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The impact of conflict on the shadow economy and FDI: evidence from causal and spatial inference

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To those who believed and invested in my future

To my father, mother, and aunt Etaf

To the soul of my lovely sister Hala

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Abstract

Conflict affects governance policies, rendering them fewer effective tools, which motivates people to move into the informal sector. The shadow economy activities are labour intensive and suitable for adoption with low-return capital and small-scale production. They inefficiently use the factors of production, and distort the investment environment. Moreover, the shadow economy affects official macroeconomic measurements such as of gross domestic product, consumption expenditure, the unemployment rate, and the labour force. This motivates researchers and policymakers to pay more interest to study the phenomena of the shadow economy. Therefore, this study uses the event study approach to infer whether contemporaneous conflict affects the size of the shadow economy in subsequent years. Further investigations using the difference in differences approach are conducted to test the impact of Intifada, a political conflict event that has harmed the Palestinian and Israeli economies, on the size of the shadow economy in both countries.

While conflict is one phase of political unrest, it harms economies, and diminishes capital stock when armed forces and rebels target infrastructure, which is either damaged or demolished. Moreover, armed conflict increases the depreciation rate, encourages capital flight, deters new investment opportunities, and accelerates loss for businesses. Motivated by these facts, this thesis also tests the hypothesis that conflict could have an impact on FDI in the mining sector. To do that, an event-study approach is implemented that focuses on the possible dynamic and spatial spillover effects of conflict on FDI.

The study finds that conflict has had a dynamic impact on the shadow economy that remains statistically significant over a span of three years. Moreover, its impact becomes higher when conflict turns out to be more intensive, yet it loses dynamism. Additionally, Intifada is found to have affected the Palestinian economy, but not the Israeli one.

The results show inconsistency across different groups of countries for the dynamic impact of conflict on FDI in the mining sector. Furthermore, the study does not find significant spillover effects across neighbouring countries.

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Abbreviations

CDHES	The non-governmental Salvadoran Human Rights Commission
DiD	Difference in Differences
FDI	Foreign Direct Investment
FMLN	Farabundo Martí National Liberation Front
MENA	Middle East and North Africa
MIMIC	Multiple indicators multiple causes
MNC	Multinational corporations
OLS	The ordinary least square
PCBS	The Palestinian Central Bureau of statistics
PMA	The Palestinian Monetary Authority
PPP	Purchasing Power Parity
PSM	Propensity score matching
SAR	Spatial Autoregressive mode
SDM	The Spatial Durbin Model
SEM	Structural equation models
SEM	The Spatial Error Model
SUTVA	The Stable Unit Treatment Value Assumption
UCDP	Uppsala Conflict Data Program
JCCL	Jiangxi Copper Company Limited

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1 Introduction

This chapter provides an overview of the thesis, which aims to examine the impact of conflict on the shadow economy and sectorial FDI by using causal inference, including the difference in differences and the event study approaches, besides using the spatial models.

This chapter starts with this general introduction, which is followed by the research rationale section. The subsequent section is designed to outline the research aims. The section entitled “Research contribution” illustrates the main contributions of this research. Finally, the following section briefly explains the different methodologies that have been used to achieve the research aims.

1.1 Research rationale

Political unrest, civilians’ deaths, and violence are forms of conflict that occur even in secure and stable economies. However, there is a significant cross-national difference in terms of these conflicts' severity, as well as their ability to undermine state power. Conflict in developed countries has less frequently taken the form of organized violence in recent decades, and such conflict barely impedes the state's power. This mild impact on socio-economic indicators does not hold for the less developed countries. However, in the case of political conflict, the conflict between the ruling regimes and opposing parties is more often expressed as organized violence (Moaddel, 1994)

Seminal studies in the area of conflict resolution have pinpointed different patterns for identifying sources of conflict e.g., (Fink, 1968; Mack & Snyder, 1957). However, Katz (1965) suggested a typology that differentiates between three key sources of conflict: economic conflict, which comprises rival motivations to conquer scarce resources; value conflict, which entails a mismatch between different life aspects and beliefs; and third, the power conflict that takes place when each movement or party desires to retain or boost the influence that they exert in the social setting.

In fact, the sources of conflict are not limited to Katz's perspective. Conflict could arise due to ethnic reasons, and religious and beliefs backgrounds. Besides, conflict can take place into different levels, this includes, Interpersonal conflict, Role conflict, intergroup conflict, multi-Party conflict, and international conflict.

Conflict can harm not only economic indicators but the social ones as well. It has an impact on health, gender equality, schooling, infrastructure, social ties, and social services. Social relations may be affected negatively by conflict, causing a reduction in civic engagement, undermining social capital, and demonising resilience. These social disintegrations may lead to sociological, psychological, and economic impacts within society. The social consequences of conflict do not have a contemporaneous effect only, as the impact may last longer, and a conflict could have second-order impacts as well. For example, fear of suffering and anxiety has the potential to take place where long conflict has been based on individual beliefs and perceptions of the situation (Prenzel & Vanclay, 2014). Moreover, internal conflicts are mostly destructive, since they cause shocks in both the demand for and supply of social services and healthcare services. It can be the case that violent behaviour increases demand for health services: yet societies in conflict are less able to deliver these services, as resources are directed mainly to militarised purposes, besides the demobilising of vital infrastructure such as health centres, hospitals, and the transportation network (Gates, et al., 2015).

Collier (1999) argues that economies lose 2.2 percent of their GDP growth for each year of conflict experienced. Furthermore, Abadie and Gardeazabal (2003) found that per capita GDP decreased by 10% after an outbreak of terrorist attacks in the Basque region when compared with selected control regions where terror attacks had not taken place. Moreover, the study finds that conflict has an immediate negative impact on the stock prices of companies listed on the stock exchange. Lopez and Wodon (2005) found that the per capita GDP would be 25%-30% greater in Rwanda if the conflict had not existed, while Costalli, et al. (2017) found that the average annual loss of GDP per capita was 17.5% in a sample of 20 countries that had witnessed years of armed conflict. Nordhaus (2002) reports that most studies limit the cost of conflict to one country, neglecting international negative externalities. For example, internal conflicts can have devastating long-term economic effects on both the states that experience them and their neighbours (Murdoch & Sandler, 2004). Furthermore, researchers can expand their conflict cost estimations by including opportunity costs.

Nonetheless, conflict in some cases can have a positive impact on the economy and on society. Modernisation theory claims that, viewed in the long term, conflict is an essential result of alteration from the "traditional" to the "modern" phase of development (Olson, 1963; Pye, 1966; Feierabend, et al., 1969).

