with lagged ratio conflict measure

Table 22: Regression results for the effect of perceived crisis risk on the realized U.S. stock market volatility[5]

*This table contains the estimation results for the GARCH model as expressed in equation (2): $MKTRF_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 Crisis_t + \eta_t$. $MKTRF_t$ is the daily U.S. stock market excess return (in %) from January 02, 1979 until February 14, 2014 including 8,861 business day observations and $Crisis_t$ denotes the one-day lagged conflict frequency from day t. The estimates are reported for All conflicts, for the conflicts in the sub-samples and the Severity index. The t-statistics are based on heteroskedasticity-robust standard errors and are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Mean		Volatility			
	Constant	Crisis	Constant	β_1	β_2	Crisis
All conflicts						
Coefficient (%)	0.0699**	-0.0478	-3.6647***	0.2491***	0.6660***	2.9051***
t-Statistics	(2.06)	(-0.49)	(-8.21)	(23.02)	(29.23)	(4.96)
Disapprove [11]						
Coefficient (%)	0.0715***	-0.1900	-4.1107***	0.2365***	0.7195***	4.3912
t-Statistics	(3.24)	(-0.86)	(-3.75)	(21.24)	(26.37)	(1.27)
Coerce [17]						
Coefficient (%)	0.0470**	0.1355	-3.7182***	0.2413***	0.7046***	7.9926**
t-Statistics	(2.25)	(0.36)	(-5.10)	(21.91)	(28.52)	(2.19)
Fight [19]						
Coefficient (%)	0.0624***	-0.1357	-2.9925***	0.2475***	0.6589***	6.9835***
t-Statistics	(3.26)	(-0.52)	(-9.70)	(21.16)	(27.82)	(6.13)
Mass Violence [20]						
Coefficient (%)	0.0305**	3.9078	0.7508***	-0.0004*	-0.7412***	-9.2924**
t-Statistics	(2.44)	(0.57)	(6.73)	(-1.66)	(-3.71)	(-2.46)
Severity index						
Coefficient (%)	0.0699**	-0.0034	-3.6332***	0.2490***	0.6643***	0.2007***
t-Statistics	(2.11)	(-0.51)	(-8.28)	(22.67)	(29.11)	(5.11)

[5] Results for the GARCH(1,1) model are only given for four crisis definitions based on the conflict severity. The crisis risk measures on *Demand*, *Protest*, *Reduce Relations* and *Assault* conflicts do not produce an outcome due to flat log likelihood. The models for crisis risk measures on *Reject*, *Threaten* and *Military Posture* conflicts cannot be defined, because the GARCH model is not suitable for these measures.

A3.3 Implied stock market volatility effects with lagged ratio conflict measure

Table 23: Regression results for the effect of perceived crisis risk on the contemporaneous VIX index price

*This table shows the results of the regression model (3): $lnVIX_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, where the dependent variable is the natural logarithm of the adjusted closing price of the VIX index from January 02, 1990 until February 14, 2014 including 6,080 business day observations regressed on $Crisis_t$, which is the one-day lagged conflict frequency from day t. I use All conflicts, the conflicts in the sub-samples and the Severity index, respectively, to construct the proxy for crisis risk. The t-statistics, which are based on heteroskedasticity-robust standard errors, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Crisis
All conflicts		
Coefficient	2.8844***	0.1624***
t-Statistics	(191.60)	(3.71)
Demand [10]		
Coefficient	2.9207***	0.9146***
t-Statistics	(352.86)	(2.63)
Disapprove [11]		
Coefficient	2.8603***	0.8782***
t-Statistics	(230.13)	(6.63)
Reject [12]		
Coefficient	2.9205***	0.5165**
t-Statistics	(294.73)	(2.17)
Threaten [13]		
Coefficient	2.8678***	3.0569***
t-Statistics	(355.62)	(9.85)
Protest [14]		
Coefficient	2.9140***	2.5383***
t-Statistics	(487.79)	(6.48)
Military Posture [15]		
Coefficient	2.9304***	1.2474**
t-Statistics	(502.37)	(2.35)
Reduce Relations [16]		
Coefficient	2.9562***	-0.8916***
t-Statistics	(385.50)	(-2.80)
Coerce [17]		
Coefficient	2.9785***	-0.8040***
t-Statistics	(310.59)	(-4.48)
Assault [18]		
Coefficient	2.9669***	-1.6435***
t-Statistics	(427.91)	(-5.14)
Fight [19]		
Coefficient	2.9347***	0.0711
t-Statistics	(364.76)	(0.64)
Mass Violence [20]		
Coefficient	2.9411***	-4.1425*
t-Statistics	(641.96)	(-1.78)
Severity index		
Coefficient	2.9063***	0.0068**
t-Statistics	(204.81)	(2.37)

