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The Effects of Conflicts on International Financial Markets

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Abstract

This paper explores the effects that international geopolitical crises and tension exert on financial markets. A time-varying, country-specific index is created in order to proxy for the level of international hostility which is used throughout the study to test the predictive power it has across stock and currency returns in a sample of 30 countries, where half are developed economies while the other half are emerging markets. Little evidence is found to claim that the Conflict index can predict multi-asset returns in the cross section, but there is some evidence in favour of this for the Emerging Market Equities of approximately 0.8% monthly. Regarding the risk compensation, there is no evidence for risk being priced in the cross-section of equities but there is indicative information suggesting that currencies with higher exposure to the Conflict Index are negatively compensated for. Additionally, the Conflict variable was used to explain multi asset volatilities across countries, yet it appears that its explanatory power in this matter is strikingly low. Overall the conflict puzzle remains a topic of contention, despite new light being shed on new markets and asset classes.

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1 Introduction

In an era where international conflicts are as present as ever before, and considering the never ending advance of globalization, the effects of hostilities or crises are often times much more complex than they used to be in the past. Without any reasonable doubt, the most horrific consequence of any conflict is the loss of human life and the destruction of property that leads to the misery of hundred of thousands every year. As a result, there are also extremely dire economic effects that arise due to armed conflicts or the prospect of those. This is not only true for the populations that are or would be directly affected by the hostilities, but also for the different economic partners that are suddenly faced with a very high degree of uncertainty about the future, specifically about the outcome of said confrontation. The aforementioned implications are inextricably connected with the financial market performance of a country faced with the possibility of an armed conflict, and those of the countries with some relation with the parties at stake.

The chances of the materialization of full-scale wars are very limited, but would have enormously detrimental consequences. International conflicts, however, generally are shaped in much subtler ways, taking repeated steps that either escalate or de-escalate the situation. This continuous process might not have the disastrous humanitarian implications that wars do, but might share some of the financial and economic consequences while occurring much more frequently. Due to this reason, it is also paramount to cast some light upon the much more common consequences of the international Conflict that do not result in all-out-wars, but rather occur as heightening tensions between two or more actors. This rises the challenge of being able to measure a time-varying variable that acts as a proxy for a *Conflict Index* at a country level, allowing to model a continuous development of international stress degree.

However straightforward the connection between international instability and market performance might sound in theory, the literature linking financial markets to issues related to geopolitics and international relations is not only scarce, but also inconclusive due to the challenging nature to accurately quantify investors perception of conflict risk and how it affects stock and other assets performance and volatility. This literary void is particularly large with regard to emerging market economies, where many of the crises originate and where markets are more inefficient, therefore giving a potential edge to investors relying on novel data-sets and information. The aim of this paper is to contribute to the literature that aims to bring multidisciplinary techniques for the benefit of a more complete asset pricing approach where macroeconomics, geopolitics and company fundamentals complement each other.

A thorough review of the literature is conducted so as to examine previous attempts to quantify international risk and its relations to equity and foreign exchange markets. This allows to elucidate the advantages and shortcomings of various methods used in the past, to later decide on a specific variable construction technique.

The data utilized for this study originates from the GDELT (Global Data on Event, Location and Tone) Project. This source presents a colossal yet meticulous database consisting of global events, their location, origin, target and perpetrators as well as the nature and intensity of the episode where the information is gathered from news articles across the globe. Frazzini (2006) recognises the relevance of news and how they affect the behaviour of investors that trade on them, indicating that press data which is freely available is an adequate instrument for the research at hand. This rich body of data portrays itself as an interesting and growing source of big data that can be put at the service of asset pricing to the interest of practitioners, researchers and policy-makers alike who could exploit this information to chase returns, identify financial consequences of international conflicts, or truly grasp the extent of the economic ramifications of political conflicts respectively.

Because of the increasing relevance of Emerging Markets in global finances and the gradual integration that they present, the characteristics of emerging financial markets and those of developed nations are still quite distinct. Rouwenhorst (1999) claims that despite the average ongoing economic liberalization in the developing world, these markets are mostly dominated by investors who will mostly react to local events rather than international turmoil. Due to these reasons, making a clear cut distinction between emerging economies and developed ones presents an interesting opportunity to test whether the perception of conflict risk differs between more integrated and more segmented markets.

The contribution of the analysis conducted in this study is many-sided. First, it utilizes the innovative GDELT data source and puts it to the service of asset pricing. This, as well as the quantification of a conflict variable that can be applied to any country is worth noting. Second, it adds to a growing body of literature that attempts to bridge the gap between complementary disciplines in order to depict a clearer picture of economic circumstances. Third, by distinguishing between emerging and developed economies as well as stocks and currencies, it contributes to a better understanding of the cross country financial differences, and lastly the results can be of importance to better understand the financial consequences of international tensions, usually overshadowed by other facets of these events. This information can be consequently of use not only to policymakers assessing the impact of international diplomatic actions, but also to financial practitioners trying to better understand an ever more complex financial environment. Finally, the database created can be of use for further research even in completely different fields to that of investments.

This paper finds little evidence that the conflict index can be used to predict universal financial asset returns in the cross section. There is some indication that signals the existence of this conflict predictability specially in emerging market equities, however the magnitude remains small and the results are not entirely robust. Surprisingly, no predictability was found in the returns of currencies, which are often regarded as more sensitive to news-like events. Equally, this paper shows little evidence for the presence of universal risk compensation for engaging with assets with high exposure to the conflict variable, but there is some evidence indicating that currencies, and particularly emerging market currencies price the exposure to the conflict index negatively.

The remaining of the paper is structured as follows. Section 2 will review the existing literature about conflicts and their impact in financial markets, as well as a general revision on traditional asset pricing theory in order to lay the ground for this particular application. Section 3 thoroughly elaborates on the data gathering and variable construction, as well as the motivation behind it. This section is of particular relevance given the data-heavy nature of the research. Section 4 presents, interprets and further discusses the results. The study is then finished by considering its limitations and opportunities for further research and robustness, leading to a final conclusion.

2 Literature review and hypotheses

Because of the challenging nature of bringing international conflict risk and asset pricing together, there is no clear consensus on the results of the effects that the latter exert on the former. Neither is there consensus on how to properly account for this effect, which resulted in various streams of literature that take different approaches to the same question. This section is firstly based on traditional asset pricing theory which is the core of this research paper, to later expand upon the different methods that aim to link international instability with investment theory.

2.1 Traditional Asset Pricing Theory

The underlying idea behind asset pricing and investment theory lies on the fact that there are certain risk parameters for which investors demand compensation in the form of returns. This risk-return relationship is embedded in most asset pricing models, and was formalized by the famous Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), Lintner (1975) and Mossin (1966) based on the previous research on portfolio theory conducted by Markowitz (1952). From this idea, the famous market beta (β) was conceived, implying investors engaging in non diversifiable risk should be rewarded. This model assumes a single risk factor, market risk, which is supposed to capture all systemic risk in the market. As concise as it was, the CAPM was used as the basis for many other models that further extended it with with the aim to add explanatory power and capture market anomalies. Market anomalies arise when stock or any asset returns deviate from what is predicted by a central paradigm or theory, usually embodied by the CAPM, casting evidence against the efficient market hypothesis (EMH) (Malkiel & Fama, 1970).

A variety of models were later created which intended to go beyond the relative simplicity of the CAPM, by introducing a wide array of different risk factors that supposedly signify improvements in explanatory power. Among the most renowned ones there is the Fama-French (1993) 3 Factor model, whereby they account for size (SMB) and book to market ratio (HML) of firms. They further expanded said model by including two more factors, namely accounting for the firm investment policy (CMA) and profitability (RMW) (Fama

& French, 2015). Different variations and modifications to those models continue to arise, with the inclusion of a momentum factor being one of the most recurrent additions. The crux of the matter is, regardless of the particularities of the variable, that there are certain factors for which investors require a risk-premium in the form of higher returns. To assess whether international instability is also relevant for investments, a similar variable should be constructed, but this task is nothing short of a challenge.

2.2 Event Studies on Crises

Several studies have tackled the issue of conflicts on a case-by-case fashion, with an event study methodology. This approach assigns great importance to the materialization of the conflict and therefore performs a "before and after" analysis of the financial markets affected by a particular calamity.

Because of the magnitude of the conflict, there are numerous studies that assessed the impact of World War II in the world economy and particularly in capital markets. Oosterlinck (2003) evaluates the impact of the invasion of France by Nazi Germany on the price of French government bonds. He investigates how the price differential between the bonds issued by the Third Republic and those of the collaborationist regime of Vichy reflect the changing perception of investors regarding the outcome of the conflict. In a similar fashion, Frey and Waldenström (2004) test the impact of the same war on fixed income securities traded on the Zurich stock exchange as well as in Stockholm. They find that even though the outbreak of the war depressed the price of both aggressors and target countries alike, Axis victories such as the quick takeover of the Benelux significantly increased the price of their sovereign debt, while defeats such as in Stalingrad negatively affected the price of the German bond, implying a structural change in the expectations about the credit risk of those debt instruments by investors.

Similarly, event studies have been conducted with regard to more recent conflicts. Kim et al. (2011) uses U.S equity market data and explains how the predictability of said market varies throughout different episodes such as the Vietnam and Korean War, the Cuban Missile conflict among others. Equally, G. Schneider and Troeger (2006) investigate the impact that the Yugoslavian wars, the escalation of Israel-Palestine violence and the first confrontations between the U.S led coalition and Iraqi forces exerted on the British FTSE100, Dow Jones index and the French CAC finding negative reactions in all indices. Particularly, Leigh, Wolfers, and Zitzewitz (2003) utilize an interesting approach where he tracks the value of a so-called "Saddam Security" and extrapolates the change in price to the expected consequences of the war. These Saddam Securities are structured in a way that they have a classic Arrow-Debrow[1] security payoff profile, where a fixed amount is payed to the holder if Saddam Hussein is out of power, otherwise no payoff was granted. The higher the probability of Sadam's deposition, the higher the price of this security. However peculiar, this approach that intends to capture investors conflict risk presents a series of shortcomings. First, the securities in questions were highly iliquid, making a like-for-like comparison with more common financial instruments impossible, and secondly, the definition of a conflict in this method is the strict start and culmination of a military conflict, which is a very rigid definition of conflict.

As illustrated, the wide array of event studies performed still do not offer a conclusion to the effect of conflict risk and the implications on equity markets. Rather, they provide insights which are particular to a specific case, which in turn are extremely difficult to generalize. Additionally, event studies require specific dates to be set, which grant significant discretionary power to the researcher, possibly causing problems of interpretation, or neglecting the buildup of a conflict which oftentimes is more relevant than the conflict itself, as it is the case for sovereign defaults shown by Yeyati and Panizza (2011) and Brune et al. (2015) in the case of the Iraq war.

2.3 Rare Risk Disaster Studies

A comparable effort to tackle the issue of international crises and their effects on financial markets is to model the probabilities of an unlikely yet highly impactful event such as

[1] Arrow-Debrow securities are instruments mostly utilized in economic theory where the holder receives a payoff in a particular state of the world and otherwise receives nothing.

war or natural calamities and the implications that they would exert on equity returns and volatilities. In their seminar paper, Barro (2006) expands the analysis conducted by Rietz (1988) attempting to solve the equity risk-premium associated to international crises. To do so, the authors inspect GDP per capita and productivity contractions related to the main events with the more widespread international consequences of the XX$^{\text{th}}$ century: The first world war, the great depression, and the second world war, among other smaller ones. By measuring the size as well as the frequency of occurrence of these "rare disasters", Barro (2006) is able to confirm that these negative shocks are large and frequent enough to explain the equity premium.

Contributing to the same strand of academic literature, Wachter (2013) investigates the equity premium and the degree of stock volatility by modelling the probabilities of important consumption declines. The paper goes as far as to model the impact of those implied consumption disaster probabilities on the risk free rate, allowing for a partial government default on public liabilities with a certain probability. Just as in Barro (2006), the haircut given default is assumed to be the expected decline in aggregate consumption. She concludes that the fact that consumption behaves with a normal distribution with a fat left tail explains the equity premium and volatility without the need to assume an extraordinary high value of risk aversion and claims that despite the fact that the model was used to explain equities, valuable insights could be drawn from applying a similar technique to other asset classes such as exchange rates, which will be expanded upon on this paper.

Research by Berkman et al. (2011) takes a contrasting approach to the same issue. They create a time varying conflict index and relate it to global equities returns as well as volatilities. Further, the authors subset this variable and specifically account for the initiation, duration and culmination of a conflict, finding that the start of a conflict is negatively correlated with stock returns and positively correlated with the standard deviation of said returns. This implies that the number of global hostile events has a negative impact on stock markets, which is complemented by the finding that the severity of the circumstances enhances those effects. The authors also cover particular industries in the United States and conclude that those sectors with higher exposure to their conflict variable exhibit higher returns, suggesting that conflict risk is priced and compensated for, at least partially, which is similar to the way in which countries are treated in this particular study.

2.4 Political Instability and News-Level Studies

As opposed to the previously discussed approach to assessing international instability and its impact on financial markets, a stream of literature has taken a different procedure to the same issue by focusing on uncertainty arising from policy-makers decision making only. The nature of these sort of models is rooted in aiming to model time varying political instability by the means of constructing a quantitative variable which acts as an adequate proxy for the unpredictability in policy makers' decision making process. Which proxy to utilize, however, is a matter of contention in academia.

Bilson et al. (2002) examine the impact of political instability in emerging market stocks by employing a political risk index provided by the Political Risk Services' International Country Risk Guide (ICRG). This index is composed of four different risk sub-indices including political risk, economic risk, financial risk index, and an overall composite risk index, allowing for the quantification of a phenomenon which is qualitative in nature. Given that this variable incorporates political analysts forecasts and expectations, they claim that it gives a forward looking character to their study, better capturing investors expectations about the future development of a conflict, finding a positive relationship between EME stock returns and the intensity of conflict. Similarly, Chen et al. (2014) conduct a study whereby they model the threat of war by computing a military expenditure-to-GDP ratio, therefore being able to identify periods of relative tranquility and agitation. They proceed to regress this factor on the excess returns of 49 country equity indices and conclude that the exposure of emerging economies to this risk element is higher than that of developed countries, thus yielding higher returns and volatility.