Among the socio-economic indicators affected by the conflict is the shadow economy. In recent decades, governments have prioritised combating tax evasion, informal (illegal) employment, and the shadow economy. However, officials and policymakers must first realise the size and growth of the shadow economy and the structure of its labour force. Besides this, there is a need to investigate the real reasons behind the engagement of individuals in shadow economy activities.

The presence of the shadow economy and its growth indicates the ineffectiveness of economic and social policies. Indeed, manifestations of the shadow economy usually demonstrate issues with existing economic policies, such as where the intensity of regulations or taxes are overly heavy or unfair (Allingham, 1972). However, these activities negatively affect public earnings. Moreover, shadow economy activities influence the national accounts statistics in a way that may lead to ineffective execution of social reforms and wellbeing schemes, and the greater the size of the shadow economy, the more likely it is that unemployment rates are overestimated (Matthew, et al., 2000).

Based on Medina and Schneider's (2018) estimations for the size of the shadow economy from 1991-2015, the average size of the shadow economy around the world was around 32%, while the minimum size was 6% and the maximum was 72%. However, when conflict takes place, the size of the informal sector is 8.6% above the average in the absence of conflict. Very few strands of literature have discussed the impact of conflict on the size of the shadow economy. Ouédraogo (2017) reveals that internal conflict affects the informal sector negatively, whereas external conflict has a positive impact on it. However, Peksen and Early (2019) demonstrate that a large scale of internal conflict, as opposed to smaller scales, has a huge impact on increasing the activities of the shadow economy.

Furthermore, conflict could have an impact on channels of finance, and in particular external finance sources such as FDI. Therefore, conflict could form one of the political major determinants of FDI inflows. These political factors have received significant attention from economists to examine the structural factors that determine FDI behaviour (Blonigen, 2005).

Foreign Direct Investment (FDI) can be one of the main pillars of development policies in resource-abundant countries. FDI can enhance the development process in developing countries also, as it can diversify economic activities, open up access to new markets through exports, and draw in new technologies (De Ferranti, et al., 2002). In the Keynesian model of economic growth, Harrod–Domar rationalises that an economy's growth rate depends on the level of capital and saving (Harrod, 1939; Domar, 1946). Moreover, the neoclassical economic growth theory asserts that capital stock shocks, in addition to labour, are the main factor that affects economic growth (Acemoglu, 2012).

Conflict is considered one of the hard shocks, and can affect FDI directly, and economic growth as a result. Capital stock is an accumulation of investments, and therefore, when a state comes to be involved in an armed conflict, capital stock is considered to be affected in two directions (Zafeer, 2015). The first direction is due to the destructive nature of conflict, as it diminishes capital stock when armed forces and rebels target infrastructure, which is either damaged or demolished. In terms of the second direction, Solow (1956) suggests that the amount of accumulated capital depends on new investments and existing capital adjusted to depreciation. Therefore, armed conflict increases the depreciation rate, and moreover, it encourages capital flight, deters new investment opportunities, and accelerates loss for businesses.

Schöllhammer and Nigh (1984) found that the German flow of capital to less developed countries was affected negatively by internal conflict within the host state. In addition, Nigh (1985) argues that conflict affects U.S. manufacturing direct investment flow to developing countries in both conflict cases: inter and intrastate conflict. In contrast, this relationship holds for developed countries when they witness inter-state conflict only. Moreover, Biglaiser and Staats (2010) have included conflict as one of the determinants of Foreign Direct Investment in developing countries during the period 1976-2004, and the authors find a negative impact of lagged conflict on FDI.

The majority of studies find a negative association between conflict and FDI which is compatible with rational investment decisions: therefore, when it comes to new investments in conflict areas, a negative relationship is expected. However, the investment decisions in multi-national companies can be taken based on political pressure, CEO behaviour, and personal interests, and of course based on rational decisions as well. Besides, some sectors seem to be more attractive than other sectors. For these reasons, this study is interested to investigate whether the negative association between conflict and FDI stays negative in the mining sector.

1.2 Research Aims

The study is designed to test the dynamic and causal impact of conflict on the shadow economy, besides investigating whether a dynamic and spatial impact exists for conflict on greenfield FDI in the mining sector.

The main aims for the second chapter are threefold. Firstly, it will examine the causal effect of exogenous conflict on the shadow economy and test its dynamism. Secondly, the chapter will consider whether this impact, if it exists, differs according to countries' level of income. Finally, it will investigate the impact of conflict intensity on the informal sector.

The third chapter mainly aims to build on the results obtained in Chapter 2 by studying a special case of prolonged conflict, and to test whether the findings in the previous chapter apply for this case. The study employs the Difference in

Differences approach to identify whether conflict had an impact on the shadow economy in Palestine during the period 1996-2015. Moreover, it estimates the size of the shadow economy in Palestine by using the MIMIC approach.

Finally, the other purpose of this study is to investigate the impact of conflict on greenfield FDI. In other words, the study attempts to infer the existence of an impact, its direction, and magnitude, and furthermore, to test if impact direction differs among diverse areas around the world. Unlike other works, this paper focuses on testing two impacts: first, dynamic impact, in which the impact of conflict on FDI over contemporary and following periods is investigated. Second, the paper investigates the spillover impact in three directions: the expected spillover impact of the outcome variable in one country on its neighbours' outcome; the spillover impact of conflict; and the spillover impact of any unobserved variables.

1.3 Research contribution

The contribution of the second and the third chapters includes the following. To the best of the author's knowledge, very few pieces of research have attempted to test the relation between conflict and the shadow economy, and under what circumstances conflict can be considered as one of the informal sector's determinants. Furthermore, the second chapter extends the contribution domain, in testing whether conflict events affect the size of the shadow economy in the contemporaneous period and in future periods: in other words, the chapter investigates the dynamic impact of conflict on the shadow economy's size.

There are four key contributions made by the fourth chapter. Firstly, to the best of the author's knowledge, this study is amongst the pioneering empirical works in testing the conflict-FDI nexus, while most previous studies focus on terrorism and foreign firms. Secondly, most empirical studies of conflict and FDI have tested impact using aggregated data: however, this study utilises disaggregated data on a quarterly basis and exclusively for the mining sector. Thirdly, estimation depends on the event study approach to infer the dynamic impact of conflict on greenfield FDI over the 4 quarters following any conflict event breakout, and spatial econometrics to infer the spillover impact. Fourthly, this study uses a unique dataset on sectorial greenfield FDI.

1.4 Methodology and research questions

This section presents the different methods that have been used to fulfil the aims of this research. In general, all empirical chapters use econometric models to determine the impact of conflict on shadow economy size, and the impact of conflict on the greenfield FDI in the mining sector. Besides this, the section presents the research questions.