A3.4 Time-series predictive regression with lagged ratio conflict measure

Table 24: Regression results for the effect of perceived crisis risk on the expected stock market returns

*Table 24 presents the estimation results for model (5) : $MKTRF_t = \alpha + \beta_1 Expected\ Crisis\ Risk_t + \beta_2 Unexpected\ Crisis\ Risk_t + \varepsilon_t$, where $MKTRF_t$ is the daily U.S. stock market excess return (in %) from January 02, 1979 until February 14, 2014 including 8,860 business day observations, Expected Crisis Risk is the fitted value of model (4) and the unexpected risk component is the residual from the following AR model (4): $Crisis_t = \alpha + \beta_1 Crisis_{t-1} + \varepsilon_t$, $Crisis_t$ denotes the one-day lagged frequency of international conflict events from day t. For each crisis risk proxy, as including All conflicts, only the conflicts in the sub-samples or the Severity index, the expected and unexpected crisis risk has to be re-estimated with model (4). The t-statistics are based on heteroskedasticity-robust standard errors and are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Expected	Unexpected
All conflicts			
Coefficient (%)	0.0336	-0.0048	0.0912
t-Statistics	(0.42)	(-0.02)	(0.73)
Demand [10]			
Coefficient (%)	-0.1418	8.5600	0.6182
t-Statistics	(-0.96)	(1.17)	(0.90)
Disapprove [11]			
Coefficient (%)	0.1180	-0.9284	0.0808
t-Statistics	(1.31)	(-0.95)	(0.27)
Reject [12]			
Coefficient (%)	0.0189	0.3350	0.2130
t-Statistics	(0.23)	(0.16)	(0.52)
Threaten [13]			
Coefficient (%)	0.0976	-2.9018	0.4835
t-Statistics	(1.43)	(-0.95)	(0.72)
Protest [14]			
Coefficient (%)	-0.0032	3.1788	1.2533*
t-Statistics	(-0.11)	(1.23)	(1.69)
Military Posture [15]			
Coefficient (%)	-0.0153	6.0028	0.1140
t-Statistics	(-0.34)	(1.09)	(0.13)
Reduce Relations [16]			
Coefficient (%)	-0.0368	3.5831	-0.2238
t-Statistics	(-0.55)	(1.07)	(-0.39)
Coerce [17]			
Coefficient (%)	0.0047	0.5523	0.2008
t-Statistics	(0.07)	(0.43)	(0.56)
Assault [18]			
Coefficient (%)	0.0581	-1.5493	-0.2981
t-Statistics	(1.35)	(-0.62)	(-0.43)
Fight [19]			
Coefficient (%)	0.0375	-0.0873	0.1238
t-Statistics	(1.06)	(-0.16)	(0.35)
Mass Violence [20]			
Coefficient (%)	0.0484**	-47.6675	3.6030
t-Statistics	(1.99)	(-0.77)	(0.62)
Severity index			
Coefficient (%)	0.0309	0.0002	0.0056
t-Statistics	(0.43)	(0.01)	(0.67)

A3.5 Cross-sectional model with lagged ratio conflict measure

Table 25: Estimated risk premiums for the Fama-French factors and crisis sensitivity