In another attempt to quantify political and economic uncertainty, Baker, Bloom, and Davis (2016) construct a index of economic policy uncertainty (EPU) based on the newspaper coverage of uncertain events in the United States and other 12 large economies. This indicator peaks around events not only involving material actions against other countries such as the Gulf War in 1990-1991 but also at events involving major economic catastrophes such as the Collapse of Lehman Brothers during the Financial Crisis of 2008. This implies a broader definition of their conflict variable, accounting for acts not only involving official governments, but also relevant actors with a big enough role to trigger international instability. The authors resolve that a high index level is associated not only with a higher degree of stock price volatility but also with a foreshadowing decline in investments, output and employment. In another study, Pástor and Veronesi (2013) utilize the EPU index from an unpublished version of Baker et al (2016) and focus on returns rather than on volatility alone, asserting that investors require a risk premium for economic and political uncertainty, and even more so when the economic conditions are weak.

In a paper that rather than considering the equity market inspects exchange rates, Filippou, Gozluklu, and Taylor (2018) assess whether political risk is a relevant factor when explaining the returns originated from a momentum strategy when it comes to 48 different currencies. They find that unexpected political conditions are priced in the cross-section of currency momentum returns, as well as a strong predictability power that goes beyond traditional asset pricing factors, which complements the literature by expanding the analysis of the effects of international crises to yet another relevant asset class.

It is observable that many political risk studies utilize news as a source for their quantification process and variable creation. This is not surprising as data savy techniques are continuously being developed to more efficiently retrieve press information. Yet another example is the study conducted by Jones, Lamont, and Lumsdaine (1998) where macro economic related news are tracked resulting in the finding of a risk premium to said news on U.S Federal Reserve bonds as well as a positive volatility effect on the same securities. This manner permits for a broader definition of conflict, captures escalation and de-escalation effects, as well as allows for easier generalization of what is concluded, which is the direction that this study takes in an attempt to utilize news level data to form a conflict variable at country level, where actors need not be sovereign nations but can also be other parties involved in a conflict such as particular ethnic groups, non government organizations (NGOs) and corporations, thus broadening the scope of the international instability measure and therefore capturing more information.

2.5 Hypotheses

As shown by the assessment of the previous sections, the literature relating international instability to financial markets is nothing short of inconclusive. While some authors find positive effects on returns, other papers refute these claims utilizing a different variable or definition to model conflict risk. Further, there is little consensus as to which of the three different general approaches outlined depict the true effects of crises on financial markets more accurately. With the aim to clarify the conflict puzzle, and using a rich dataset on global news information while combining it with the statistical techniques of asset pricing, the following hypothesis are presented:

With regard to the financial market returns and volatilities, the hypotheses are as follows:

As far as predictability of returns is concerned: *H1a: The intensity of political conflict can predict stock and currency returns cross-sectionally.*

H1b: This predictability is stronger in Emerging Markets and in Developed Economies.

As far as risk pricing is concerned: *H2a: The intensity of political conflict risk is priced across the cross-section of equities and currency returns.*

H2b: Risk pricing of the conflict risk is more marked in Emerging Markets than in Developed Economies

As far as volatilities are concerned: *H3: Political conflict risk helps explain financial market volatility across equities and currencies*

3 Data

In this section the inputs of the paper are thoroughly explained. Data plays a vitally relevant role in this paper. Not only because of the novelty of the database used to gather news information (GDELT) which will be engineered into a variable, but also because of its extension and the degree of detail that it presents. Simultaneously, it is paramount to understand the way in which the dataset is constructed and how it relates to financial market data, as this will be of importance when using the data for statistical inference.

3.1 GDELT

The most essential source of data for this study originates from the GDELT (Global Data of Events, Location and Tone) Project. As mentioned in previous sections, this scheme has extraordinarily comprehensive databases that track global media coverage on a plethora of languages to generate quantitative indicators marking the nature of events anywhere on the planet at any determined date. The GDELT Project was created with the aim to build a more updated version of past event coding frameworks such as the WEIS (World Event Interaction Survey) which relied on a Westphalian[2] conception of world politics. This in turn had the disadvantage of only focusing on sovereign states as actors and entirely overlooking any event interaction that included non-country participants and low-level violence or cooperation (Schrodt, 2012). With GDELT, the event information is decomposed into a series of variables that, together, provide a comprehensive picture of the episode. With daily accounts of events from January 1st of 1979 to present day, the source in question is an impressive big-data attempt to quantify -both country and non-country level- information that is usually only available on a qualitative manner, therefore enhancing its uses for research motives.

This paper considers the *GDELT 1.0 Reduced* version. It consists of more than 87 million daily observations of geopolitical events across the globe and extends from 1979 to 2014,

[2]In international law, Westphalian sovereignty is a principle where countries exert sovereignty within their domains and have exclusive rights inside their boundaries. It is based on the Peace of Westphalia that ended the European Wars of Religion in 1648 and underlines traditional diplomacy that considers nations as the most important actors (Osiander, 1994).

specifying not only actors, but also whether the essence of the event was belligerent or amicable. As far as the parties involved are concerned, the GDELT Project uses the United Nations three-letter country codes for identification purposes, as well as different additions to the base code to denote ethnic groups, military, government and different sub-specifications. This later aspect does not require for two internationally recognised nations to be involved and still captures the degree of instability in a region, which is typical of modern age international relations where different non-nation stake holders might drive uncertainty.

As well as reporting the source and target of the event with the U.N country codes, this database details the nature of the event by creating a CAMEO (Conflict and mediation event observations) Code variable. This code ranges from 01 to 20, where the interval of 01-09 indicates increasing cooperation between actors and the interval of 10-20 indicates increasing degree of tension between parties. The codes have a myriad of sub-specifications denoted by added digits, but for the purpose of this paper only the first two numbers of said variable will be taken into consideration, as they capture most of the information. Yet another proxy for the nature of the event is the so called *Goldstein Scale* which ranges from -10 to +10, where negative numbers exert instability on nations, and positive countries are supposed to bring stability to the parts involved (Goldstein, 1992). The dataset also incorporates different geolocalization variables and the number of events and articles which are not relevant for this research.

3.1.1 GDELT Manipulation

The GDELT project makes an enormous amount of data available, yet its raw nature requires some alterations for valuable information to be extracted from it. As this paper focuses on how do modern investors react to international conflicts, the data has been reduced to the dates raging between the years 2000 and 2014, the last data point available. To investigate the differences between developed and emerging market countries, the 15th largest developed and emerging economies were selected, using the specification criteria of Standard & Poor's (2018)[3]. To distinguish the per-countries effects, a different Conflict index has been generated

[3]Largest economies selected according to real GDP (IMF, 2019).

Table 1: CAMEO codes specifications and their descriptions.

CAMEO Event Code

Cooperation		**Hostility**	
1	Make public statement	**10**	Demand
2	Appeal	**11**	Disaprove
3	Express intent to cooperate	**12**	Reject
4	Consult	**13**	Threaten
5	Engage in diplomatic cooperation	**14**	Protest
6	Engage in material cooperation	**15**	Exhibit force posture
7	Provide aid	**16**	Reduce relations
8	Yield	**17**	Coerce
9	Investigate	**18**	Assult
		19	Fight
		20	Use unconventional mass violence

for each nation. The method for this subsample consists of extracting the CAMEO code of an event whenever that country is involved either as a source or target of the action. Additionally, and as already discussed, only the first two digits of the CAMEO Event variable have been considered for the sake of simplicity and interpretation.

$$Conflict_{j,t} = \frac{\sum_{i=1}^{n}(HostileCAMEO)}{\sum_{i=1}^{n}(CooperationCAMEO)} \tag{1}$$

Because of the clear increase in digital press reporting, using the number of articles would imply biasing the data towards more recent dates, the construction of a standardized measure is paramount. To do so, the sum of the CAMEO Codes denoting hostility (10-20) are divided by the sum of the CAMEO Codes denoting cooperation (01-09) for each day and for each country, as shown in equation 1. In this manner, and assuming that the digital reporting has increased equally for cooperation and conflict events, a daily time series variable of conflict development can be conceived.

Table 2: *Descriptive statistics for the conflict Index on a country level basis.*

Descriptive Statistics of conflict Index

Conflict Index	**Mean**	σ	**Min**	**Max**
Italy	1.31	0.29	0.71	2.31
Japan	0.92	0.16	0.56	1.67
United States	1.54	0.17	1.05	2.25
France	1.25	0.19	0.73	1.97
UK	1.49	0.18	1.04	2.20
Austria	1.22	0.66	0.52	6.95
Germany	1.14	0.17	0.71	1.70
Netherlands	1.81	0.60	0.90	4.16
Korea (south)	0.95	0.25	0.43	2.10
Switzerland	1.20	0.43	0.67	4.59
Spain	1.58	0.61	0.84	5.74
Canada	1.36	0.41	0.45	3.81
Sweden	1.65	0.95	0.35	5.98
Belgium	1.04	0.34	0.55	2.39
Australia	1.50	0.35	0.78	4.31
China	0.97	0.19	0.61	1.91
India	2.47	1.34	1.14	15.27
Russia	1.29	0.18	0.93	1.80
Brazil	1.23	0.73	0.42	4.38
Indonesia	1.87	0.74	0.94	5.87
South Africa	1.81	0.62	0.77	4.04
Poland	1.22	0.36	0.51	2.55
Chile	1.58	1.07	0.22	9.57
Turkey	1.39	0.40	0.76	2.77
Thailand	1.81	0.59	0.79	4.51
Pakistan	2.25	0.42	1.33	3.91
Mexico	1.96	0.56	0.83	3.77
Argentina	1.70	0.89	0.55	6.13
Taiwan	1.03	0.32	0.60	3.26
Saudi Arabia	1.39	0.55	0.55	3.52

Where *conflict* denotes the conflict index at time t for country j, which is formed by summing the CAMEO event codes denoting hostility (10-20) and dividing them by the sum of the CAMEO event codes denoting cooperation or friendliness (01-09). In this way, the Conflict Index is created and guaranteed not to suffer from endogeneity while simultaneously solving the issue of media digitization bias towards more recent dates. Further, the monthly average is computed to obtain one observation per month per country.

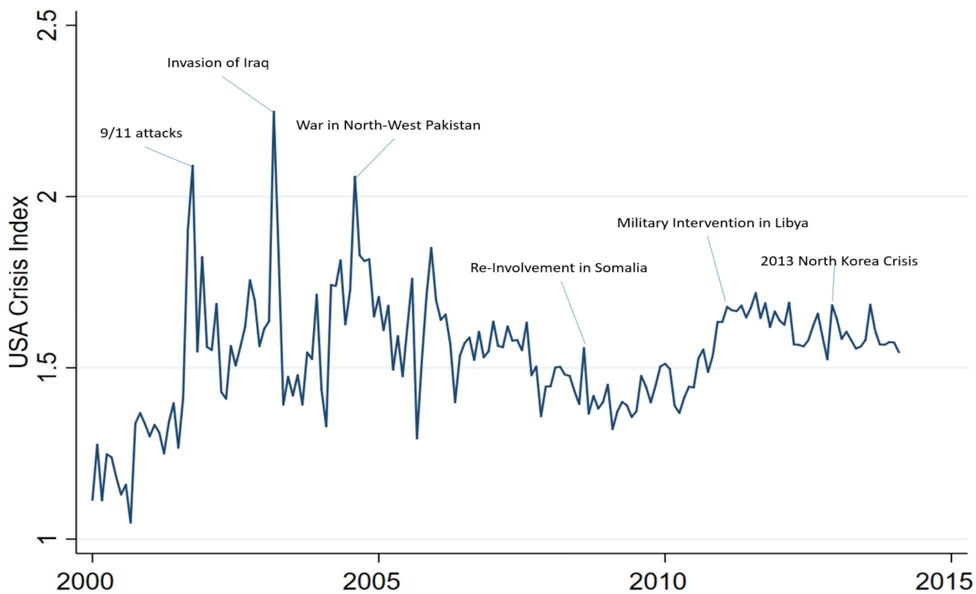

Figure 1: Illustrative display of the Conflict Index for the United States through time.

The created conflict index appears to be appropriate when it comes to capturing the international instability involving a nation. It is observable in Figure 1 that the variable spikes perfectly coincide with months involving major geopolitical conflicts where the United States played an active role, either as a target or source. The other increases are attributed to escalations or de-escalations of ongoing conflicts involving the country in question. It is assumed that the same effect applies to the whole sample of 30 countries.

3.2 Market and Macroeconomic Data

To be able to inspect the relation between the newly created conflict variables and financial markets, financial and macroeconomic information is certainly necessary. Consequently, the pricing data of the largest stock market indices for each country were gathered from Datastream, from where returns were calculated on a monthly basis. The equity indices are quoted in US dollars to avoid currency fluctuations playing a role in their performance and therefore biasing results. Additionally, the Fama French MKT, HML, SMB, CMA, RMW and MOM global factors were obtained from the publicly available online library of Kenneth R. French.[4]

For a more comprehensive look at the impact of crises on capital markets, currencies are also regarded with the same objective as this would provide insights into another asset class. In fact, the forex (FX) market is clearly the largest financial market in terms of daily turnover, as stated by research of the Bank for International Settlement's (2016), yet only a scarce amount of literature has focused on this particular asset class. For this purpose, monthly exchange rates were gathered from Datastream for each of the currencies with regard to the US dollar. The currencies are considered against the US dollar so that an appreciation in this latter currency is reflected by a higher spot rate $S_{t,j}$. Because of this reason, the US dollar had to be dropped from the sample, and the European countries that adopted the Euro are considered as one unit under the euro-zone, following the procedure performed by Filippou et al. (2018)[5].

Additionally, and with the purpose to serve as control variables, month-over-month GDP growth, month-over-month core inflation rates (CPI) and the monthly averages of the 3 Month Interbank Rate were gathered per country. This posed a challenge, considering that not all countries continuously report the aforementioned statistics, and consequently gaps of data were present when using the official country statistics reported by Datastream. Consequently, the World Bank Development Indicators Database was used to fill those spaces when information was missing[6]. Something that must be noted is the fact that many emerg-

[4]See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data$_{l}$*ibrary.html*

[5]Those being Germany, France, Spain, Italy, Austria, The Netherlands and Belgium.