1.4.1 The impact of conflict on the shadow economy: country analysis using the event study approach

To achieve the aims of this study, various questions are set as follows:
"*Does a dynamic impact exist for the relationship between conflict and the shadow economy?*"

To examine the effect of exogenous conflict variation on the size of the shadow economy, this study follows Karafiath's (1998) model representing the event studied by using dummies.

1.4.2 The impact of Intifada on the shadow economy in Palestine, an empirical study using the Difference in Differences approach

This chapter answers the main question:

“ Did the 2nd Intifada affect the size of the shadow economy in Palestine?”

The study employs the Difference in Differences approach to study whether conflict had an impact on the shadow economy in Palestine during the period 1996-2015. Moreover, to estimate the size of the shadow economy in Palestine, the study uses the MIMIC approach.

1.4.3 Conflict and greenfield FDI in the mining sector: an investigation for dynamic and spillover impact

This chapter answers the following question:
“ Does conflict have dynamic and/or spatial-spillover effects on the greenfield FDI in the mining sector?”

This chapter uses two methods. Firstly, the event study approach is applied to test dynamic impact. Secondly, spatial models including the Spatial Durbin model, the Spatial Autoregressive model, and the Spatial Error model are used to test spillover impact.

1.5 Thesis structure

This thesis consists of five chapters. The findings of the three empirical investigations are provided in the form of journal articles presented in Chapters 2, 3, and 4. This structure allows the chapters to present the findings of each study alongside an explanation of the methodology used to acquire the findings.

1.5.1 Chapter Two: The impact of conflict on the shadow economy: a cross-country analysis using the event study approach

This chapter presents the empirical results of the first empirical study. Mainly, it aims to investigate, using the event study approach, the dynamic impact of conflict on the size of the shadow economy across countries. The sample of study includes the large sample of high income and non-high-income countries.

Besides this, the chapter has the additional objectives of testing the aggregate impact of conflict over the first 5 years on the shadow economy's size, and also tests the mechanism for the way this impact behaves through level of income.

1.5.2 Chapter Three: The impact of Intifada on the shadow economy in Palestine: an empirical study using the Difference in Differences approach

This chapter presents the empirical results of the second empirical study. The study employs causal inference based on a Difference in Differences approach, to study whether conflict had an impact on the shadow economy in Palestine during the period 1996-2015. Moreover, it estimates the size of the shadow economy in Palestine using the Multiple Indicators Multiple Indirect Causes (MIMIC) approach. The chapter's investigations represent a case study of a prolonged and contemporaneous conflict.

1.5.3 Chapter Four: Conflict and greenfield FDI in the mining sector: an investigation for dynamic and spillover impact.

This chapter presents the empirical results of the third empirical study. The aim of the chapter is to examine the impact of conflict on greenfield FDI in the mining sector. In other words, the study tries to examine the existing impact, its direction, and magnitude. Additionally, it tests whether the impact direction holds across different groups of countries around the world.

This chapter concentrates on testing two different effects. First, the dynamic impact, which investigates the impact of conflict on greenfield FDI in the mining sector over the contemporaneous and the following periods. Second, the paper investigates different spatial spillovers: the expected spillover impact of the outcome variable, FDI in the mining sector, in one country on its neighbours' outcome; the spatial spillover impact of conflict; and the spillover impact of any unobserved variables.

1.5.4 Chapter 5: Discussion and Conclusions

The conclusion to the thesis is included in this chapter, which restates the research questions raised in Chapter 1 and includes key findings from the studies in Chapters 2, 3, and 4.

2 The impact of conflict on the shadow economy: a cross-country analysis using the event study approach

2.1 Introduction

Recently, the shadow economy has attracted researchers' and policymakers' interest because of its widespread effects on economic and social development: particularly in developing countries, where it is one of their most common features. Shadow economy activities are labour intensive and suitable for adoption with low-return capital and small-scale production. They inefficiently use the factors of production and distort the investment environment. Moreover, the shadow economy affects official macroeconomic measurements such as gross domestic product, consumption expenditure, the unemployment rate, and the labour force. Thus, fiscal and monetary policies can be rendered less effective (Blackburn, et al., 2012; Schneider & Enste, 2000; Capasso & Jappelli, 2013). Different studies have urged that tax burden and employability are the main determinants of the shadow economy (Allingham, 1972; Portes, et al., 1989; Schneider & Enste, 2000). There is considerable evidence that these are important drivers that motivate individuals to participate in informal economic activities.

However, institutional factors such as political instability, including corruption, and economic freedom can also be an influential determinant for the shadow economy (Friedman, et al., 2000; Johnson, et al., 1998; Murdoch & Sandler, 2002; Elbahnasawy, et al., 2016). One can think about institutional quality as "the degree to which institutions reduce uncertainty for economic decision-makers and offer incentives for productive behaviour" (Berggren, et al., 2012). Consequently, institutional instability can be the result of any failure to reduce uncertainty in any of the above-mentioned factors. Besides these factors, internal and external conflict are major components to consider in quantifying countries' political instability.

The main aims for this chapter are three-fold: firstly, to examine the causal effect of exogenous conflict on the shadow economy and test its dynamism; secondly, to examine whether this impact, if it exists, differs according to countries' level of income; and finally, to investigate the impact of conflict intensity on the informal sector.

This chapter consists of six sections. Previously, the introduction has clarified the main objectives of this chapter, while in the second section, the study reviews different strands of literature which discuss possible links between conflict and the shadow economy. The collected data, which covers 156 countries during the period 1991-2015, are discussed in Section Three; the subsequent section is designed to check the exogeneity of conflict events; Section Five introduces the model, results, and discussion; and finally, conclusion is given.

2.2 Literature Review

Different studies have attempted to investigate the impact of political instability on economic growth. Grossman (1991) analysed revolutions to investigate the relationship between political instability and growth. The study found that, in countries where rulers are weak, the possibility of revolutions is higher, and people have a higher motivation to take part in revolutionary activities rather than market-productive activities. Conversely, revolutions are unlikely to succeed and people's engagement in market activities will be more favourable when strong rules exist. Kormendi and Meguire (1985) and Barro (1989) find that the extent of political rights is positively associated with growth. Alesina et al. (1996) found that in countries and periods with a high tendency for government collapses, growth is significantly lower than otherwise. Alesina and Tabellini (1989) provide a direct investigation of the relationship between political uncertainty and economic growth, examining the effect of political uncertainty on investment and capital flight. The study demonstrates that government collapse may lead to new government regulations related to capital tax, and productive activities that encourage consumption and capital flight. Thereby, this may lead to a reduction in domestic production.