*In this table the averages of the risk premiums for each month from the second-stage cross-sectional regression equation (7) reported: $RIRF_{i,m} = \gamma_m + \gamma_m^{MKTRF}\beta_{i,m-1}^{MKTRF} + \gamma_m^{SMB}\beta_{i,m-1}^{SMB} + \gamma_m^{HML}\beta_{i,m-1}^{HML} + \gamma_m^{Crisis}\beta_{i,m-1}^{Crisis} + \varepsilon_{i,m}$. $RIRF_{i,m}$ is the monthly excess return (in %) of the 49 Fama-French industry portfolios i in month m from January 1980 until January 2014 including 409 monthly observations. $\beta_{i,m-1}^{MKTRF}$, $\beta_{i,m-1}^{SMB}$, $\beta_{i,m-1}^{HML}$ and $\beta_{i,m-1}^{Crisis}$ denote are the factor loadings, or respectively the rescaled decile rank of the factor loading, for each industry portfolio i on the last day of month m-1. The factor loadings are estimated from first-stage time-series regression (6) using an overlapping 250-day window: $RIRF_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKTRF}MKTRF_t + \beta_{i,t}^{SMB}SMB_t + \beta_{i,t}^{HML}HML_t + \beta_{i,t}^{Crisis}Crisis_t + \varepsilon_{i,t}$. Note that the first-stage regression is applied on daily data. $RIRF_{i,t}$ is the daily excess return (in %) of the industry portfolio i on day t, $MKTRF_t$, SMB_t and HML_t are the Fama-French factors for market, size and value on day t and $Crisis_t$ denotes the one-day unexpected perceived crisis risk as obtained from model (4) from day t. The estimates are reported for All conflicts, for the conflicts in the sub-samples and the Severity index. The t-statistics, which are based on autocorrelation-adjusted standard errors using the Newey and West (1986) correction with three lags, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	MKTRF	SMB	HML	Crisis
All conflicts				
Coefficient (%)	0.2261	-0.0164	0.0115	-0.1799
t-Statistics	(0.72)	(-0.10)	(0.07)	(-1.32)
Demand [10]				
Coefficient (%)	0.2741	-0.0598	0.0452	-0.0504
t-Statistics	(0.84)	(-0.35)	(0.29)	(-0.38)
Disapprove [11]				
Coefficient (%)	0.2397	-0.0404	0.0558	-0.0036
t-Statistics	(0.76)	(-0.23)	(0.36)	(-0.03)
Reject [12]				
Coefficient (%)	0.2799	-0.0324	0.0079	0.0945
t-Statistics	(0.86)	(-0.19)	(0.05)	(0.65)
Threaten [13]				
Coefficient (%)	0.2964	-0.0303	0.0381	-0.1474
t-Statistics	(0.92)	(-0.18)	(0.24)	(-1.11)
Protest [14]				
Coefficient (%)	0.2852	0.0014	0.0432	0.0889
t-Statistics	(0.89)	(0.01)	(0.28)	(0.70)
Military Posture [15]				
Coefficient (%)	0.2823	-0.0404	0.0161	0.0084
t-Statistics	(0.89)	(-0.23)	(0.11)	(0.06)
Reduce Relations [16]				
Coefficient (%)	0.3016	-0.0373	0.0499	-0.0078
t-Statistics	(0.94)	(-0.22)	(0.33)	(-0.06)
Coerce [17]				
Coefficient (%)	0.2733	-0.0464	0.0057	-0.0401
t-Statistics	(0.86)	(-0.27)	(0.04)	(-0.29)
Assault [18]				
Coefficient (%)	0.2895	-0.0309	0.0449	-0.2482*
t-Statistics	(0.90)	(-0.18)	(0.28)	(-1.88)
Fight [19]				
Coefficient (%)	0.3071	-0.0386	0.0194	-0.3788**
t-Statistics	(0.96)	(-0.22)	(0.13)	(-2.57)
Mass Violence [20]				
Coefficient (%)	0.2928	-0.0232	0.0466	0.2119
t-Statistics	(0.91)	(-0.13)	(0.31)	(1.38)
Severity index				
Coefficient (%)	0.2241	-0.0138	0.0150	-0.2561**
t-Statistics	(0.71)	(-0.08)	(0.10)	(-1.98)