[6]See https://data.worldbank.org/

ing market countries have a track-record of misrepresenting some of their national accounts. A case in point being the dramatic underreporting of inflation by Argentina, as denounced by the International Monetary Fund (2013). In addition to the strictly macroeconomic variables, a time varying "democracy-index" was used to account for the change and variation in institutional quality of the nations inspected throughout this study (Roser, 2019)[7].

4 Methodology

To be able to inspect the veracity of the hypotheses presented in section 2.5, a battery of statistical and econometric tools are employed. This section outlines the motives and reasoning behind each method and describes their workings in a stylized way while simultaneously referring to previous research that utilises similar approaches to relatable inquiries. First, a series of univariate and bivariate regressions will be explained with the aim to capture the initial relationship between the global conflict risk and financial market returns, be them expected or unexpected. Secondly, the cross-section will be explained with Fama-MacBeth (1973) regressions and with portfolio sorts. Third, the effect of the Conflict variable on the level of realized volatility will be outlined, where a GARCH (1,1) model is utilized.

4.1 Relation Between Returns and the Conflict Level

As a preliminary inspection of the relationship between perceived conflict risk and multi asset returns, an univariate panel OLS regression with country high dimensional fixed effects is conducted, based on the method introduced by Correia (2016). This robust method, however elementary, serves as an introductory test that seeks to capture whether there is a significant correlation between the two variables while exploiting within country variations that would be underreported should the sample be aggregated. Additionally, clustered standard errors were utilized so as to account for different standard deviations among countries in the sample. The following model is estimated for the complete sample and the two sub-samples (emerging

[7]The index is updated yearly by the Oxford University. See https://www.oxfordmartin.ox.ac.uk/global-development/

and developed).

$$R_{it} = \eta + \delta Conflict_t + \epsilon_t \tag{2}$$

Where R_{it} is the monthly equity and currency returns in excess of the risk free rate per country, η is the constant, $\delta Conflict$ is the per-country Conflict index and ϵ_t represents the error term. This will allow for the assessment of whether the stock and forex markets are positively or negatively associated to international conflict risk, consistent with the methodology of Berkman et al. (2011).

$$Conflict_t = \eta + \delta Conflict_{t-1} + \epsilon_t \tag{3}$$

Similarly, it is assumed that not all perception of conflict risk can be foreseen or accounted for by investors. Thus, in model 3, the Conflict variable is assumed to follow an autorregressive AR(1) process where the lagged conflict variable is regressed on the standard conflict variable to then extract the residuals of that regression. The residuals represent the fraction of a conflict remains unexplained by the previous conflict value and therefore considered unanticipated. Those error terms are consequently extracted to form an *Unanticipated Conflict* variable that complements the previously described univariate model, resulting in a bivariate one.

$$R_{it} = \mu + \delta AnticipatedConflict_t + \delta UnanticipatedConflict_t + \epsilon_t \tag{4}$$

4.2 Cross Section: Predictability

To assess whether the Conflict Index can predict international stock and currency returns, a combination of Fama-MacBeth (1973) regressions as well as portfolio sorts are used. First, and in tandem with a series of control variables, the country specific conflict Index is used as an independent variable to try to explain excess returns across countries, with the Fama-MacBeth specification. Secondly, the Conflict Index is used to sort quantile portfolios, whose returns are regressed on a series of asset pricing models to further inspect the cross-section of asset returns.

In asset pricing and investment theory, a factor is said to exist whenever diversified portfolios of assets sorted according to a specific criteria can generate abnormal returns without the need of net investment. These arbitrage opportunities are created by short-selling the lowest portfolio and using those proceeds to long the highest portfolio, thus generating an exposure to a particular risk or miss-pricing factor with no initial capital and therefore generating alpha.

In a similar fashion in which Fama and French (1993), Fama and French (2015) and Carhart (1997) identify risk factors that expand the explanatory power of the traditional CAPM by detecting market anomalies, this paper follows the same portfolio sorting approach to analyse whether the returns of portfolios sorted according to their conflict level can generate a significant alpha that is not explained by traditional asset pricing models. For this purpose, the 30 equity indices were sorted on 5 diversified portfolios of 6 indices each, and their average monthly returns were extracted to be used as the left hand side variable and regressed on the CAPM, the Fama & French 3 factor model (1993), the Carhart Four Factor model (1997) and the Fama & French 5 factor model (2015) respectively. The zero net investment conflict portfolio is constructed in a way where the quantile with the highest conflict risk is longed and the one with the least exposure is shorted. The LHS and RHS of the regressions used to inspect the sign and significance of the intercepts are denoted by the previously mentioned linear models.

The models are constructed where the LHS ($R_{Conflict} - rf$) are the excess returns of the equally weighted portfolios sorted according to their conflict value, alpha (α) is the intercept and center of the analysis, R_{SMB}, R_{HML}, R_{CMA} and R_{RMW} are the Fama-French (1993) and (2015) factors accordingly and R_{MOM} is a (12-2) momentum factor also retrieved from the French data library, all with their respective coefficients. From table 4 it is also noticeable that due to the relatively low cross-correlations among the variables, multicolinearity does not present a real threat to biasing the factor loadings of any of the variables. If the four models fail to fully explain the returns generated by this criteria therefore leaving a significant alpha, a conflict anomaly would be identified.

Table 3: Descriptive statistics for the factors and the newly created zero net investment portfolio denoted as Conflict (H-L) for the complete sample of equities and currencies.

Variable	Monthly Eret.	Std. Dev	Min	Max	Cross-Correlations						
	Panel A: Equities				Conflict (H-L)	Mktrf	Smb	Hml	Cma	Rmw	Mom
Conflict (H-L)	0.0081	0.0344	-0.1218	0.1126	1						
Mktrf	0.0032	0.0478	-0.1952	0.1142	-0.1219	1					
Smb	0.0033	0.0201	-0.0861	0.083	-0.0919	0.0204	1				
Hml	0.0066	0.0262	-0.1013	0.1222	0.0073	-0.1625	-0.0855	1			
Cma	0.0054	0.0211	-0.0503	0.098	0.0287	-0.4423	-0.1049	0.7425	1		
Rmw	0.0041	0.0172	-0.0583	0.0641	-0.0257	-0.4906	-0.2491	0.3911	0.3601	1	
Mom	0.0039	0.0433	-0.2425	0.0935	-0.0639	0.0255	-0.0487	-0.0350	0.0184	0.0059	1
Variable	Monthly Eret.	Std. Dev	Min	Max	Cross-Correlatons						
	Panel B: Currencies				Conflict (H-L)	Mktrf	Smb	Hml	Cma	Rmw	Mom
Conflict (H-L)	-0.0016	0.0165	-0.04807	0.0396	1						
Mktrf	0.0032	0.0478	-0.1952	0.1142	0.0926	1					
Smb	0.0033	0.0201	-0.0861	0.083	-0.0416	0.0204	1				
Hml	0.0066	0.0262	-0.1013	0.1222	-0.0142	-0.1625	-0.0855	1			
Cma	0.0054	0.0211	-0.0503	0.098	-0.0359	-0.1049	-0.1049	0.7425	1		
Rmw	0.0041	0.0172	-0.0583	0.0641	-0.0165	-0.2491	-0.2491	0.3911	0.3601	1	
Mom	0.0039	0.0433	-0.2425	0.0935	-0.1474	-0.0487	-0.0487	-0.0350	0.0184	0.0059	1

For the currencies, the very same approach was taken, with the difference that the number of exchange rates is smaller than that of the equities after dropping the exchange rates previously mentioned in the data section. For this reason, and due to the fact that the US and the Eurozone countries are all developed, only 2x portfolios of 4 exchange rates were considered in the developed market subsample. This is similar to the method used by Fama and French (2015) where "Small" and "Big" firms are considered on a 50% split of the data, resulting in a broad separation between High conflict risk and Low conflict risk portfolios.

4.3 Cross-section: Risk Compensation

To thoroughly inspect the existence of risk pricing when it comes to the relation between conflict risk and the equity and currency markets, the same econometric methods as in the previous section were used. First, a series of Fama-MacBeth (1973) regressions were conducted, this time however, the betas of this variable were used as input. Then, portfolio sorts were generated, this time also with the betas rather than the Conflict Index itself. Should there be cross-sectional evidence of conflict risk being priced, then assets with higher exposure to international conflicts showcase higher average returns, indicating that the risk in question is priced by the market.

The Fama-MacBeth approach consists of two separate steps. First, a series rolling and overlapping time-series regressions with a 12 month window are ran, where the equity and currency excess returns are regressed on the Conflict variable together with other country specific control variables that will help measure the conflict effect with greater precision. This model will indicate the risk sensitiveness to the conflict in the cross section of equity and currency returns, in a very similar fashion to what conducted by Berkman et al. (2011).

$$R_{it} = \alpha_{it} + \beta_{it}^{Conflict} Conflict_t + \mathbf{\bar{x_{it}}} \mathbf{b_t} + \epsilon_{it} \tag{5}$$

R_{it} denotes the excess return of an index or currency i at a given month t, $alpha_{it}$ is the intercept, and $conflict$ is the previously outlined country specific conflict variable, all with their respective coefficients. The $\mathbf{\bar{x}_i b_i}$ term is a series of commonly used control variables which change depending on the model specification, followed by a residual term. This first step provides the betas for the conflict variable and the other factors, which will be utilized in the next steps. Before moving on to the final step of the classic Fama-MacBeth procedure, a slight modification is performed, following the methodology of Berkman et al. (2011). The betas for each month and country generated via the rolling regressions are converted into decile ranks, 10 being the highest and 1 the lowest. These ranks are then standardized to restrict the range of the variable between zero and one, and those standardized values are then used for the final crossectional step of the procedure, in order to facilitate the interpretation of the coefficients and increase their robustness.

$$R_{im} = \gamma_m + \gamma_m^{Crsisi} \beta_{it}^{conflict} + \gamma_m \mathbf{\bar{x_{it}}} \mathbf{b_t} + \epsilon_{it} \tag{6}$$

Where R_{im} is the excess return of the asset at a given month and $\beta_{it}^{Conflict}$ represents the rescaled rank of the variable. Finally, the coefficients are averaged taking the shape of a respective γ per factor, yielding their crossectional risk sensitivity. For this last practice, Newey-West (1986) standard errors with three lags were employed to obtain more robust t-statistics.

Further, and as mentioned in the previous subsection, quantile portfolios sorted according to the beta of the conflict variable were generated and the returns regressed on the aforementioned four asset pricing models to inspect the alphas arising from those regressions.

4.4 Realized Volatility

Equally relevant to asset pricing as understanding excess returns, is being able to accurately model the volatility of these returns to better grasp the risks embedded in certain financial securities. International conflicts seem to be an important source of volatility for financial markets, which would suggest a clear pattern of volatility clustering around times of increasing hostility, and a decrease of it in times of a more calm and diplomatic environment.

There are two principal manners to account for volatility when it comes to financial markets: (1) a forward-looking implied volatility, usually calculated by using options on a certain market index to consequently extrapolate this as the expected volatility of that particular market (the Chicago Board Options Exchange Market Volatility Index *VIX* being the most extensively used measure), and (2) realized volatility which is simply the backward-looking historic standard deviation of returns of a particular asset. Ideally, both measures would be put at the service of the analysis in a complementary fashion, using ordinary least squares (OLS) on the natural logarithm of a *VIX* equivalent index and a more sophisticated method for realized volatility. However, due to data availability on options of emerging market country indices, this paper will only regard historic volatility.

With this aim in mind, and following the approach of Berkman et al. (2011) and Schneider (2006), a Generalized Autoregressive Conditional Heteroskedasticity GARCH (1,1) model with the *Conflict Index* as an exogenous variable was deemed the most appropriate to capture the realized volatilities of both equity and currency returns, as described by Engle (2002) and considered robust by Hansen and Lunde (2005) who claim there is no significant evidence that more sophisticated volatility models outperform a GARCH (1,1) when it comes to both equities and exchange rates.

$$(Er_t - rf_t) = \upsilon_t + \alpha_1 ConflictIndex_t + \epsilon_t$$
$$\epsilon_t \sim \mathcal{N}(\mu,\, \sigma^2)\,. \tag{7}$$
$$\sigma_t^2 = \beta_0 + \beta_1 \epsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 ConflictIndex_t + \epsilon_t.$$

This method consists of a two-step estimation where the conditional volatility of the error term of the mean model, once controlled for the *Conflict Index*, is used to establish whether the immediately prior squared residual, immediately prior conditional variance and contemporaneous level of the *Conflict Index* variable can significantly explain contemporaneous conditional variance of the error term. The first line of equation (7) is the mean model from where residuals are extracted, assuming they are normally distributed, and are later used on the second part of the model to determine whether current volatility is affected by past period volatility, where $\beta_1 \epsilon_{t-1}^2$ is the ARCH term with one lag, $\beta_2 \sigma_{t-1}^2$ marks the GARCH term with one lag, and $\beta_3 ConflictIndex_t$ represents the conflict variable which was constructed with its respective coefficient, lastly followed by an error term.

This time series approach to volatility modelling is applied to each country separately, to the whole sample of countries, and finally grouping countries in Emerging and Developed to inspect these effects separately, by averaging the *Conflict variable* across emerging markets, developed economies and the entire dataset resulting in a global conflict variable.

5 Empirical results and discussion

5.1 Preliminary Inspection

A simple OLS regression serves as an introductory test to assess the correlation between returns and the Conflict Index. However rudimentary, it serves as an informal indication. With this purpose, first the coefficients of the Conflict Index variable of the simple regression is inspected, where a positive and significant value would denote that times of crises are on average associated with higher returns, or the opposite should the values be negative and statistically significant.