Others have studied the impact of conflict on major economic indicators: e.g., Barro (1991) examined the impact of political unrest on growth rate. He used the number of assassinations and occurrence of violent revolutions and military coups as indicators for political unrest and found that political unrest affected the average growth level in cross-sectional data significantly.

Collier (1999) argues that economies lose 2.2% of their GDP growth for each year that they experience conflict. Furthermore, Abadie and Gardeazabal (2003) found that the per capita GDP decreased by 10% after the outbreak of terrorist attacks in the Basque region when compared with synthetic control regions where terror attacks had not occurred. Moreover, the study finds that conflict has an immediate negative impact on share prices for companies listed on the stock exchange. Lopez and Wodon (2005) found that the per capita GDP would be 25%-30% greater in Rwanda if the conflict had not taken place, while Costalli et al. (2017) found that the average annual loss of GDP per capita was 17.5% in a sample of 20 countries that had witnessed years of armed conflict. Nordhaus (2002) reports that most studies limit the cost of conflict to one country, neglecting international negative externalities: e.g., internal conflicts can have devastating long-term economic effects on both the states that experience them and their neighbours (Murdoch & Sandler, 2004). Furthermore, the researchers expanded their conflict cost estimations by including opportunity cost.

Nonetheless, conflict in some cases can have a positive impact on the economy and on society in the long run. Modernisation theory claims that conflict is an essential result of the alteration from the "traditional" to the "modern" phase of development (Olson, 1963; Pye, 1966; Feierabend, et al., 1969).

A study by Elbahnasawy et al. (2016) concludes that the political environment is considered an important determinant for the informal economy. Using selected specifications, the study finds that the informal economy is directly affected by political instability and polarisation. Moreover, the authors found varied evidence that the authority pattern is imperative, wherein more democratic political systems are linked with a lower size of informal economy, but also find consistent evidence that substantial changes in the authority pattern of the political system, including a substantial change from more authoritarian to more democratic systems, increases the size of the informal economy.

Nevertheless, there is insufficient evidence that links conflict either as a consequence or as a cause for the shadow economy. Ouédraogo (2017) uses data for 23 Sub-Saharan African countries to analyse the relationships between governance, corruption, and the size of the informal economy by including internal and external conflict as two socio-political stability indicators. The results show that internal conflict affects the informal sector negatively, whereas external conflict has a positive impact on it.

Peksen and Early (2019) explore how shadow economies are affected by violent internal conflicts. The study finds that a large scale of internal conflict as opposed to smaller conflicts has a huge impact on increasing the activities of the shadow economy. The authors extended their study objectives to include the impact of internal conflict activities on the shadow economy in neighbour states, and found that negative externalities accompanying the internal conflicts leak out to affect the shadow sector in those neighbouring states. Collier and Duponchel (2013) report similar results, in which Sierra Leone's civil war was also linked to a spectacular increase in the black market and shadow sector activities, which subsequently spilled over to affect neighbouring states.

The contribution of this paper comes in two areas. Firstly, to the best of the author's knowledge, very few pieces of research have attempted to test the relation between conflict and the shadow economy, and to explore under what circumstances conflict can be considered as one of the informal sector's determinants. Secondly, the study tests whether conflict events affect the size of the shadow economy in the contemporaneous period and in future periods.

2.3 Methodology

The methodology section entails three sub-sections: the first sub-section introduces the data, justifies its uses, and identifies the sources used. The next sub-section discusses the exogeneity of conflict events, which is an essential condition for regression to reduce the possibility of endogeneity problems. Finally, the last section introduces the model and its specifications.

2.3.1 Data collection

The study employed estimated results of shadow economy size as a percentage of GDP across 158 countries around the world (see Appendix 1). These data were obtained by Medina and Schneider (2018) during the period 1991 to 2015.

The treatment variable in this model is conflict, which represents the yearly number of fatalities for those falling during armed conflict. The data was retrieved from the one-sided violence[1] data set produced by the Uppsala Conflict Data Program (UCDP) and was obtained from Eck and Hultman (2007) and Petterson et al. (2019). The Uppsala dataset has three different estimations for one-sided violence, but this used the "best estimate"[2].

Essentially, the analysis depends on annually combined individual events of organised conflict that took place within a specified territory and year, and the total number of individual events before annual combinations is 152,617 events.

UCDP defines a conflict event as "*an incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date*".

The controlling variables that have been used are: GDP per capita adjusted to the Purchasing Power Parity (PPP); share of self-employment to the total labour force; unemployment rate; government expenditure as a share of GDP; trade openness, which is measured by dividing the summation of imports and exports by GDP;

[1] One-sided violence is the use of armed force by the government of a state or by a formally organized group against civilians which results in at least 25 deaths. Extrajudicial killings in custody are excluded. (Pettersson, 2019)

[2] Best estimate: The UCDP Best estimate consist of the aggregated most reliable numbers for all incidents of one-sided violence during a year. If different reports provide different estimates, an examination is made as to what source is most reliable. If no such distinction can be made, UCDP as a rule include the lower figure given. (Pettersson, 2019)

inflation calculated by GDP deflator; and domestic credit provided by the financial sector as a share of GDP. These data were subtracted from World Bank development indicators. Furthermore, the model uses control of corruption as an additional controlling variable. Data for corruption was obtained from the Worldwide Government indicators, with the estimate of corruption in standard normal units ranging from -2.5 (weak) to 2.5 (strong) control of corruption (Kraay, et al., 2010).

2.3.2 Checking for conflict exogeneity:

In ordinary least square (OLS) regression, the outcome variable can depend on the residuals. Thus, as a standard assumption, the explanatory variables must be independent of the outcome variable: otherwise, endogeneity will lead to inconsistent OLS estimation.

This section investigates the exogeneity of conflict events. In other words, it is important to be sure that the conflict event's origins have not stemmed from any economic cause. Consequently, the reverse causality problem from the treatment to the outcome should not be an issue in the model.

Therefore, the study implements a narrative check for the treatment of exogeneity following three steps:

- Step one: Choose a proper sample size by following the widely used formula put forward by Krejcie and Morgan (1970)

$$n = \frac{\chi^2 * N * P * (1-P)}{\left(ME^2 * (N-1)\right) + (\chi^2 * P * (1-P))} \quad \text{Equation 1}$$

  Where:

n: sample size

χ^2: Chi-square for specific confidence interval at one degree of freedom (3.8416)

N: the population size (152,617)

P: population proportion (each observation is assumed to have the same proportion)

ME: the proportional desired margin of error (assumed to be 5%)

- Step two: randomly select 383 observations out of the full sample.
- Step three: check the randomly selected sample narratively to identify the conflict event origins.