A4 Robustness tests with one-day lagged relative conflict measure

A4.1 Stock market mean returns with lagged relative conflict measure

Table 26: Regression results for the effect of perceived crisis risk on the contemporaneous U.S. stock market returns

*In this table the regression results for model (1) are reported: $MKTRF_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, where $MKTRF_t$ is the daily U.S. stock market excess return (in %) from January 02, 1979 until February 14, 2014 including 8,861 business day observations and $Crisis_t$ is the one-day lagged conflict frequency constructed as the ratio of the total number of international conflict events to the total number of all international conflict and cooperation events concerning the U.S. on day t-1 according to the GDELT database. I report the estimates for the crisis risk variable including All conflicts, the variables on the conflicts in the sub-samples and the variable of the Severity index. The t-statistics, which are based on heteroskedasticity-robust standard errors, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Crisis
All conflicts		
Coefficient (%)	0.0048	0.1080
t-Statistics	(0.10)	(0.55)
Demand [10]		
Coefficient (%)	0.0196	0.8109
t-Statistics	(1.11)	(0.88)
Disapprove [11]		
Coefficient (%)	0.0356	-0.0571
t-Statistics	(1.21)	(-0.14)
Reject [12]		
Coefficient (%)	0.0200	0.4172
t-Statistics	(0.98)	(0.72)
Threaten [13]		
Coefficient (%)	0.0257	0.3631
t-Statistics	(1.43)	(0.40)
Protest [14]		
Coefficient (%)	0.0160	2.0180*
t-Statistics	(1.12)	(1.95)
Military Posture [15]		
Coefficient (%)	0.0303**	0.2545
t-Statistics	(2.20)	(0.21)
Reduce Relations [16]		
Coefficient (%)	0.0365**	-0.3417
t-Statistics	(2.13)	(-0.42)
Coerce [17]		
Coefficient (%)	0.0205	0.3150
t-Statistics	(0.98)	(0.61)
Assault [18]		
Coefficient (%)	0.0413***	-0.7692
t-Statistics	(2.66)	(-0.86)
Fight [19]		
Coefficient (%)	0.0329	-0.0263
t-Statistics	(1.51)	(-0.06)
Mass Violence [20]		
Coefficient (%)	0.0310***	2.9774
t-Statistics	(2.64)	(0.38)
Severity index		
Coefficient (%)	0.0119	0.0055
t-Statistics	(0.26)	(0.43)

A4.2 Realized stock market volatility effects with lagged relative conflict measure

Table 27: Regression results for the effect of perceived crisis risk on the realized U.S. stock market volatility[6]