From Table 4 it is clear that no discernible relation is present between the returns and the conflict variable. With the majority of the coefficients being insignificantly different from zero, little evidence be inferred from it. Despite the fact that the coefficient for the Conflict Index is significant and negative for the Developed equities as well as for the overall currency sample, the magnitude of the coefficient is relatively small, and this pattern is not persistent in the other sub-samples. When adding the Unexpected term to the model, the magnitude of the coefficients is reduced and their explanatory power eliminated, casting doubts about the suitability of the bivariate model, possibly due to collinearity issues between the two variables used.

Table 4: Preliminary univariate and bivariate regression outputs capturing the correlation between the level of conflict risk on excess returns their respective samples.

Variable	Complete Sample	Developed Countries	Emerging Markets
Panel A: Equities			
Conflict Index	-0.001	-0.002*	0.001
t-statistic	(-0.76)	(-1.79)	(0.24)
Intercept	-0.014*	0.003**	0.004
t-statistic	(1.83)	(-2.71)	(0.27)
Panel B: Currencies			
Conflict Index	-0.002**	-0.002	-0.001
t-statistic	(-2.03)	(-1.69)	(-1.61)
Intercept	0.003**	0.000	0.004***
t-statistic	(2.79)	(0.49)	(3.20)
Panel C: Equities			
Conflict Index	0.000	0.006	0.003
t-statistic	(0.007)	(1.39)	(0.40)
Unexpected Risk	0.011	0.001	0.009
t-statistic	(0.75)	(0.23)	(1.09)
Intercept	-0.0085***	0.023	-0.031
t-statistic	(-4.84)	(-1.40)	(-1.46)
Panel D: Currencies			
Conflict Index	-0.001	-0.001	-0.000
t-statistic	(-0.08)	(-0.15)	(-0.66)
Unexpected Risk	-0.079	-0.002	-1.366**
t-statistic	(-1.48)	(-0.84)	(-2.51)
Intercept	0.001	0.003	0.002
t-statistic	(1.17)	(0.38)	(1.35)

Note: *t*-statistics between brackets, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

5.2 Cross Section: Predictability of returns and the Conflict Index

Albeit the correlations found using the *Conflict Index* were relatively inconclusive, further and more elaborate research on the topic might allow for the disentanglement of the conflict effect in the cross section of returns. To see whether cross sectional differences in the Conflict Index yield significant differences in stock and currency returns, the Conflict Index was used to conduct Fama-MacBeth (1973) regressions and to sort diversified portfolios for both the equities and the currencies. This allows for the test of a conflict effect, by inspecting the magnitude, sign and significance of the intercepts and coefficients.

5.2.1 Fama-MacBeth Regressions

Table 5 shows the results of the two step Fama-MacBeth regressions. The different specifications (1 to 4) utilized across asset classes intend to control for omitted variables and therefore present more robust results. There is some evidence that the Conflict Index is an adequate predictor for the complete sample of equities in model 1 and 2 of 0.2% on a monthly level, however this power disappears as more controls are added to the model, possibly indicating that the variable was capturing unintended effects of the error term. For the currencies and the other two subsamples, there appears not to be any evidence to suggest that the conflict variable can predict excess returns internationally. Additionally, the control variables are also insignificant, signalling that the model fit could be improved so as to present a more accurate depiction of the cross-section.

In the light of the weak evidence in favour of the Conflict Index and the insignificance of the coefficients of many control variables, portfolio sorts are conducted to further disentangle the effect in the cross section.

5.2.2 Portfolio Sorts

As far as the portfolio sorts of equities are concerned, Table 6 exhibits the results for alphas of the complete sample composed of 30 countries, the developed markets, as well as for the emerging market subsample which will be analyzed in turn. For the *Complete Sample*,

Table 5: Fama-MacBeth regressions output with Conflict Index.

	Equities				Currencies			
Variable	1	2	3	4	1b	2b	3b	4b
Panel A: Complete Sample								
Conflict Index	0.002*	0.002*	0.007	0.0008	0.0002	0.0004	-0.006	-0.0005
t-statistic	(1.65)	(1.82)	(0.49)	(0.56)	(0.18)	(0.30)	(-0.49)	(-0.37)
ln(GDP)			0.03	0.03			0.011	-0.006
t-statistic			(1.46)	(1.44)			(0.29)	(-0.01)
3 Month Interbank Rate			0.04	0.04			0.006**	0.006**
t-statistic			(1.41)	(1.31)			(2.45)	(2.42)
CPI			0.06***	0.06***			-0.03	-0.014
t-statistic			(3.01)	(3.20)			(-0.02)	(-0.07)
Democracy		-0.001		0.0005		-0.0007		-0.001*
t-statistic		(-0.07)		(0.20)		(-0.15)		(-1.71)
Intercept	0.0009	0.008	-0.002	-0.002	-0.003	-0.006	-0.04*	-0.03
t-statistic	(0.23)	(0.24)	(-0.57)	(-0.69)	(-0.15)	(-0.30)	(-1.95)	(-1.52)
Average r2	0.03	0.14	0.19	0.2	0.06	0.08	0.32	0.34
N of Obs	5460	5460	5460	5460	3910	3910	3910	3910
Panel B: Developed Countries								
Conflict Index	0.001	0.0007	0.0002	0.0003	-0.005	-0.006	-0.003	-0.004
t-statistic	(0.50)	(0.42)	(0.14)	(0.13)	(-0.20)	(-0.21)	(-0.84)	(-0.96)
ln(GDP)			0.03	0.03			-0.024	-0.05
t-statistic			(1.34)	(1.36)			(-0.56)	(-1.02)
3 Month Interbank Rate			0.012	0.015			0.024	0.016
t-statistic			(0.20)	(0.25)			(0.27)	(0.17)
CPI			-0.08	-0.015			0.17	-0.029
t-statistic			(-0.28)	(-0.50)			(0.42)	(-0.06)
Democracy		0.001		0.016		0.011		0.006
t-statistic		(0.64)		(0.84)		(1.23)		(0.66)
Intercept	-0.001	-0.01	-0.003	-0.018	-0.001	-0.1	-0.002	-0.064
t-statistic	-0.15	(-0.62)	(-0.40)	(-0.87)	(-0.48)	(-1.24)	(-0.29)	(-0.63)
Average r2	0.07	0.1	0.35	0.38	0.14	0.22	0.66	0.73
N of Obs	2730	2730	2730	2730	1360	1360	1360	1360
Panel B: Emerging Markets								
Conflict Index	0.015	0.0004	0.001	0.0007	0.0005	-0.007	0.0008	0.003
t-statistic	(0.77)	(0.18)	(0.63)	(0.30)	(0.35)	(-0.40)	(0.40)	(1.06)
ln(GDP)			-0.008	0.03			-0.05	-0.009*
t-statistic			(-0.01)	(0.03)			(-1.28)	(-1.78)
3 Month Interbank Rate			0.04	0.015			0.038	0.05
t-statistic			(1.11)	(0.41)			(1.26)	(1.30)
CPI			0.07**	0.07**			0.16	-0.013
t-statistic			(2.18)	(2.44)			(0.49)	(-0.30)
Democracy		0.0005		0.0002		0.0003**		0.00001
t-statistic		-1.46		(0.70)		(2.12)		(0.10)
Intercept	0.006	0.005	-0.01	0.0002	0.02	0.002	-0.002	-0.003
t-statistic	(1.19)	(1.15)	(-0.15)	(0.03)	(0.65)	(0.82)	(-0.73)	(-0.51)
Average r2	0.05	0.18	0.34	0.45	0.12	0.29	0.59	0.7
N of Obs	2730	2730	2730	2730	2550	2550	2550	2550

Note: *t*-statistics between brackets, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

it is noticeable that the intercepts turn less negative as the portfolios increase in the Conflict Index for the four models used. This almost monotonic relation indicates that portfolios composed of equities with a higher value of Conflict Index generate on average higher returns than those with lower values for the variable in question. Most importantly, the furthest right column (H-L) shows the alpha of the zero net investment portfolio. These alphas are positive and significant for all four models, the largest being that associated with the CAPM. It should be noted that both the significance and the magnitude of the zero net investment portfolio alphas are reduced as the models increase in RHS variables from Panel A to Panel D.

Further on to the *Developed Markets*, the alphas show a similar pattern to that of the complete sample, yet it appears that the difference between the Low and the High portfolios are not statistically significant to exhibit meaningful alphas for any of the models. This suggests that the CAPM, Three Factor, Four Factor and Five Factor model adequately explain the returns of the developed markets, leaving no alpha to be captured. This is not surprising, given that richer countries usually have more integrated and efficient financial markets where outperforming has become increasingly difficult (Bekaert et al., 2007). On the bottom section of the same table, evidence for the *Emerging Markets* is presented. This case is particularly akin to that of the overall sample. In this instance, the alphas do not increase as monotonically as in the complete sample, but the 5-1 alphas are on average larger and more significant. As mentioned, the equity markets of emerging economies usually contain more market imperfections and anomalies are less traded on, leaving room for the capturing of alphas that would otherwise be eliminated.

Regarding the foreign exchange market, Table 7 depicts the results of the intercepts across portfolios, generated by the same models used on the equities. The *Complete Sample* presents mostly positive alphas, as opposed to the equities section which was marked by a generally below zero factor, yet they are largely insignificant at a 10% level. The alphas associated to the 5-1 portfolios are also insignificant and positive, but it is relevant to note that the High portfolios present positive and significant alphas for all models except for the CAPM, which eliminates it completely. Concerning the *Developed Markets*, no statistical significance is present in any of the intercepts for the High or Low portfolios, nor for the H-L counterpart.

These ambiguous results can potentially be explained by the under-discrimination in the process of portfolio separation. Halving the data in half might not be the most adequate manner to separate the currencies, yet it was deemed the most appropriate mean to deal with the Euro appropriation and the U.S dollar being the reference currency. On to the last section, the *Emerging Markets* currencies present a less straight forward development of the alphas. No clear (decreasing or increasing) pattern is discernible across the quantiles, and the zero net investment alphas are all negative and statistically insignificant. Similarly to what reported for the complete sample, however, the alphas of the highest portfolio are also all positive and significant at the 10% level.

In light of the results provided by the portfolio Fama-MacBeth regressions as well as the portfolio sorts, the evidence is rather weak to support the existence of predictability across the cross section by using the Conflict Index. At least, if looking at both asset classes, and considering that the results are not robust to the two testing methods. There is stronger evidence suggesting some effect in the Emerging Market equities stemming from the portfolio sorts, but this outcome is not consistent with the Fama-Macbeth regressions. This is a surprising finding as currencies were expected to react more strongly to the conflict variable and to the news coverage of them.

Consequently, hypothesis 1a is rejected and hypothesis 1b only confirmed for the stock market, however with discretion, and based mostly on the portfolio sort returns. These results are consistent with what was found by Bailey and Chung (1995), where they reported the presence of an equity premium for political risk in emerging markets, but nothing at all for the developed world. They give the example of countries such as the Philippines and Thailand, where democratization processes and demilitarizations drastically harmed big corporations and monopolies with close ties to the military and respective governments. Further, they argue that this could be given by mostly importing firms not being able to hedge currency fluctuations in a cost effective manner, adversely affecting importers in local depreciations, and benefiting them in appreciations. Thus, those shares might show an ex-ante premium for uncertainty risk. Political risk can have a similar impact by affecting firms with a high degree of foreign financing, foreign suppliers, or any international relation of dependency which might expose them to adverse changes in those affiliations.

Table 6: Alphas of the equities sorted portfolios according to their conflict level

Complete Sample Equities						
	Low	(2)	(3)	(4)	High	(H-L)
Panel A: CAPM alphas						
Alpha	-0.008***	-0.001	-0.001	-0.003	-0.000	0.008***
t-statistic	(-3.29)	(-0.26)	(-0.23)	(-1.06)	(-0.15)	(2.98)
Panel B: Three Factor alphas						
Alpha	-0.009***	-0.002	-0.001	-0.003	-0.002	0.007**
t-statistic	(-3.53)	(-0.61)	(-0.44)	(-1.09)	(-0.92)	(2.58)
Panel C: Four Factor alphas						
Alpha	-0.009***	-0.002	-0.002	-0.004	-0.002	0.006**
t-statistic	(-3.46)	(-0.69)	(-0.52)	(-1.12)	(-0.97)	(2.48)
Panel D: Five Factor alphas						
Alpha	-0.008***	-0.002	-0.001	-0.003	-0.002	0.005*
t-statistic	(-2.89)	(-0.74)	(-0.41)	(-1.09)	(-1.01)	(1.89)
Developed Market Equities						
Panel A: CAPM alphas						
Alpha	-0.006*	-0.06	-0.003	-0.007*	-0.004	0.003
t-statistic	(-1.67)	(-1.63)	(-0.70)	(-1.74)	(-0.94)	(1.04)
Panel B: Three Factor alphas						
Alpha	-0.005	-0.008*	-0.002	-0.06*	-0.003	0.002
t-statistic	(-1.43)	(-1.89)	(-0.74)	(-1.66)	(-0.82)	(0.87)
Panel C: Four Factor alphas						
Alpha	-0.006	-0.007*	-0.003	-0.007*	-0.003	0.003
t-statistic	(-1.41)	(-1.88)	(-0.71)	(-1.69)	(-0.77)	(0.91)
Panel D: Five Factor alphas						
Alpha	-0.005	-0.008*	-0.003	-0.008*	-0.004	0.001
t-statistic	(-1.22)	(-1.76)	(-0.76)	(-1.87)	(-0.93)	(0.41)
Emerging Market Equities						
Panel A: CAPM alphas						
Alpha	-0.006*	0.001	0.003	-0.004	0.004	0.009**
t-statistic	(-1.82)	(0.40)	(0.86)	(-1.07)	(1.29)	(2.45)
Panel B: Three Factor alphas						
Alpha	-0.008**	-0.000	0.000	-0.004	0.002	0.008**
t-statistic	(-2.30)	(-0.04)	(0.06)	(-1.09)	(0.52)	(2.23)
Panel C: Four Factor alphas						
Alpha	-0.007**	-0.000	0.001	-0.004	0.001	0.009**
t-statistic	(-2.36)	(-0.13)	(0.03)	(-1.17)	(0.40)	(2.18)
Panel D: Five Factor alphas						
Alpha	-0.006**	-0.001	0.002	-0.004	0.002	0.008**
t-statistic	(-1.98)	(-0.24)	(0.58)	(-1.10)	(0.60)	(1.98)