After applying the previous three steps, it was found that all the events in the sample are exogenous: in other words, the events of conflict had not arisen due to any economic causes. The sample statistics show that 78.5% of the conflicts occurred because of political issues, 12.6% were ethnic-based conflicts, 7.5% religious-based conflicts, and roughly 1.4% of conflicts were outbreaks based on illegal activities such as drug gangs.

Examples of conflict events involved in the chosen random sample are described below. In the armed conflict between the government of El Salvador and a leftist group called Farabundo Martí National Liberation Front (FMLN), in mid-September 1990, 23 FMLN members were reported killed in clashes (Little, 1994). The FMLN launched a major attack aiming to depose President Alfredo Cristiani's government in November 1989 (Hilsdon, et al., 2000). According to the non-governmental Salvadoran Human Rights Commission (CDHES), 2,868 persons were killed by armed forces between May 1989 and May 1990.

Another example is the Bosnian War, which was an international armed conflict that took place in Bosnia and Herzegovina between 1992 and 1995. The main combatants were the forces of the Republic of Bosnia and Herzegovina and those of Herzeg-Bosnia and Republika Srpska, proto-states led and supplied by Croatia and Serbia, respectively. The Bosnian War was marked by harsh fighting, indiscriminate bombardment of cities and towns, ethnic cleansing, and systematic mass violations (Wood, 2013).

Other examples of political conflict include wars between the Government of Congo and the Cocoye militia, the Sri Lankan civil war, the Israeli-Palestinian conflict, and tension between India and Pakistan in Kashmir. Ethnic conflicts selected include the Burundian Civil War, The Iran–PJAK armed conflict between the Islamic Republic of Iran and Kurdish rebels of the Kurdistan Free Life Party, and The Popular Liberation Front of Azawad, which was one of various militant rebel groups active during the Tuareg Rebellion in northern Mali from 1990 to 1995. Religious conflict examples include the Islamic-Christian conflict in Nigeria and the Philippines conflict. Finally, drug based-conflict examples include the Medellín Cartel conflict.

2.3.3 The event study approach

To examine the effect of exogenous conflict variation on the size of the shadow economy, the study follows Karafiath (1998) model which representing the event studies by using dummies.

In the finance literature, stock market studies widely examined the effect of financial and economic events on a firm’s financial performance. Research of this type is generally named an “event study” (Mackinlay, 1997). The conventional event study is a two-step process. first, the study attempts to estimate the parameters of market model regression pre-event. second, abnormal returns and t-statistics are estimated for the “event window’’ using regression parameters from the pre-event data and market data from the “event window.’’

However, Karafaith (1988) has suggested a model that can estimate the impact of not only an event, yet multiple events on the outcome variable. His approach enables investigating the dynamic impact, which represents the impact over each single period specified in the model. This approach is valid when we don’t expect the event to have a forever impact on the outcome variable, which is the case for most of the policy programs and events. Therefore, analysis can provide causal evidence on how much is the impact over each period.

Moreover, it can provide a robust and reliable estimate by mitigating the traditional econometric problems, eliminating the impact of control variables on the outcome, and by using the heteroscedasticity-consistent standard errors and ensuring that the error terms were independent of each other within groups. Besides, this approach can include a placebo period prior to the surge of the event which gives the method a better advantage in estimating the causal inference of the event on the outcome variable. Finally, one can estimate the cumulative impact over a period.

2.3.4 The model

$$\mathrm{Y_{it}} = \alpha + \boldsymbol{\varphi_i}\mathbf{X}_{\mathrm{it}} + \sum_{\mathrm{j=1}}^{-3} \beta\, \mathrm{D_{t+j}} + \gamma_t + \varepsilon_{\mathrm{it}} \qquad \text{Equation 2}$$

Where, i and t represent country and time respectively, γ_t is the year fixed effect which controls for fixed unobserved heterogeneity for year-specific or any other shocks that affect the size of the shadow economy globally. $\mathrm{Y_{it}}$ is the size of the shadow economy as a percentage of GDP.

$\boldsymbol{X_i}$ is a set of covariates including GDP per capita adjusted to Purchasing Power Parity (PPP) (Peksen & Early, 2019). The informal economy usually uses the existing capital in the formal sector, and therefore, changes in capital formation and GDP in return are considered to have an impact on shadow economy size. It is assumed here that the GDP per capita as a proxy for the formal economy has a negative impact on the shadow economy. Labour in the shadow usually works under illegal conditions, such as with insufficient safety and security safeguards, and at wages and salaries under the minimum official pay rate, since the shadow economy is a labour-intensive sector. Therefore, workers are more likely to move from the shadow economy to the growing formal sector, where work conditions are much better.

The second controlling variable is the share of self-employment to the total labour force (Dell'Anno, 2007; Dobre & Alexandru, 2009; Herwartz, et al., 2015). According to Bordginon and Zanardi (1997), having a significant fraction of small firms and a large proportion of entrepreneurs and self-employed persons in comparison to the total workforce is an important determinant that explains the higher level of the shadow economy. The possibilities for evading taxes are more are greater for this kind of firm, as they can easily misreport their income and sales statements.

From the literature (Gutmann, 1977; Tanzi, 1999; Dell'Anno & Solomon, 2008; Dobre & Alexandru, 2009), the unemployment rate is an important control variable. The impact of unemployment on the shadow economy can be interpreted in two different ways. First, unemployment negatively affects GDP growth: as mentioned earlier a negative impact of GDP per capita on the shadow economy is expected. Conversely, officially registered unemployed workers can still work for all or part of their time in the shadow economy and therefore, the assumption for unemployment is that it has a positive impact on the shadow economy.

Moreover, the model controls for government expenditure as a share of GDP. Government expenditures have a positive impact on growth, and hence, an increase in government expenditures can decrease the size of the shadow economy.

Trade openness, measured by dividing the summation of imports and exports by GDP (Peksen & Early, 2019), has a chance to decrease the size of the shadow economy, as economic activities with the external world can be easily inspected by the government, while inflation encourages workers to move into black markets (Peksen & Early, 2019). In this model, inflation is calculated by a GDP deflator. Additionally, the model includes the domestic credit provided by the financial sector as a share of GDP (Peksen & Early, 2019). Finally, the model includes control of corruption, following Johnson et al. (1998). Corruption as an indicator for political instability has an impact on the shadow economy, and the more control there is of corruption, the smaller the shadow economy should be. φ_i is a victor of coefficients.