*This table contains the estimation results for the GARCH model as expressed in equation (2): $MKTRF_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \beta_0 + \beta_1\varepsilon_{t-1}^2 + \beta_2\sigma_{t-1}^2 + \beta_3 Crisis_t + \eta_t$. $MKTRF_t$ is the daily U.S. stock market excess return (in %) from January 02, 1979 until February 14, 2014 including 8,861 business day observations and $Crisis_t$ denotes the one-day lagged conflict frequency calculated as the ratio of the number of international conflict events scaled by the number of all international conflict and cooperation events on day t-1, in which the U.S. is involved. The estimates are reported for All conflicts, for the conflicts in the sub-samples and the Severity index. The t-statistics are based on heteroskedasticity-robust standard errors and are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Mean		Volatility			
	Constant	Crisis	Constant	β_1	β_2	Crisis
All conflicts						
Coefficient (%)	0.0669	-0.0537	-4.3429***	0.2507***	0.6575***	7.0058***
t-Statistics	(1.49)	(-0.30)	(-7.42)	(22.28)	(28.00)	(5.09)
Disapprove [11]						
Coefficient (%)	0.0681***	-0.2089	-4.3872***	0.2363***	0.7207***	9.2123
t-Statistics	(2.79)	(-0.61)	(-2.95)	(20.82)	(25.55)	(0.98)
Reject [12]						
Coefficient (%)	0.0202	0.4142	0.7598***	-0.0006**	-0.6717***	-1.8222***
t-Statistics	(0.84)	(0.56)	(8.82)	(-2.49)	(-4.27)	(-5.45)
Reduce Relations [16]						
Coefficient (%)	0.0602***	-0.4331	-4.1607***	0.2322***	0.7348***	-20.3177
t-Statistics	(4.09)	(-0.49)	(-2.86)	(20.97)	(26.85)	(-0.30)
Coerce [17]						
Coefficient (%)	0.0435**	0.2836	-3.9291***	0.2398***	0.7107***	12.4403*
t-Statistics	(1.98)	(0.52)	(-4.19)	(21.48)	(27.50)	(1.77)
Fight [19]						
Coefficient (%)	0.0638***	-0.2160	-3.0837***	0.2472***	0.6560***	12.2782***
t-Statistics	(3.11)	(-0.55)	(-9.67)	(20.87)	(27.59)	(6.40)
Mass Violence [20]						
Coefficient (%)	0.0310**	3.6542	0.7482***	-0.0004	-0.7370***	-11.6929**
t-Statistics	(2.48)	(0.39)	(6.50)	(-1.63)	(-3.58)	(-2.34)
Severity index						
Coefficient (%)	0.0695	-0.0046	-4.2628***	0.2499***	0.6573***	0.4681***
t-Statistics	(1.61)	(-0.39)	(-7.57)	(21.88)	(27.87)	(5.29)

[6] Results for the GARCH(1,1) model are only given for six crisis definitions based on the conflict severity. The crisis risk measures on *Demand*, *Protest*, *Military Posture* and *Assault* conflicts do not produce an outcome due to flat log likelihood. The model for the crisis risk measure on *Threaten* conflicts cannot be defined, because the GARCH model is not suitable for this measure.

A4.3 Implied stock market volatility effects with lagged relative conflict measure

Table 28: Regression results for the effect of perceived crisis risk on the contemporaneous VIX index price

*This table shows the results of the regression model (3): $lnVIX_t = \mu + \alpha_1 Crisis_t + \varepsilon_t$, where the dependent variable is the natural logarithm of the adjusted closing price of the VIX index from January 02, 1990 until February 14, 2014 including 6,080 business day observations regressed on $Crisis_t$, which is the one-day lagged conflict frequency from day t. I use All conflicts, the conflicts in the sub-samples and the Severity index, respectively, to construct the proxy for crisis risk. The t-statistics, which are based on heteroskedasticity-robust standard errors, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Crisis
All conflicts		
Coefficient	2.8608***	0.3154***
t-Statistics	(147.18)	(4.05)
Demand [10]		
Coefficient	2.9224***	1.1192**
t-Statistics	(347.44)	(2.35)
Disapprove [11]		
Coefficient	2.8429***	1.4514***
t-Statistics	(203.02)	(7.08)
Reject [12]		
Coefficient	2.9219***	0.6460*
t-Statistics	(286.66)	(1.96)
Threaten [13]		
Coefficient	2.8624***	4.4694***
t-Statistics	(341.48)	(10.03)
Protest [14]		
Coefficient	2.9141***	3.4535***
t-Statistics	(473.80)	(6.07)
Military Posture [15]		
Coefficient	2.9323***	1.3312*
t-Statistics	(499.05)	(1.83)
Reduce Relations [16]		
Coefficient	2.9591***	-1.4090***
t-Statistics	(382.29)	(-3.28)
Coerce [17]		
Coefficient	2.9847***	-1.2652***
t-Statistics	(295.69)	(-4.89)
Assault [18]		
Coefficient	2.9700***	-2.4934***
t-Statistics	(419.25)	(-5.52)
Fight [19]		
Coefficient	2.9362***	0.0671
t-Statistics	(338.66)	(0.40)
Mass Violence [20]		
Coefficient	2.9411***	-5.6517*
t-Statistics	(641.87)	(-1.79)
Severity index		
Coefficient	2.8988***	0.0113**
t-Statistics	(162.29)	(2.27)