Note: *t*-statistics between brackets, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 7: Alphas of the currencies sorted portfolios according to their conflict level

Complete Sample Currencies						
	Low	(2)	(3)	(4)	High	(H-L)
Panel A: CAPM alphas						
Alpha	0.001	0.001	0.001	0.000	0.002	0.002
t-statistic	(0.47)	(0.68)	(0.29)	(0.19)	(1.56)	(1.39)
Panel B: Three Factor alphas						
Alpha	0.002	0.001	0.001	0.001	0.003**	0.002
t-statistic	(0.88)	(0.70)	(0.72)	(0.69)	(1.85)	(1.21)
Panel C: Four Factor alphas						
Alpha	0.002	0.001	0.002	0.001	0.003**	0.01
t-statistic	(1.07)	(0.64)	(0.79)	(0.68)	(1.88)	(1.02)
Panel D: Five Factor alphas						
Alpha	0.001	0.000	0.001	0.000	0.002*	0.002
t-statistic	(0.50)	(0.02)	(0.41)	(0.24)	(1.62)	(1.39)

Developed Market Currencies			
	Low	High	(H-L)
Panel A: CAPM alphas			
Alpha	-0.002	-0.001	-0.00
t-statistic	(-0.90)	(-0.89)	(-0.20)
Panel B: Three Factor alphas			
Alpha	-0.001	-0.001	-0.000
t-statistic	(-0.61)	(-0.53)	(-0.01)
Panel C: Four Factor alphas			
Alpha	-0.001	-0.001	0.000
t-statistic	(-0.61)	(-0.42)	(0.19)
Panel D: Five Factor alphas			
Alpha	-0.002	-0.002	-0.000
t-statistic	(-0.78)	(-0.80)	(-0.21)

Emerging Market Currencies						
	Low	(2)	(3)	(4)	High	(H-L)
Panel A: CAPM alphas						
Alpha	0.001	0.002	0.003	0.004	0.003*	0.002
t-statistic	(0.82)	(1.02)	(1.55)	(1.57)	(1.94)	(1.03)
Panel B: Three Factor alphas						
Alpha	0.002	0.001	0.003*	0.005**	0.003*	0.001
t-statistic	(1.31)	(0.93)	(1.80)	(2.14)	(1.92)	(0.45)
Panel C: Four Factor alphas						
Alpha	0.003	0.002	0.003*	0.005**	0.003*	0.001
t-statistic	(1.42)	(0.99)	(1.86)	(2.18)	(1.93)	(0.34)
Panel D: Five Factor alphas						
Alpha	0.002	-0.000	0.003	0.004*	0.003*	0.001
t-statistic	(0.86)	(-0.03)	(1.52)	(1.88)	(1.64)	(0.68)

Note: t-statistics between brackets, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

5.3 Cross-sectional analysis: Risk Compensation

In order to adequately assess the presence and pricing of conflict risk in the cross section of equity and currency returns, the same Fama-Macbeth and portfolio sorts methods are applied, but with the exposure to the betas. This will allow for the assessment of compensation for the risk entailed in trading said assets with a higher exposure to the conflict variable.

5.3.1 Fama-MacBeth Regressions

The presence of conflict or crisis risk in the cross section of equity and currency returns is evaluated firstly with a two-step Fama & MacBeth (1973) approach as described in the methodology section where the dependent variables is the excess returns of the equity indices and the country exchange rates to the U.S dollar. Firstly, the sensitivity of the equity indices and the currencies is estimated for each month with the aid of the rolling regressions with a forming window of 12 months. For the sake of obtaining betas for the first observations of 2000, data was gathered for all variables from January 1999 onward. After the transformation of the betas into deciles and their corresponding [0,1] standardization, these values are used for the second and final step of the regressions. In a monthly manner, the excess returns are then regressed on the sensitivities of a series of control variables and on the modified conflict risk sensitivities, in accordance with Berkman et al. (2011). The time-series means of the coefficients, as well as their t-statistics, model average R^2 and observations for equities and currencies and their respective sub-samples are reported on Table 8.

Starting with the equities, column 1 of Table 8 reports a model where only the sensitivity to the Conflict Index is used. The coefficient is highly insignificant for the complete sample, as well as for the emerging and developed subsamples. Column 2 is an expansion of the first model, where the Democracy variable described in the methodology section is used as a control variable, in an attempt to capture the institutional quality of the country and form a political risk model. The coefficients are again insignificant for all equity samples. Column 3 ads the natural logarithm of GDP in a order to control for the size of a country's economy, in an attempt to extrapolate the ln(size) used in Fama and French (1993), as well as the monthly average of the 3 month interbank rate and the inflation rate of that nation, generating a model that controls for macroeconomic factors. All variables appear to be insignificant, except for the interbank rate which is negative and significant at the 10% level for both the whole sample and the emerging market subsample. Moving to the right, Column 4 utilizes all the variables in a complete model. In this case, the interbank rate as well as the democracy variable appear to be negatively yet marginally (less than 0.2%) associated to the excess returns in the overall and emerging sample. This which could be explained by the rising opportunity costs for financial institution's holding securities.

The furthest right section of the table repeats the procedure but for the currencies of the sample. The number of observations is reduced due to the issue of the Euro and the U.S Dollar, but this does not appear to alter the results significantly, when compared to equities. In fact, it is surprisingly analogous. In the first model, (column 1b), the Conflict Index is not significant and nor is the intercept. In the second model, the variable remains insignificant, yet Democracy appears to be negative and significant at the 10% level, in an extremely similar magnitude to that of the equities for all samples. Equally, column 3b depicts an almost identical situation to that of the equities, where the 3 month interbank rate is marginally negative and significant for the complete and emerging market samples, and the picture is repeated once more in column 4b, where the 3 month interbank rate and the democracy variable remain negative and significant for the complete and emerging sample, yet their magnitude is reduced.

Importantly, the Conflict Index is never significant, regardless of the specification of the model, the asset class, and the level of development of the country, diminishing support for Hypotheses 2a and 2b implying that the conflict risk is not sufficiently priced in the cross section of international equities and currencies. The explicit insignificance of the conflict coefficient can have several reasons. The composition and constituencies of the country equity indices might vary substantially throughout countries, resulting in some industries that might be relatively insensible to conflict risk being over or under represented in the overall sample. Additionally, the Fama-MacBeth method uses error loaded and estimated betas as inputs in a new model, therefore biasing the results of the last step, and there has been evidence that the approach performs poorly when the absolute values of the betas are relatively small (Khalaf & Schaller, 2011).

Table 8: Fama-MacBeth regressions results with exposure to Conflict Index (β)

	Equities				Currencies			
Variable	1	2	3	4	1b	2b	3b	4b
Panel A: Complete Sample								
bets_Conflict Index	-0.002	-0.0037	-0.0007	-0.0026	-0.0016	-0.0038	-0.0004	-0.0026
t-statistic	(-0.79)	(-1.29)	(-0.27)	(-0.77)	(-0.49)	(1.01)	(-0.13)	(-0.59)
ln(GDP)			0.00	-0.0000			-0.0001	-0.0001
t-statistic			(0.34)	(-0.68)			(-0.70)	(-0.67)
3 Month Interbank Rate			-0.0017*	-0.0031**			-0.0002*	-0.00037****
t-statistic			(-1.73)	(-2.41)			(-1.75)	(-2.63)
CPI			-0.0002	-0.0002			-0.0001	-0.0001
t-statistic			(-1.49)	(-1.49)			(-0.97)	(-0.82)
Democracy		-0.0236*		-0.0384*		-0.022*		-0.0033*
t-statistic		(-1.88)		(-1.95)		(-1.72)		(-1.67)
Intercept	0.0043	0.0039	0.0044	0.0056	0.0055	0.0067	0.0051	0.0062
t-statistic	(1.09)	-0.96	(1.19)	(1.59)	(1.36)	(-1.70)	(1.35)	(1.63)
Average R^2	0.07	0.08	0.19	0.24	0.06	0.12	0.21	0.28
Number of observations	5280	5280	5280	5280	4048	4048	4048	4048
Panel B: Developed Countries								
bets_Conflict Index	-0.001	-0.0003	-0.0017	-0.0009	-0.0043	-0.0011	-0.0024	-0.0005
t-statistic	(-0.62)	(0.08)	(-0.74)	(-0.27)	(-1.39)	(-0.27)	(-0.65)	(-0.08)
ln(GDP)			0.00	0.0003			0.0001	0.0001
t-statistic			(0.93)	(1.00)			(0.32)	(0.41)
3 Month Interbank Rate			0.0002	0.0001			0.0002	-0.0001
t-statistic			(1.13)	(0.42)			(1.62)	(-0.03)
CPI			-0.0001	-0.0002			-0.0006	0.0001
t-statistic			(-1.36)	(-1.36)			(-0.34)	(0.47)
Democracy		0.016		0.029		0.0026		0.0055
t-statistic		(0.56)		(0.60)		(0.67)		(0.57)
Intercept	0.0003	-0.0001	0.0021	0.0019	0.0022	0.0067*	0.0048	0.0029
t-statistic	(0.08)	(-0.03)	(0.53)	(0.44)	(0.54)	(1.70)	(1.30)	(0.63)
Average R^2	0.09	0.20	0.34	0.44	0.16	0.34	0.60	0.73
Number of observations	2640	2640	2640	2640	1408	1408	1408	1408
Panel C: Emerging Markets								
bets_Conflict Index	0.0012	-0.0009	-0.0003	-0.0026	0.00123	-0.0009	-0.0003	-0.0026
t-statistic	(0.23)	(-0.15)	(-0.06)	(-0.46)	(0.23)	(-0.15)	(-0.06)	(-0.46)
ln(GDP)			0.00	-0.001			0.0002	-0.000
t-statistic			(0.54)	(-0.14)			(0.54)	(-0.14)
3 Month Interbank Rate			-0.0006**	-0.0008**			-0.0006**	-0.0078**
t-statistic			(-2.57)	(-2.55)			(-2.27)	(-2.55)
CPI			-0.0001	-0.0002			-0.0001	-0.0003
t-statistic			(-0.56)	(-0.83)			(-0.56)	(-0.83)
Democracy		-0.0192		-0.058*		-0.020		-0.0057*
t-statistic		(-1.18)		(-1.91)		(-1.18)		(-1.91)
Intercept	0.0066	0.0074	0.0065	0.0073	0.0055	0.0074	0.0064	0.007
t-statistic	(1.40)	(1.58)	(1.43)	(0.49)	(-1.40)	(1.56)	-1.43	(1.57)
Average R^2	0.08	0.18	0.34	0.42	0.08	0.18	0.35	0.43
Number of observations	2640	2640	2640	2640	2640	2640	2640	2640

Note: t-statistics between brackets, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

5.3.2 Portfolio Sorts

After obtaining the exposure to the Conflict Index in the shape of rolling betas, these betas can be used to sort portfolios in the same way that the actual Index was used in the previous section to further verify the results obtained from the previous section in Table 8. It is clear from Table 9, that there appears not to be any sort of risk compensation for the stock market in neither of the development levels nor globally. This is evident by regarding the insignificance of the alphas across portfolios generated by the 4 distinct asset pricing models. In addition, the intercepts do not show a clear increasing or decreasing pattern through quantiles that would indicate any sort of evidence in favour of this hypothesis. This subsequently suggests that political risk is not priced in the cross section of equity returns.

The same exercise was performed for the FX market with the same distinctions, as shown in Table 10. This picture is somewhat different from the one depicted by equities, as there appears to be some significance in the alphas, specially in the zero net investment portfolio created by longing the higher betas and shorting the lower betas to the Conflict Index. The magnitude of the coefficients, however, are minuscule of a maximum of -0.06% monthly. This effect is again present in the overall sample of currencies as well as in the emerging market sample, signalling that the driving force for the phenomenom originates in developing nations rather than in the developed world where no effect is discernible.

With the portfolio sorts as well as the Fama-MacBeth results in mind, there is no evidence to suggest that conflict risk is being priced for the international equity markets. With regard to the currencies however, there appears to be some evidence indicating that exchange rates with higher betas to the conflict variable are negatively compensated for, and especially again among the emerging economies. As a result, there is no significant evidence to indicate risk compensation for the exposure to the conflict variable in the financial markets overall, but rather only within the currency subsabmple, therefore hypotheses 2a and 2b are simultaneously rejected.

Table 9: Alphas of the equity portfolio sorts according to their exposure to the conflict variable.

	Low	2	3	4	High	(H-L)
Complete Sample Equities						
Panel A: CAPM Alphas						
Alpha	0.003	0.005	0.003	0.004	0.001	-0.002
t-statistic	(0.87)	(1.56)	(0.98)	(1.1)	(0.34)	(-0.53)
Panel B: Three Factor Alphas						
Alpha	0.005	0.006*	0.004	0.005	0.002	-0.005
t-statistic	(1.60)	(-1.68)	(1.27)	(1.37)	(0.31)	(-1.31)
Panel C: Four Factor Alphas						
Alpha	0.005	0.005	0.003	0.004	0.0002	-0.005
t-statistic	(1.47)	(1.52)	(1.10)	(1.20)	(0.07)	(-1.43)
Panel D: Five Factor Alphas						
Alpha	0.007*	0.006*	0.005	0.006	0.003	-0.004
t-statistic	(1.83)	(1.93)	(1.52)	(1.60)	(0.67)	(-1.15)
Developed Markets Equities						
Panel A: CAPM Alphas						
Alpha	-0.004	-0.002	-0.001	-0.002	-0.002	-0.0018
t-statistic	(-0.10)	(-0.66)	(-0.14)	(-0.57)	(-0.56)	(-0.81)
Panel B: Three Factor Alphas						
Alpha	-0.002	-0.003	-0.002	-0.003	-0.004	-0.001
t-statistic	(-0.43)	(-0.99)	(-0.55)	(-0.70)	(-0.91)	(-0.81)
Panel C: Four Factor Alphas						
Alpha	-0.003	-0.004	-0.003	-0.004	-0.005	-0.002
t-statistic	(-0.62)	(-1.23)	(-0.79)	(-0.98)	(-1.17)	(-0.94)
Panel D: Five Factor Alphas						
Alpha	-0.002	-0.002	-0.001	-0.002	-0.003	-0.0015
t-statistic	(-0.27)	(-0.65)	(-0.18)	(-0.53)	(-0.62)	(-0.60)
Emerging Markets Equities						
Panel A: CAPM Alphas						
Alpha	0.002	0.01***	0.008**	0.006	0.004	0.002
t-statistic	(0.58)	(3.20)	(2.53)	(1.57)	(1.02)	(0.25)
Panel B: Three Factor Alphas						
Alpha	0.001	0.01***	0.006*	0.005	-0.0003	-0.001
t-statistic	(0.21)	(2.94)	(1.76)	(1.28)	(-0.08)	(-0.21)
Panel C: Four Factor Alphas						
Alpha	0.001	0.01***	0.005	0.005	-0.0008	-0.002
t-statistic	(0.22)	(3.05)	(1.62)	(1.23)	(-0.20)	(-0.29)
Panel D: Five Factor Alphas						
Alpha	0.0001	0.01***	0.005	0.007*	-0.007	-0.0008
t-statistic	(0.02)	(2.91)	(1.44)	(1.87)	(-0.18)	(-013)

Note: t-statistics between brackets, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 10: Alphas of the currency portfolio sorts according to their conflict variable exposure.