D_{t+j}: denotes the treatment effect if conflict breaks out at year $t + j,\ j \in (1, -3)$, where D is a binary measure that represents conflict in which the aggregate number of fatalities is equal to or above 25 persons in a certain year and country. Later, as a check of robustness, this identification will be replaced by defining the binary variable as the aggregate number of fatalities equal to or greater than 100, 200 or 500 persons. Consequently, the dummy reflects the dynamic effect of conflict events on the size of the shadow economy during five periods. The first dummy period is a placebo to test if the treatment has any impact on the outcome before its outbreak. In other words, the current conflict event has no effect on the shadow economy size of the last year. Therefore, one could expect that the coefficient of this dummy should be insignificant. The second dummy represents the contemporaneous year of the conflict event, and the coefficients of the remaining dummies represent the impact of the current conflict event on the shadow economy in the subsequent three years.

ε_{it} : is the error term

The concern here is the magnitude, sign, and the statistical precision of the binary measure coefficient β, which reflects the impact of conflict on the size of the shadow economy.

One of the shortages in this model that it does not consider a geo-localized data, this may cause bias in estimations.[3]

[3] Data on the shadow economy and the other control variables are on the country level and annual basis. Which unable me to do the analysis based on the geo-localised data. However, the conflict is transformed into a dummy variable which can reduce the resulted bias. Moreover, the models include a country fixed effect which captures any time-invariant fixed effects.

To test the heteroscedasticity problem, the Breusch-Pagan / Cook-Weisberg test was used, and the results showed inconsistent estimation. Consequently, under heteroscedasticity, the OLS estimator still delivers unbiased and consistent coefficient estimates, yet the estimator will be biased for standard errors. Hence, biased standard errors lead to biased inferences.

To solve the inconsistent variance bias, the model includes Huber-White's heteroscedasticity-consistent standard errors which are used to allow the fitting of a model that contains heteroscedastic residuals (White, 1980).

The OLS method is used to calculate the coefficients of the regression in the Huber-White's Robust Standard Errors approach. However, the covariance matrix of the coefficient matrix is estimated by

$$cov(\beta) = (X^T X)^{-1} X^T S X (X^T X)^{-1}$$

where S stands for the residual's covariance matrix, which under the assumption that the residuals have mean 0 and are not autocorrelated, β is the estimated parameter, X is the set of independent variables, and T denotes the transpose matrix.

Huber-White's robust standard errors do not change the magnitude of the coefficient estimates, yet the test statistics will produce more accurate p-values as a result of changing the standard errors and relaxing the assumption that the errors are identically distributed. Finally, the model used the Eicker-Huber-White test to

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In 2001, the conflict in India caused 1716 fatalities; However, a similar number had been observed in Eritrea one year before. The model doesn't consider the proportion of fatalities to the land or population size. Yet, the available data is on a country level not geo-localised .

ensure that the error terms were independent of each other within groups (Williams, 2012).

2.4 Results and discussion

The descriptive statistics for each variable included in the model are shown in Table 1, the average size of the shadow economy of the 158 countries is 31.9, Table 2 emphasis that the size of the shadow economy differs according to countries' level of income.

Medina and Schneider (2018) argued that the median is slightly higher than the mean. The three largest shadow economies are Zimbabwe with 60.6, Bolivia with 62.3 and Georgia with 64.9. The three smallest shadow economies are Austria with 8.9, the United States with 8.3 and Switzerland with 7.2. For example, the shadow economy in Zimbabwe like in Africa has been known for different causes varying from tax evasion to criminal activity. Medina and Schneider (2018) claim that the main causes of the shadow economy in Zimbabwe are unemployment, seeking for survival, and internal migration. Table 3 emphasises that the mean of the shadow economy differs across conflict and non-conflict observations.

To investigate the dynamic impact of conflict on the shadow economy's size, the study starts its estimations without including corruption, and as mentioned in the data section, the estimation includes 4 models. In each model, the dependent variable is the shadow economy, and the key independent variable is conflict, which is represented by a binary variable that takes a value of 1 when the aggregate number of fatalities is equal to or above 25 persons for a certain year and country, in the other models and for robustness checks, this identification will be replaced, defining the binary variable as the aggregate number of fatalities equal to or greater than 100, 200 or 500 persons.

The estimated results in Table 4 show that the coefficients of the one single period dummy before the surge of and conflict event are insignificant in all models. These results are desirable and demonstrate the assumption stated that conflict has no impact on the shadow economy before its outbreak. In contrast, the results found a positive and significant impact for conflict on the shadow economy extending up to the next two years, displaying the same direction and descending magnitude. As displayed in Table 3 for model 1, when a conflict event breaks out, the size of the shadow economy increases by 0.7 percent for the same year, 0.31 the following year and 0.42 in the second year., After this, by the third year, the impact becomes insignificant.

The impact of conflict on the shadow economy becomes higher once the model reidentifies conflict events considering higher observations of violence, as applied in models 2 and 3. The confidence interval for the contemporaneous dummy in model 1 lies between 0.20 and 1.2, while the coefficients in models 2 and 3 are 0.617 and 0.904 respectively, and both lie between the lower and upper values of the above-mentioned confidence interval. Therefore, it cannot be agreed that this increase is statistically significant. However, model 4 represents higher conflict intensity compared with the previous three models and finds that the outbreak of a conflict event increases the size of the shadow economy by 1.12 percent. This increase is significantly different from the previous models. Figure 1 shows the dynamic effects of conflict on the shadow economy, starting from the year when the conflict breaks out, and continuing for the next two years when the binary conflict event is defined as greater than or equal to 25 fatalities.

Next, the study investigates whether level of income affects the dynamic impact of conflict, and estimates in Table 4 show the impact of conflict on the shadow economy in high and non-high-income countries. The classification of the countries according to their level of income is based on the World Bank's classification. The odd models represent the high-income countries, in which the results failed to conclude any significant impact even when countries witnessed higher conflict. However, in the non-high-income countries, the even models, the impacts are significant in all models. Besides, when conflict becomes extremely high, as shown in model 8 in Table 4, the impact becomes statistically higher.

Johnson et al. (1998) find that corruption is one of the determinates for the shadow economy. However, while corruption is more likely to be fuelled in continued conflict, it encompasses a span of different scales: e.g., large-scale corruption associated with political powers and the armed industries vary from the small-scale corruption behaviour of ordinary individuals who sometimes behave in illegal ways to seek a means of survival (Lindberg & Orjuela, 2011). Furthermore, corruption has been found to be positively correlated with higher risk of political instability (Le Billon, 2003). This study conducts a simple investigation of the nexus between conflict and corruption and finds that the relationship between conflict and corruption is bidirectional from corruption to conflict. More details are displayed in Appendix 2.