A4.4 Time-series predictive regression with lagged relative conflict measure

Table 29: Regression results for the effect of perceived crisis risk on the expected stock market returns

*Table 29 presents the estimation results for model (5) : $MKTRF_t = \alpha + \beta_1 Expected\ Crisis\ Risk_t + \beta_2 Unexpected\ Crisis\ Risk_t + \varepsilon_t$, where $MKTRF_t$ is the daily U.S. stock market excess return (in %) from January 02, 1979 until February 14, 2014 including 8,860 business day observations, Expected Crisis Risk is the fitted value of model (4) and the unexpected risk component is the residual from the following AR model (4): $Crisis_t = \alpha + \beta_1 Crisis_{t-1} + \varepsilon_t$, $Crisis_t$ denotes the one-day lagged frequency of international conflict events from day t. For each crisis risk proxy, as including All conflicts, only the conflicts in the sub-samples or the Severity index, the expected and unexpected crisis risk has to be re-estimated with model (4). The t-statistics are based on heteroskedasticity-robust standard errors and are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	Constant	Expected	Unexpected
All conflicts			
Coefficient (%)	0.0237	0.0323	0.1245
t-Statistics	(0.23)	(0.08)	(0.59)
Demand [10]			
Coefficient (%)	-0.1823	14.3435	0.7307
t-Statistics	(-1.08)	(1.27)	(0.79)
Disapprove [11]			
Coefficient (%)	0.1406	-1.6020	0.0390
t-Statistics	(1.23)	(-0.95)	(0.09)
Reject [12]			
Coefficient (%)	-0.0012	1.1728	0.3758
t-Statistics	(-0.01)	(0.36)	(0.64)
Threaten [13]			
Coefficient (%)	0.1087	-4.6518	0.5213
t-Statistics	(1.33)	(-0.93)	(0.58)
Protest [14]			
Coefficient (%)	-0.0120	5.4489	1.8022*
t-Statistics	(-0.34)	(1.31)	(1.72)
Military Posture [15]			
Coefficient (%)	-0.0182	8.6865	0.0183
t-Statistics	(-0.40)	(1.14)	(0.02)
Reduce Relations [16]			
Coefficient (%)	-0.0383	4.9691	-0.4794
t-Statistics	(-0.55)	(1.03)	(-0.58)
Coerce [17]			
Coefficient (%)	0.0059	0.7220	0.2788
t-Statistics	(0.08)	(0.37)	(0.54)
Assault [18]			
Coefficient (%)	0.0634	-2.5566	-0.6549
t-Statistics	(1.36)	(-0.69)	(-0.72)
Fight [19]			
Coefficient (%)	0.0400	-0.1769	0.0185
t-Statistics	(1.03)	(-0.21)	(0.04)
Mass Violence [20]			
Coefficient (%)	0.0509**	-74.4268	3.7298
t-Statistics	(2.11)	(-0.89)	(0.47)
Severity index			
Coefficient (%)	0.0248	0.0020	0.0065
t-Statistics	(0.28)	(0.08)	(0.46)

A4.5 Cross-sectional model with lagged relative conflict measure

Table 30: Estimated risk premiums for the Fama-French factors and crisis sensitivity