Complete Sample Currencies

	Low	2	3	4	High	(5-1)
Panel A: CAPM Alphas						
Alpha	0.003	0.0001	0.001	0.001	-0.001	-0.004**
t-statistic	(1.32)	(0.55)	(0.50)	(0.76)	(-0.75)	(-2.42)
Panel B: Three Factor Alphas						
Alpha	0.003	0.002	0.0009	0.001	-0.007	-0.0048*
t-statistic	(1.32)	(1.08)	(0.63)	(0.86)	(-0.33)	(-1.96)
Panel C: Four Factor Alphas						
Alpha	0.003	0.002	0.001	0.002	-0.001	-0.004*
t-statistic	(1.33)	(1.11)	(0.81)	(1.08)	(-0.31)	(-1.95)
Panel D: Five Factor Alphas						
Alpha	0.0006	0.001	0.001	0.001	-0.0007	-0.001
t-statistic	(0.26)	(0.79)	(0.71)	(0.80)	(-0.35)	(-0.71)

Developed Markets Currencies

	Low	High	(H-L)
Panel A: CAPM Alphas			
Alpha	-0.002	-0.02	-0.0002
t-statistic	(-0.89)	(-1.10)	(-0.23)
Panel B: Three Factor Alphas			
Alpha	-0.001	-0.002	-0.0007
t-statistic	(-0.54)	(-0.98)	(-0.68)
Panel C: Four Factor Alphas			
Alpha	-0.0009	-0.002	-0.008
t-statistic	(-0.46)	(-0.92)	(-0.72)
Panel D: Five Factor Alphas			
Alpha	-0.002	-0.003	-0.001
t-statistic	(-0.67)	(-1.23)	(-0.86)

Emerging Markets Currencies

	Low	2	3	4	High	(5-1)
Panel A: CAPM Alphas						
Alpha	0.007**	0.002	0.0007	0.002	0.0008	-0.006**
t-statistic	(2.38)	(1.62)	(0.62)	(0.99)	(0.41)	(-2.16)
Panel B: Three Factor Alphas						
Alpha	0.007**	0.003**	0.001	0.002	0.001	-0.006*
t-statistic	(2.31)	(2.20)	(0.76)	(1.26)	(0.63)	(-1.93)
Panel C: Four Factor Alphas						
Alpha	0.007**	0.004**	0.002	0.002	0.001	-0.006*
t-statistic	(2.32)	(2.25)	(1.04)	(1.45)	(0.62)	(-1.94)
Panel D: Five Factor Alphas						
Alpha	0.003	0.003*	0.001	0.002	0.002	-0.0007
t-statistic	(0.97)	(1.90)	(0.86)	(1.07)	(1.01)	(-0.25)

Note: t-statistics between brackets, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

5.4 Realized Volatility and the Conflict Index

As described in the methodology sections, the realized volatility of the selected country indices individually, as well as grouped according to their development level and in a general fashion was inspected with the aid of a GARCH (1,1) model with the added *Conflict Index* as the exogenous variable. The model employed, however backward looking in nature, presents important insights which do not deviate from the previously obtained results, particularly when the two steps of this model are inspected in turn. The same process was applied to the exchange rates.

With regard to the equity indices, the first step of the models, presented under the *mean* columns on Table 11 shows that the conflict variables are not associated with a significant effect on the mean excess return of the different country equity indices in the aggregated level (developed, emerging, all), which supports the little evidence of the same variable being able to explain the cross section of returns as shown in previous sections. Moving to the second step of the model, presented under the *Variance* columns, it is observable that both the ARCH and GARCH terms are usually highly significant which suggests the existence of conditional heteroskedasticity for most of the equity indices. However, as most of the coefficients for the mean models are insignificant, the results from the variance models have to be regarded with caution, as they might be biased and therefore no serious interpretation can be elucidated from them.

As far as the exogenous *conflict* variable is concerned, little can be inferred. With the vast majority of the coefficients being statistically indistinguishably different from zero and with the countries that happen to present statistically significant coefficients having opposing sings, no concrete conclusion can be deduced from these results (see appendix for a detailed version of Table 11 where countries are accounted for separately). This implies that international conflicts generally do not affect the market volatility of the countries involved in them, with some exceptions which have to regarded in a case-by-case manner, as it is apparent that conflicts have a positive effect on the volatility of countries such as Spain, but quite a negative one on Argentina, Japan, and Pakistan. This could be explained by differences in investor preferences and interpretations to a period of relative geopolitical instability. The aggravation of a conflict could be seen by investors more present in some countries as the consolidation of this process leading to reduced volatility, while the opposite could be inferred by investors in other countries where a higher conflict term is associated with more drastic market movements.

With regard to the currencies and FX market, the results are reasonably analogous to those of the equities. It is observable in Table 17 (See appendix) that most of the mean models suffer from insignificance concerning their coefficients, hence again casting doubts about the reliability of the variance models that exert from them. Equally to what was reported under the equities, the exogenous *Conflict* variable does not appear to significantly explain the countries exchange rate returns for the vast majority of cases. In the occasions where the variable is significant, its sign changes from country to country, backing what was previously found about different investors reacting to perceived conflict risk in dissimilar manners. South Korea, for instance shows a positive and significant coefficient of 1.73, as was expected. However, the case of India shows the opposite picture, with a negative and significant coefficient of -0.22.

This inconclusive series of results which unequivocally refute hypothesis 3 are surprising given the considerable presence that international conflicts have on the financial press. It appears that investors responses to an aggravating conflict is not internationally homogeneous, but mostly, the markets seemingly do not turn significantly more turbulent as a conflict unfolds. At the same time, these results could be attributed to the GARCH models fitting the data in a poor manner due to the residuals not following a normal distribution, or due to the presence of serial correlation in the residual term. These two aspects would render the models inconsistent and could therefore explain the unambiguous behaviour of the coefficients outlined in Table 16 for equities and 17 (see appendix) for currencies. However, there appears to be evidence suggesting that both the equities and currency markets are marked by GARCH (1) and ARCH(1) processes, as these variables are on average highly significant.

Table 11: GARCH(1,1) output for equities and currencies.

	Mean		Variance			
	Intecept	conflict	Intercept	$\beta 1$	$\beta 2$	conflict
Panel A: Equities						
All Sample	-0.003	0.02	-6.37	0.15	0.76***	-2.00
t-statistic	(-1.94)	(2.16)	(-1.61)	(1.62)	(5.33)	(0.74)
Developed Countries	-0.01	0.000	-5.03***	0.34**	0.44**	-1.10
t-statistic	(-1.01)	(1.12)	(2.60)	(2.55)	(2.38)	(-1.36)
Emerging Markets	-0.01	0.000	-6.32***	0.27**	0.56***	-0.66
t-statistic	(-0.63)	(0.99)	(3.08)	(2.94)	(5.24)	(-0.68)
Panel B: Currencies						
All Sample	0.01	-0.01	-7.04***	0.44***	0.19*	-2.00
t-statistic	(0.86)	(-0.70)	(-2.14)	(3.09)	(1.61)	(-0.74)
Developed Countries	-0.01	-0.000	-7.74***	0.19	0.32	-0.25
t-statistic	(-0.09)	(-0.66)	(-8.55)	(1.40)	(0.76)	(-0.64)
Emerging Markets	0.10	-0.001*	-4.65***	0.07	0.47	-0.148***
t-statistic	(1.46)	(-1.70)	(-5.12)	(0.95)	(1.47)	(-3.95)

Note: t-statistics between brackets,$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

6 Robustness

It is paramount to assess the degree of robustness of the results outlined in the previous sections. Embeded in the research, there are elements which can be used to determine the sensitivity of the reuslts, and consequently the validity and ability to extrapolate these outcomes further.

First, this study looks at different asset classes and further segregates them according to the level of development to precisely act as a robustness check. The results differ across equities and currencies, where equities show a stronger effect in the Conflict Index level portfolio sorts, specially driven by the Emerging Market subsample. Similarly, the compensation of risk tests showed that currencies with higher exposure to conflict variable have a slightly stronger negative coefficient than those of the equities, even if the trend is not monotonous. These factors show that not all asset classes behave identically as far as their response to international crises, and therefore should be accounted for individually as many times they act as substitutes of each other. Equally, even within the asset classes, it is observable that different markets behave differently. This signals that global financial markets are yet not fully integrated and can present different characteristics to the same phenomenon, again stressing the importance of discerning among them.

To further strengthen the validity of the results presented in this paper, a series of variations are applied to the previously explained results to assess how sensitive those results are to different alterations in estimation methods as well as sample selection. First and foremost, by looking at different asset classes throughout different levels of development (EME vs developed), this acts as a robustness indicator to whether the issue is relatable to different investment vehicles. In the case at hand, the equities tend to have a stronger effect than currencies and the effect tends to be stronger in emerging markets. This casts some doubts upon the degree of extrapolation of the results to other asset classes, specially in the developed world.

The fact that the Fama-MacBeth regression results do not fully support some of the portfolio sort findings is an issue that weakens the implications of these later results. This could be rooted in a variety of reasons. On the one hand, it is observable in Table 5 that the Conflict index has some power of predictability when used in isolation, which would support the portfolio sorting results, but loses that strength when control variables are included in the model. The improvable fit of the model could be tackled by better variable selection which would in turn allow for each variable to capture its own effect. Further, by relying on Newey-West standard errors, the coefficients are not corrected for. By rather resorting to the Shenken correction, the intercepts would also be modified accordingly, possibly presenting a more accurate picture. A critical element of this research is the ad-hoc construction of the Conflict Index and whether this is a reasonable proxy for reality. In a descriptive attempt to validate this, Figure 1 casts informal evidence in its favour. To formally assess the issue, a Suprenum Wald structural break test was conducted on the Index for the U.S, showing a structural break in the time series in the month 9 of 2001, perfectly coinciding with the 9/11 attacks on U.S soil and the subsequent trail of armed conflicts that followed the ongoing "war on terror" (Table 13 in the Appendix). This portrays the scale as robust and an adequate Representative of the degree of international hostility. However, by using one time period only, it is being assumed that the conflict risk premium is constant over time, when it might be more present in some periods than in others.

Additionally, a series of different asset pricing models were used to test the portfolio sorts alphas and a number of different models with distinct macroeconomic variables were employed for the Fama-MacBeth regressions which all showed consistent results. Further, the initial correlation assessment was also estimated without the country specific fixed effects but rather averaging out results and Conflict Index conflict as reported in Table 18 in the Appendix, and the second set of Fama-MacBeth regressions were also performed without the re-scaling of the betas, with analogous results reported in Table 18 in the appendix. Overall the results seem to be robust to the tests performed, but strongly advocate for the individual assessment of different asset classes and markets.

7 Limitations and opportunities for further research

It is clear from the empirical results presented in this paper and those of different academic publications in the same topic, that the conflict puzzle is far from straight forward. This study thus acknowledges some of the complexities that were faced while trying explain conflict risk and its impact on international financial markets.

Firstly and most importantly, the construction of the conflict Variable is fully dependent on the categorization of events by GDELT, and its standardization method subjective. Reliance on other data sources, categorization and standardization procedures could output different Conflict Indices and therefore disparate results to those presented throughout this research. Additionally, the GDELT database does not provide information about the degree of independence of events, making it impossible to discern whether the value on a certain date is an escalation of an ongoing event, or whether a certain conflict has come to an end or is ongoing. This has particular econometric implications given that if the independence assumption would be violated, many of the OLS methods used would not be the most appropriate ones to inspect this phenomenon.

Referring to the models utilized, the fit of a GARCH model with a (1,1) specification does not appear to be the most adequate in order to capture clusters of volatility around times of high international instability. This might be the case due to the fact that GARCH models require vasts amount of observations to adequately output the coefficients. An alternative that could have been used are the stochastic volatility (SV) models, which are often regarded as appropriate alternatives to the widely used ARCH family of models. Furthermore, the Fama-MacBeth method utilized to inspect the crossection of conflict risk has been widely criticised for imputing error loaded variables in the second step, therefore resulting in estimation inconsistencies. The Newey-West standard errors attempt to provide a more robust significance to the coefficients than normal OLS standard errors, but their inclusion does not change the coefficients themselves. The utilization of the Shanken (1992) correction would have presented even more robust results to the test at hand. Lastly, when inspecting the alphas generated by the different asset pricing models across quantiles, the joint significance of these alphas could have been tested with a GRS statistic, in a more elaborate fashion and following the approach outlined by Gibbons, Ross, and Shanken (1989).