Thus, when the study included control of corruption as an additional control variable, the consistent dynamic impacts disappear, and only the contemporaneous impact remains significant, Table 5 displays estimations of the dynamic impact of conflict on the size of the shadow economy by controlling for corruption.

The previous results showed the marginal impact of how a conflict event affects the size of the shadow economy contemporaneously and in each following year. However, to examine the aggregate impact of conflict on the shadow economy, the study suggests using the following equation:

$$\mathrm{Y_{it}} = \alpha + \boldsymbol{\gamma_i}\mathbf{X}_{\mathrm{it}} + \beta \mathrm{D_p} + \varepsilon_{\mathrm{it}} \qquad \text{Equation 3}$$

Where p represents an interval of the years that are included in the estimation: in this model p $\in (1,5)$ years.

Table 5 includes four different estimations, and each one represents different conflict intensities. $\mathrm{D_p}$ is a conflict dummy that equals 1 for the next five years if the number of fatalities in a year is greater than or equal to 25 in model 1, greater than or equal to 100 in model 2, greater than or equal to 200 in model 3, and greater than or equal to 500 in model 4.

The results demonstrate that, when conflict arises, the size of the shadow economy increases by 1.025 percent in aggregate for the first five years, as displayed in model 1 in Table 6. This aggregate impact increases when conflict becomes more vigorous, yet this increase is not statistically significant in models 2, 3 and 4.

However, the interaction between the 5-year conflict interval and GDP per capita suggests that level of income plays an important role in controlling the impact of conflict on the shadow economy's size.

Nevertheless, the slope of the relationship between the size of the shadow economy and the country's level of income would be steeper for observations that have not witnessed any conflict events. In contrast, the responsiveness of the change in the size of the shadow economy to change in level of income would be less after controlling for conflict.

Moreover, the intensity of conflict makes the slope less steep: in other words, more violent conflict events require a greater change in per capita level of income to cause a specified change in the size of the shadow economy. Figure 2 summarizes the above discussion.

To determine the five-year aggregate impact of conflict on the shadow economy when the interaction between conflict and GDP per capita takes place, the first derivative must be taken. In regression models, interaction happens when the impact of an explanatory variable on dependent variable changes is dependent on the value of another explanatory variable.

The following equation can be used to estimate the marginal impact of the 5-year conflict interval on the shadow economy for different levels of income:

$$\frac{d\ Shadow\ economy}{d\ conflict} = \beta + \gamma \times\ Log\ GDP\ per\ capita \qquad \text{Equation 4}$$

Where β is the coefficient of conflict and γ is the coefficient of the interaction term between conflict and GDP per capita. For example, model 1 in Table 7 shows that GDP per capita diminishes the impact of conflict on the shadow economy according to the following equation:

$$\frac{d\ Shadow\ economy}{d\ conflict} = (7.021) - (0.710) \times\ Log\ GDP\ per\ capita \qquad \text{Equation 5}$$

Figure 3 summarises the aggregate impact of the 5-year conflict interval on the shadow economy after interacting with the country’s level of income. The results show that lower-income countries wittiness a higher impact from conflict on the shadow economy’s size. However, this impact shrinks to zero when the country’s annual level of income per capita is approximately equal to 22,000 US dollars. Furthermore, the impact becomes negative when the GDP per capita exceeds this level. Moreover, the impact becomes steeper when the intensity of conflict increases, this indicates that smaller changes in GDP per capita incrementally influence the impact of conflict on the shadow economy size, yet in a contradictory direction.

Further analysis, including more interaction terms, can be found in Appendix 3. Table 10 presents results for the interaction between conflict and domestic credit to the private sector, and Table 11 introduces the results for interaction between conflict and inflation.

2.5 Conclusion:

In this paper, the event study approach was used to investigate the dynamic impact of conflict on the shadow economy. Furthermore, it has examined whether there are significant differences between developed and developing countries when an impact exists, and sought to test whether conflict intensity moderates this impact.

The contribution of this paper is two-fold. Firstly, to the best of the author’s knowledge, very few pieces of research have attempted to test the relation between conflict and the shadow economy, and under what circumstances conflict can be considered as one of the informal sector’s determinants. Secondly, the study tests if conflict events affect the size of the shadow economy both in the contemporaneous period and in future periods.

The study employed data for 156 countries, including the size of the shadow economy as a dependent variable, and conflict as the key independent variable.

data on conflict was combined annually from organised individual conflict events that took place in a specific territory and time and triggered casualties.

The results show that conflict has a dynamic impact on the shadow economy that remains statistically significant over three periods, starting from the contemporaneous year, and encompassing the following two years. Also, the study found that lower intensity conflict events increase the size of the shadow economy by less than one percent for each following year, whereas high-scale conflict events increase its impact by 1.3 percent for the contemporary year and 1.2 percent for the next year only.

The study extended the analysis to include not only the marginal impact but the aggregate impact also. The results suggest that the outbreak of conflict increases informal economy activities by less than 2 percent within the first 5 years, and that this impact increases when conflict becomes more severe.

Nevertheless, the investigations conclude that there is a statistically significant difference between high and non-high-income countries on the impact of conflict on the shadow economy, in which the impact becomes insignificant in high-income countries, unlike for other countries.