In this table the averages of the risk premiums for each month from the second-stage cross-sectional regression equation (7) reported: $RIRF_{i,m} = \gamma_m + \gamma_m^{MKTRF}\beta_{i,m-1}^{MKTRF} + \gamma_m^{SMB}\beta_{i,m-1}^{SMB} + \gamma_m^{HML}\beta_{i,m-1}^{HML} + \gamma_m^{Crisis}\beta_{i,m-1}^{Crisis} + \varepsilon_{i,m}$. $RIRF_{i,m}$ *is the monthly excess return (in %) of the 49 Fama-French industry portfolios i in month m from January 1980 until January 2014 including 409 monthly observations.* $\beta_{i,m-1}^{MKTRF}$, $\beta_{i,m-1}^{SMB}$, $\beta_{i,m-1}^{HML}$ *and* $\beta_{i,m-1}^{Crisis}$ *denote are the factor loadings, or respectively the rescaled decile rank of the factor loading, for each industry portfolio i on the last day of month m-1. The factor loadings are estimated from first-stage time-series regression (6) using an overlapping 250-day window:* $RIRF_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKTRF}MKTRF_t + \beta_{i,t}^{SMB}SMB_t + \beta_{i,t}^{HML}HML_t + \beta_{i,t}^{Crisis}Crisis_t + \varepsilon_{i,t}$. *Note that the first-stage regression is applied on daily data.* $RIRF_{i,t}$ *is the daily excess return (in %) of the industry portfolio i on day t,* $MKTRF_t$, SMB_t *and* HML_t *are the Fama-French factors for market, size and value on day t and* $Crisis_t$ *denotes the one-day lagged unexpected perceived crisis risk as obtained from model (4) from day t. The estimates are reported for All conflicts, for the conflicts in the sub-samples and the Severity index. The t-statistics, which are based on autocorrelation-adjusted standard errors using the Newey and West (1986) correction with three lags, are reported in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.*

	MKTRF	SMB	HML	Crisis
All conflicts				
Coefficient (%)	0.2431	-0.0171	0.0121	-0.1764
t-Statistics	(0.77)	(-0.10)	(0.08)	(-1.29)
Demand [10]				
Coefficient (%)	0.2750	-0.0562	0.0463	-0.0327
t-Statistics	(0.85)	(-0.33)	(0.30)	(-0.25)
Disapprove [11]				
Coefficient (%)	0.2231	-0.0331	0.0610	0.0352
t-Statistics	(0.70)	(-0.19)	(0.39)	(0.24)
Reject [12]				
Coefficient (%)	0.2712	-0.0340	0.0105	0.0969
t-Statistics	(0.84)	(-0.20)	(0.07)	(0.67)
Threaten [13]				
Coefficient (%)	0.3108	-0.0318	0.0339	-0.0865
t-Statistics	(0.97)	(-0.19)	(0.22)	(-0.67)
Protest [14]				
Coefficient (%)	0.2860	0.0111	0.0315	0.1111
t-Statistics	(0.89)	(0.06)	(0.20)	(0.87)
Military Posture [15]				
Coefficient (%)	0.2974	-0.0375	0.0158	0.0589
t-Statistics	(0.94)	(-0.22)	(0.10)	(0.45)
Reduce Relations [16]				
Coefficient (%)	0.3067	-0.0425	0.0468	0.0283
t-Statistics	(0.95)	(-0.25)	(0.31)	(0.23)
Coerce [17]				
Coefficient (%)	0.2928	-0.0461	0.0017	-0.0179
t-Statistics	(0.92)	(-0.27)	(0.01)	(-0.13)
Assault [18]				
Coefficient (%)	0.2834	-0.0319	0.0489	-0.2661**
t-Statistics	(0.88)	(-0.18)	(0.31)	(-2.07)
Fight [19]				
Coefficient (%)	0.3080	-0.0337	0.0232	-0.4003***
t-Statistics	(0.96)	(-0.19)	(0.15)	(-2.65)
Mass Violence [20]				
Coefficient (%)	0.2907	-0.0190	0.0450	0.2195
t-Statistics	(0.91)	(-0.11)	(0.30)	(1.45)
Severity index				
Coefficient (%)	0.2528	-0.0109	0.0115	-0.2629**
t-Statistics	(0.80)	(-0.06)	(0.07)	(-2.00)