Despite that both equities and currencies were utilized in this study, presenting a somewhat complete picture of different asset classes, debt issues and any sort of bonds and money market securities were completely ignored. This clearly weakens the validity to extrapolate the results found to the whole universe of financial assets, and could certainly be researched in the future. It would be considerably valuable to inspect the relation of sovereign debt and the relation to the conflict variable, to assess the degree to which investors loose confidence in the capacity of a distressed state to meet its financial obligations. It is also relevant to note that even though the 30 countries utilized in this study compose the vast majority of the world gross product and dominate the international diplomatic scene, the inclusion of more countries would only expand the analysis and allow for the currencies to be sorted in quantiles or even deciles in the same way as equities. No additional countries were incorporated in this paper due to the lack of availability of data that some of the emerging economies present. This trend is being reduced rapidly, and future researchers could certainly profit from richer, more accurate and more comprehensive datasets.

Additionally, the portfolios constructed for this piece of research were equally weighted. This unequivocally overrepressents the smaller stock markets, which happen to coincide with those of emerging markets, where the conflict effect is more pronounced, possibly driving the results in the overall sample. A more accurate picture could be drawn by value weighting these portfolios, be it by means of the time varying share that those countries GDPs represent to the worlds GDP, or by means of the market capitalization of those exchanges. However, the lack of data availability for a significant number of countries and substantial evidence in academia showing no clear difference in results when value weighting as opposed to equally weighting contributed to opting for the latter.

Finally, transaction costs were ignored throughout this research which could potentially offset the conflict effect, specially for smaller investors, depending on how the transaction cost asumption would be incorporated. There is no doubt that there is still a lot to investigate when it comes to international conflicts and financial markets to be able to draw more concise, robust, and clear settlements.

8 Conclusion

It is evident that accounting for the full impact of international crises on financial markets is not a trivial matter. Because of the challenges embedded in measuring a variable which is qualitative in nature in a quantitative way and because of the responsibility that dealing with conflicts entails, certain degree of scrutiny is required. This lead to a stream of literature which has tried to account for the financial consequences of geopolitical tensions, which are oftentimes overlooked by policymakers as well as financial practitioners. This paper is no exception.

By the utilization of a novel and vast dataset, a country specific time varying Conflict Index was generated for 30 countries around the world, jointly accounting for more than 90% of the worl's GDP, when usually these studies focus on a single country or a single asset class. This variable reflect the level of hostility that a certain country has not only to the rest of the world but also internally, therefore accounting for domestic crises that usually are ignored in this stream of academic literature. The Conflict Index is a major contribution of this study, as it can be made readily available for a plethora of other studies tackling the issue of multilateral instability.

Moreover, the conflict variable was put at the service of asset pricing. A preliminary check with both expected and unexpected conflict risk bore no significant correlation between countries assets excess returns and their correspondent conflict level. Those results were confirmed when Fama-MacBeth (1973) style regressions were conducted with the conflict variable itself. As portfolios were created using the conflict variable, some evidence showed that equities with a higher conflict variable exert higher returns than those with a lower conflict variable, showing significant results for the zero net investment portfolios. These results are true for the overall sample of equities as and particularly strong in the emerging market subsample. As far as the currencies go, no clear predictability was found when using the Conflict Index, which is a surprising finding, given the belief that exchange rates are highly sensitive to country specific events.

Later, the inspection of risk compensation to the exposure to the conflict variable was assessed with the same methods. Similarly to the previous case, the Fama-MacBeth regressions did not cast any significant results when using the betas. As far as the stock market is concerned, when sorting portfolios according to the betas to the conflict variable, no significance was found across subsamples indicating no pricing of risk. Concerning the currencies, however, there is indicative evidence suggesting a negative compensation for engaging with exchange rates that have higher betas to the conflict variable. This is also more prevalent in the emerging markets subsample where the effect in question is more seizable.

As far as volatility is concerned, the conflict Variable seems to have little to no explanatory power when it comes to explaining the standard deviation of country specific returns. The relatively small period of time utilized and the particularities of a GARCH (1,1) model might be of explanation for this phenomenom, or because there is simply not a measurable relation between the two.

The relationship between conflicts and markets is one that is far from straight forward. It is clear that different asset classes as well as different kinds of markets react diversely to them. This study intended to cast some light upon an unresolved issue by showing the relation between conflicts and financial asset returns. It is true that this is only a small fraction of the consequences that geopolitics play in the world, yet they should not remain unstudied because of the inherent complications that they present. Rather, continuously analysing them contributes to defining in a more detailed manner the extent to which conflicts are consequential, and to measure the materiality of those consequences accordingly. By expanding the array of countries studied and the asset classes, a broader and more universal version of the issue was depicted.

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9 Appendices

Table 12: Extended Correlation Table accounting for the cross correlation between the currency and equity excess returns produced by the conflict anomaly. (Eq) denotes the equity indices returns and (Curr) indicates the currency reuturns.

Variable	Monthly Eret.	Std. Dev	Min	Max	Cross-Correlatons							
Panel A: Equities and Currencies					(Eq) (H-L)	Mktrf	Smb	Hml	Cma	Rmw	Mom	(Curr) (H-L)
(Eq) (H-L)	0.0081	0.0344	-0.1218	0.1126	1							
Mktrf	0.0032	0.0478	-0.1952	0.1142	-0.1219	1						
Smb	0.0033	0.0201	-0.0861	0.083	-0.0919	0.0204	1					
Hml	0.0066	0.0262	-0.1013	0.1222	0.0073	-0.1625	-0.0855	1				
Cma	0.0054	0.0211	-0.0503	0.098	0.0287	-0.4423	-0.1049	0.7425	1			
Rmw	0.0041	0.0172	-0.0583	0.0641	-0.0257	-0.4906	-0.2491	0.3911	0.3601	1		
Mom	0.0039	0.0433	-0.2425	0.0935	-0.0639	0.0255	-0.0487	-0.0350	0.0184	0.0059	1	
(Curr) (H-L)	-0.0016	0.0165	-0.04807	0.0396	-0.0462	0.0926	-0.0416	-0.0142	-0.0359	-0.0165	-0.1474	1

Table 13: Robustness check for parameter stability with a Suprenum-Wald test and structural break in illustrative Conflict Indices

Spurenum Wald Test	Estimated Break	t-statistic
Conflict Index Us	2001m9***	103.6
Average Conflict Index	2003m12	6.77
Nº observations	182	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 14: Equity indices and countries that are considered throughout the study. The largest indices in terms of market capitalization as of 2019 were selected.

Equity Indices			
Developed countries		Emerging Markets	
United States	*NYSE*	China	*SHCOMP*
UK	*FTSE 100*	India	*JENSEX*
France	*CAC 40*	Russia	*MOEX*
Germany	*DAX*	Brasil	*BOVESPA*
Netherlands	*AEX*	South Africa	*JSE*
Belgium	*BEL 20*	Indonesia	*JCI*
Spain	*IBEX 35*	Mexico	*IPC*
Australia	*ASX 200*	Chile	*IPSA*
Italy	*FTSE MIB*	Poland	*WIG*
Canada	*TSX*	Turkey	*XU 100*
Sweden	*OMX 30*	Thailand	*SET*
Switzerland	*SMI*	Argentina	*MERVAL*
Austria	*ATX*	Saudi Arabia	*TASI*
Korea (South)	*KOSPI*	Pakistan	*KSE 100*
Japan	*Nikkei 225*	Taiwan	*TAIEX*

Table 15: Portfolio returns sorted according to conflict variable and the difference in returns from the extreme portfolios tested with a two-sample t-test.

	Low	2	3	4	High	(H-L)	t-statistic
Panel A: Equities Complete Sample							
	-0.003	0.003	0.005	-0.00214	0.005	0.008**	(1.61)
Panel B: Equities Developed Countries							
	-0.007	0.005	-0.005	-0.005	-0.005	0.001	(0.28)
Panel C: Equities Emerging Markets							
	-0.006	0.001	-0.001	-0.003	0.001	0.007**	(1.95)
Panel D: Currencies Complete Sample							
	0.001	0.001	0.002	0.000	0.002	-0.001	(-0.70)
Panel E: Currencies Developed Countries							
	0.001	0.002	0.002	0.003	0.002	-0.002	(-0.71)
Panel F: Currencies Emerging Markets							
	-0.002	0.001	-0.003	-0.001	-0.003	-0.001	(-0.33)

Note: t-statistics between brackets,$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 16: Output for the GARCH (1,1) models for each equity index per country as well as for the emerging market group, the developed economies and the whole sample.

Developed Countries

	Mean		Variance			
	Intercept	Conflict	Intercept	β_1	β_2	Conflict
[Belgium] BEL 20						
Coefficient (%)	-0,01	0,01	-7.24***	0.57***	0.30***	-0,07
T-statistic	(-0.60)	(0.47)	(-8.14)	(3.86)	(3.08)	(-0.65)
[Sweden] OMX 30						
Coefficient (%)	0,01	0,00	-6.11***	0.17*	0.75***	-1,53
T-statistic	(0.77)	(-0.49)	(-3.27)	(1.95)	(7.20)	(-0.86)
[Austria] ATX						
Coefficient (%)	-0,01	0,01	-6.72***	0.23***	0.63***	-0,65
T-statistic	(-0.52)	(0.86)	(-5.33)	(2.43)	(5.4)	(-0.55)
[Spain] IBEX 35						
Coefficient (%)	0.00	0.00	-5.21***	0.20*	0.59***	1.24*
T-statistic	(-0.23)	(0.11)	(-7.10)	(1.69)	(2.85)	(-1.88)
[Korea (s)] KOSPI						
Coefficient (%)	-0,02	0,02	-4.77***	0.09	0.79***	-2.87
T-statistic	(-0.74)	(0.84)	(-3.23)	(1.11)	(5.67)	(-1.53)
[Australia] ASX 200						
Coefficient (%)	-0,02	0,01	-6,34	0.19*	0.71***	-1,68
T-statistic	(-1.06)	(1.08)	(-1.66)	(1.98)	(6.05)	(-0.63)
[Switzerland] SMI						
Coefficient (%)	-0.01	0.00	-7.39***	0.22**	0.60***	-0.39
T-statistic	(-0.63)	(0.39)	(-6.96)	(2.81)	(3.96)	(-0.44)
All developed						
Coefficient (%)	-0.01	0.00	-5.03***	0.34**	0.44**	-1.10
T-statistic	(-1.01)	(1.12)	(-2.6)	(2.55)	(2.38)	(-1.36)
[US] NYSE						
Coefficient (%)	-0,03	0.02	-6.81***	0.36***	0.37*	-0.35
T-statistic	(-0.92)	(0.93)	(-3.53)	(3.34)	(1.81)	(-0.33)
[UK] FTSE 100						
Coefficient (%)	-0.01	0.01	-6.40***	0.42**	0.20	-0.52
T-statistic	(-0.35)	(-0.25)	(-4.15)	(2.16)	(0.81)	(-0.52)
[France] CAC 40						
Coefficient (%)	0.00	-0.01	-7.06***	0.28**	0.48**	-0.06
T-statistic	(0.05)	(-0.09)	(-2.86)	(2.21)	(2.17)	(-0.03)
[Germany] DAX						
Coefficient (%)	0,01	-0.00	-8.01***	0.29***	0.52***	0.86
T-statistic	(0.18)	(-0.14)	(-4.24)	(2.83)	(3.13)	(0.54)
[Netherlands] AEX						
Coefficient (%)	0,00	-0,01	-6.58***	0.32***	0.57***	-0.53
T-statistic	(0.23)	(-0.34)	(-4.26)	(2.71)	(4.21)	(-0.62)
[Japan] Nikkei 225						
Coefficient (%)	-0.04	0,04	-3.96**	0.01	0.85***	-4.29*
T-statistic	(-1.42)	(1.29)	(-2.14)	(0.22)	(6.12)	(-1.67)
[Canada] TSE						
Coefficient (%)	0.00	0.00	-8.42***	0.19**	0.73***	-0.15
T-statistic	(-0.22)	(0.32)	(-3.72)	(2.13)	(5.60)	(-0.10)
[Italy] FTSE MIB						
Coefficient (%)	0,01	0,01	-5.26***	0.48***	0.40***	-1,46
T-statistic	(0.32)	(0.30)	(-2.93)	(3.12)	(2.69)	(1.07)
All countries						
Coefficient (%)	-0,03	0,02	-6,37	0,15	0.76***	-2.00
T-statistic	(-1.99)	(2.16)	(-1.61)	(1.62)	(5.33)	(-0.74)

Emerging Markets

	Mean		Variance			
	Intercept	Conflict	Intercept	β_1	β_2	Conflict
[China] SHCOMP						
Coefficient (%)	-0.01	0.00	-8.38***	0.13*	0.83***	0.10
T-statistic	(-0.027)	(0.09)	(-3.71)	(1.78)	(8.25)	(0.05)
[Russia] MOEX						
Coefficient (%)	0.02	-0,01	-9.05**	0.19***	0.73***	1.21
T-statistic	(0.47)	(-0.34)	(-2.24)	(2.66)	(6.91)	(0.44)
[India] SENSEX						
Coefficient (%)	0.00	0.00	-7.57***	0.12	0.83	-0.22
T-statistic	(0.10)	(0.05)	(-3.81)	(2.08)	(9.78)	(-0.23)
[South Africa] JSE						
Coefficient (%)	0.00	0.00	-5.21***	0.31	0.38	-1.10**
T-statistic	(0.27)	(0.31)	(-5.95)	(2.05)	(2.07)	(-2.16)
[Argentina] MERVAL						
Coefficient (%)	0.01	0.00	-1,24	0.06	0.79***	-4.15***
T-statistic	(0.48)	(-0.15)	(-1.61)	(1.12)	(10.65)	(-4.88)
[Mexico] IPC						
Coefficient (%)	-0.01	0.01	-10.27***	0.15**	0.80***	0.75
T-statistic	(-0.47)	(0.75)	(-4.31)	(2.42)	(11.04)	(0.87)
[Thailand] SET						
Coefficient (%)	0.03	-0.01	-5.80***	0.19***	0.70***	-0.96
T-statistic	(1.53)	(-1.52)	(-4.17)	(3.92)	(9.93)	(-1.05)
[Brazil] BOVESPA						
Coefficient (%)	0.01	-0.01	-6.44***	0.19	0.31	0.36
T-statistic	(0.64)	(-0.55)	(-8.05)	(1.37)	(0.78)	(1.31)
[Saudi Arabia] TASI						
Coefficient (%)	-0.01	0.01**	-5.94***	0.44***	0.46***	-0.89
T-statistic	(-1.37)	(2.07)	(-6.68)	(3.10)	(3.89)	(-0.19)
[Pakistan] KSE 100						
Coefficient (%)	0.00	0.00	-3.70***	0.00	-0.05	-0.53*
T-statistic	(0.19)	(0.04)	(-5.37)	(-0.07)	(-0.14)	(-1.69)
[Poland] WIG						
Coefficient (%)	-0.01	0,01	-4.95**	0.17	-0.33	-0.24
T-statistic	(-0.31)	(0.44)	(-14.44)	(1.53)	(-1.24)	(1.03)
[Turkey] XU 100						
Coefficient (%)	0.02	-0.01	-14.06	0.23***	0.78***	3.30
T-statistic	(0.95)	(-0.56)	(-1.47)	(3.38)	(10.64)	(0.86)
[Indonesia] JSI						
Coefficient (%)	0.00	0.01	-5.60***	0.28***	-0.12	0.02
T-statistic	(0.29)	(0.83)	(-11.13)	(2.91)	(-0.46)	(0.12)
[Taiwan] TAIEX						
Coefficient (%)	-0.03	0.02	-8.96**	0.17**	0.81***	-0.19
T-statistic	(-1.5)	(1.42)	(-1.98)	(2.16)	(8.77)	(-0.06)
[Chile] IPSA						
Coefficient (%)	0.03	-0.01	-6.75***	0.23*	-0.15	0.14
T-statistic	(0.57)	(-0.41)	(11.81)	(1.89)	(-0.58)	(0.73)
All Emerging						
Coefficient (%)	-0.01	0.00	-6.32***	0.27***	0.56***	-0.66
T-statistic	(-0.63)	(0.99)	(-3.08)	(2.94)	(5.24)	(-0.68)
All developed						
Coefficient (%)	-0.01	0.00	-5.03***	0.34**	0.44**	-1.10
T-statistic	(-1.01)	(1.12)	(-2.6)	(2.55)	(2.38)	(-1.36)

Note: t-statistics between brackets, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 17: Output for the GARCH (1,1) models for each exchange rate per country as well as for the emerging market group, the developed economies and the whole sample.

	Developed Countries					
	Mean		Variance			
	Intercept	Conflict	Intercept	b1	b2	Conflict
[UK] GBP to u$d						
Coefficient (%)	0.00	-0.04	-9.45**	0.06**	0.83***	0.04
T-statistic	(0.20)	(-0.34)	(-2.35)	(2.31)	(8.85)	(0.02)
[Eurozone] EUR to u$d						
Coefficient (%)	-0.02	0.00	-7.42***	0.08*	0.77***	-1.11
T-statistic	(0.16)	(-0.15)	(-3.51)	(1.70)	(4.94)	(-0.74)
[Japan] JPY to u$d						
Coefficient (%)	0.03	-0.00	-5.80***	0.21***	0.81***	-0.96
T-statistic	(1.53)	(1.51)	(-4.17)	(3.08)	(9.89)	(-1.02)
[Canada] CAD $ to u$d						
Coefficient (%)	-0.05	0.01	-8.51***	0.24**	0.26	0.48
T-statistic	(-0.51)	(0.21)	(-10.26)	(2.34)	(1.22)	(1.03)
[Korea (s)] KRW to u$d						
Coefficient (%)	-0.01**	0.01	-9.29***	0.80***	-0.08*	1.73***
T-statistic	(-2.13)	(1.21)	(-17.27)	(4.14)	(-1.86)	(3.33)
[Australia] AUD to u$d						
Coefficient (%)	-0.06	-0.01	-5.58***	0.17**	0.48*	-1.38
T-statistic	(-0.42)	(-0.17)	(-4.54)	(2.13)	(1.81)	(-1.42)
[Swtz] CHF to u$d						
Coefficient (%)	-0.07	0.00	-8.21***	0.14**	0.07***	-0.29
T-statistic	(-0.96)	(0.19)	(-4.75)	(2.23)	(4.01)	(-0.26)
All developed						
Coefficient (%)	-0.01	0.00	-7.74***	0.19	0.32	-0.25
T-statistic	(-0.09)	(-0.66)	(-8.55	(1.40)	(0.76)	(-0.64)
All countries						
Coefficient (%)	0.01	-0.01	-7.06***	0.44***	0.19*	-2.00
T-statistic	(0.86)	(-0.70)	(-2.14)	(3.09)	(1.61)	(-0.74)
All Emerging						
Coefficient (%)	0.10	0.001***	-4.65***	0.07	0.47	-0.148***
T-statistic	(1.46)	(-1.70)	(-5.12)	(0.95)	(1.47)	(-3.95)

	Emerging Markets					
	Mean		Variance			
	Intercept	Conflict	Intercept	b1	b2	Conflict
[China] RMB to u$d						
Coefficient (%)	-0.00	-0.00	-8.1***	2.53***	0.12***	1.53***
T-statistic	(-0.027)	(0.09)	(-14.71)	(14.39)	(3.94)	(10.40)
[Russia] RUB to u$d						
Coefficient (%)	0.12	-0.01	-35.90*	0.30***	0.77***	15.57
T-statistic	(1.41)	(-1.57)	(-1.75)	(5.02)	(22.07)	(1.33)
[India] INR to u$d						
Coefficient (%)	-0.001	0.000	-5.06**	0.17***	0.80***	-0.22***
T-statistic	(-0.36)	(0.03)	(-2.52)	(3.07)	(16.05)	(-2.75)
[S. Africa] ZAR to u$d						
Coefficient (%)	-0.15	0.08	-5.87***	0.28**	0.10	-0.32
T-statistic	(-1.24)	(1.37)	(-10.00)	(2.14)	(0.56)	(-1.04)
[Argentina] ARS to u$d						
Coefficient (%)	0.01	0.00	-6.96***	0.09***	0.79***	0.61
T-statistic	(0.21)	(0.05)	(8.88)	(5.51)	(10.65)	(0.52)
[Mexico] MXN to u$d						
Coefficient (%)	0.02	-0.007***	-7.15***	0.69***	0.04	-0.44
T-statistic	(1.50)	(-1.94)	(-9.86)	(5.05)	(0.67)	(-1.29)
[Thailand] THB to u$d						
Coefficient (%)	0.01	-0.04*	-8.98***	-0.11	0.54	0.22
T-statistic	(1.32)	(-1.69)	(-11.36)	(-1.53)	(1.41)	(1.11)
[Brazil] BRL to u$d						
Coefficient (%)	0.01	-0.01	-6.44***	0.19	0.31	0.36
T-statistic	(0.64)	(-0.55)	(-8.05)	(1.37)	(0.78)	(1.31)
[Saudi Ar] SAR to u$d						
Coefficient (%)	-0.00***	0.001**	-23.69***	0.61**	0.36***	2.63
T-statistic	(-3.32)	(2.50)	(-8.28)	(2.18)	(3.28)	(1.32)
[Pakistan] PKR to u$d						
Coefficient (%)	-0.00	-0.00	-10.05***	0.94***	0.44***	-0.91
T-statistic	(-0.55)	(-0.56)	(-5.55)	(-1.01)	(8.09)	(-1.01)
[Poland] PLN to u$d						
Coefficient (%)	-0.01	0.03	-9.53***	0.10***	0.84***	0.33
T-statistic	(-0.11)	(-0.33)	(-6.19)	(2.64)	(14.40)	(0.26)
[Turkey] TRY to u$d						
Coefficient (%)	0.01	-0.00	-11.91	0.21***	0.61***	1.11
T-statistic	(0.61)	(-0.56)	(-1.01)	(3.31)	(9.61)	(0.11)
[Indonesia] IDR to u$d						
Coefficient (%)	-0.02	-0.02	-10.03***	1.08***	0.23***	0.40
T-statistic	(0.45)	(-0.79)	(-9.21)	(6.33)	(9.08)	(0.67)
[Taiwan] TWD to u$d						
Coefficient (%)	-0.01**	-0.01***	-8.81***	0.69	0.75	-1.42
T-statistic	(1.93)	(-2.61)	(-5.71)	(1.14)	(5.51)	(-1.17)
[Chile] CLP to u$d						
Coefficient (%)	-0.001	-0.007	-6.89***	0.30***	0.24	-0.38
T-statistic	(-0.39)	(-0.55)	(-11.44)	(3.38)	(0.97)	(-1.14)

Note: t-statistics between brackets, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 18: Fama Macbeth outputs for currencies and equities without the ranking andstandarization process

	Equities				Currencies			
Variable	1	2	3	4	1	2	3	4
Panel A: Complete Sample								
bets_Conflict Index	-0.01	-0.0184	-0.0002	-0.0065	-0.0146	-0.0276	-0.0059	-0.0133
t-statistic	(-0.68)	(-1.30)	(-0.02)	(-0.53)	(-0.85)	(-1.62)	(-0.45)	(-0.92)
ln(GDP)			0.000	-0.001			-0.000	-0.0002
t-statistic			(-0.30)	(-0.48)			(-0.59)	(-0.70)
3 Month Interbank Rate			-0.0016*	-0.00			-0.0002*	-0.0003**
t-statistic			(-1.75)	(0.03)			(-1.91)	(-2.49)
CPI			-0.0002	-0.001			-0.0002	-0.00012
t-statistic			(-1.61)	(-1.49)			(-1.09)	(-0.71)
Democracy		-0.0218*		-0.0359*		-0.021*		-0.0307
t-statistic		(-1.82)		(-1.78)		(-1.72)		(-1.53)
Intercept	0.0039	0.0039	0.0045	0.0004	0.0055	0.0058	0.0055	-0.0053
t-statistic	(-0.93)	-0.96	-1.15	(1.23)	(1.34)	(1.43)	(1.38)	(1.34)
Average R2	0.0	0.11	0.22	0.25	0.06	0.14	0.22	0.29
Number of observations	5280	5280	5280	5280	4048	4048	4048	4048
Panel B: Developed Countries								
bets_Conflict Index	-0.0051	-0.0001	-0.0082	0.0071	-0.0157	-0.0087	-0.0146	0.0025
t-statistic	(-0.49)	(0.02)	(-0.76)	(0.45)	(-0.76)	(-0.41)	(0.80)	(0.04)
ln(GDP)			0.00	0.00			-0.000	-0.000
t-statistic			(0.68)	(1.04)			(-0.20)	(-0.21)
3 Month Interbank Rate			0.0002	0.0002			0.0002	-0.005
t-statistic			(1.39)	(0.59)			(1.35)	(-1.05)
CPI			-0.0002	-0.0001			-0.0002	0.0001
t-statistic			(-1.19)	(-1.36)			(-0.63)	(0.03)
Democracy		0.0192		0.052		0.0046		0.0032
t-statistic		(0.63)		(0.93)		(1.02)		(0.24)
Intercept	-0.0001	0.0003	0.0014	0.0018	0.0003	0.0016	0.0031	0.0025
t-statistic	(0.03)	(0.04)	(0.36)	(0.49)	(-0.08)	(0.45)	(0.90)	(0.66)
Average R2	0.10	0.22	0.36	0.45	0.17	0.37	0.61	0.76
Number of observations	2640	2640	2640	2640	1408	1408	1408	1408
Panel C: Emerging Markets								
bets_Conflict Index	-0.0099	-0.0173	-0.0031	-0.0239	-0.001	-0.0173	-0.0032	-0.0239
t-statistic	(-0.42)	(-0.71)	(-0.16)	(-1.02)	(-0.42)	(-0.71)	(-0.16)	(-1.02)
ln(GDP)			0.0001	-0.001			0.0002	0.0003
t-statistic			(0.54)	(-0.11)			(-0.54)	(0.06)
3 Month Interbank Rate			-0.0006**	-0.0008**			-0.0005**	-0.0008**
t-statistic			(-2.81)	(-2.38)			(-2.18)	(-2.38)
CPI			-0.0001	-0.002			-0.0002	-0.0002
t-statistic			(-0.54)	(-0.66)			(-0.54)	(-0.66)
Democracy		-0.0183		-0.0541		-0.01827		-0.0054*
t-statistic		(-1.13)		(-1.65)		(-1.13)		(-1.66)
Intercept	0.0082*	0.0083*	0.007*	0.0069*	0.008*	0.0083*	0.007*	0.0069*
t-statistic	(1.82)	(1.83)	(1.66)	(1.66)	(1.82)	(1.83)	(1.66)	(1.66)
Average R2	0.09	0.19	0.25	0.43	0.09	0.19	0.35	0.43
Number of observations	2640	2640	2640	2640	2640	2640	2640	2640

Note: t-statistics between brackets,$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 19: Replication of table 4 without the implementation of country fixed effects but rather with the aggregation of all the returns and indices in *Complete Sample, Developed Economies and Emerging Markets.*

Variable	Complete Sample	Developed Countries	Emerging Markets
Panel A: Equities			
Conflict Index	-0.001	-0.002*	0.001
t-statistic	(-0.76)	(-1.79)	(0.24)
Intercept	-0.014*	0.003**	0.004
t-statistic	(1.83)	(-2.71)	(0.27)
Panel B: Currencies			
Conflict Index	-0.002**	-0.002	-0.001
t-statistic	(-2.03)	(-1.69)	(-1.61)
Intercept	0.003**	0.000	0.004***
t-statistic	(2.79)	(0.49)	(3.20)
Panel C: Equities			
Conflict Index	0.000	0.006	0.003
t-statistic	(0.007)	(1.39)	(0.40)
Unexpected Risk	0.011	0.001	0.009
t-statistic	(0.75)	(0.23)	(1.09)
Intercept	-0.0085***	0.023	-0.031
t-statistic	(-4.84)	(-1.40)	(-1.46)
Panel D: Currencies			
Conflict Index	-0.001	-0.001	-0.000
t-statistic	(-0.08)	(-0.15)	(-0.66)
Unexpected Risk	-0.079	-0.002	-1.366**
t-statistic	(-1.48)	(-0.84)	(-2.51)
Intercept	0.001	0.003	0.002
t-statistic	(1.17)	(0.38)	(1.35)

Note: *t*-statistics between brackets,$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$