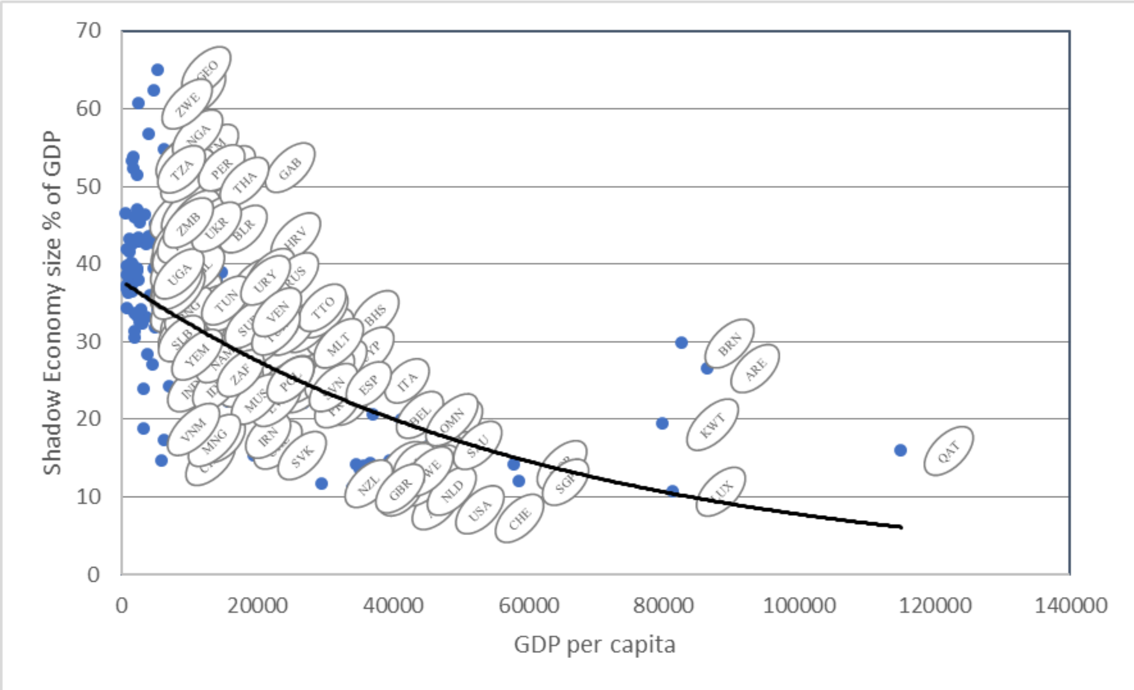
Moreover, the suggested technique failed to reach any dynamic impact once the model controlled for corruption. Both strands of literature and further applied simple investigations assume that there is a possibility of multicollinearity when considering conflict and corruption in the same model.

The study has extended analysis in this area by moderating the model by the level of income of each country, and the results reveal that the interaction between conflict and GDP per capita can better interpret the relationship between conflict and the shadow economy: thus, more economic growth is required to decrease the size of the shadow economy when conflict exists. Additionally, more intensified conflict events steepen the marginal impact of conflict on the shadow economy.

These results should encourage researchers and policymakers to consider conflict as one of the shadow economy's determinants in their research and policy programmes. In particular, for less developed countries, future research is recommended to focus on in-depth investigations of this relation, and how the interaction between conflict and other shadow economy determinants can impact this impact: namely, the quality of government and the rule of law.

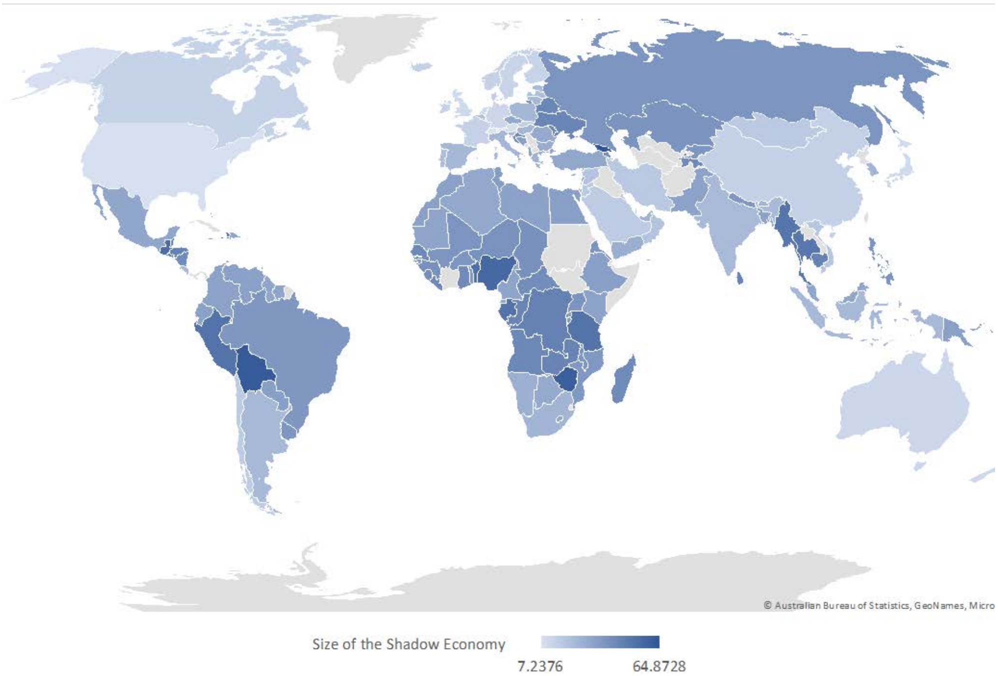
2.6 Figures:

Figure 1: The correlation between the size of the shadow economy and the GDP per capita



Source: Author's work

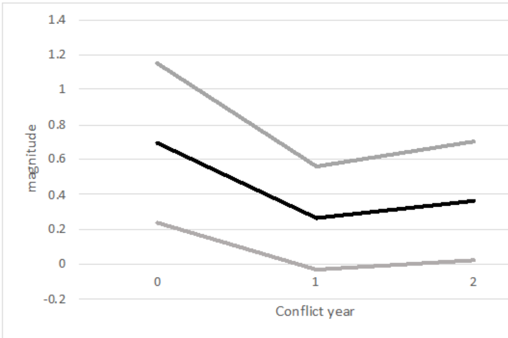
Figure 2: The average size of the shadow economy around the world (1991-2015)



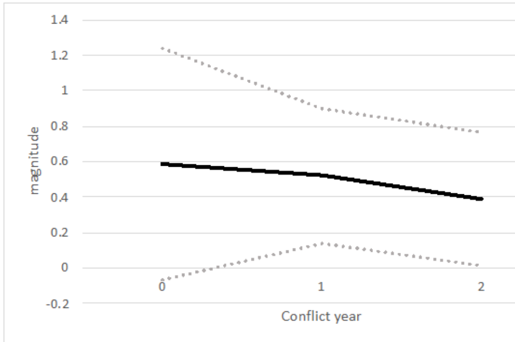
Source: Author's work, based on Medina and Schneider (2018) calculations

Figure 3: The dynamic effect of conflict on the shadow economy size

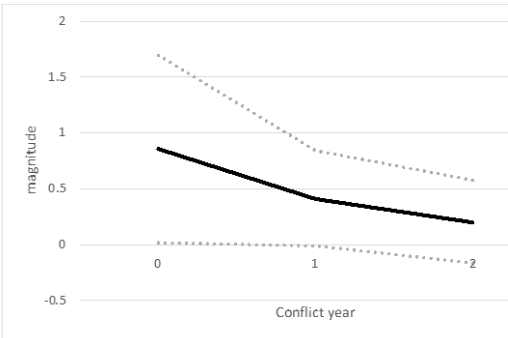
(1) Fatalities ≥ 25



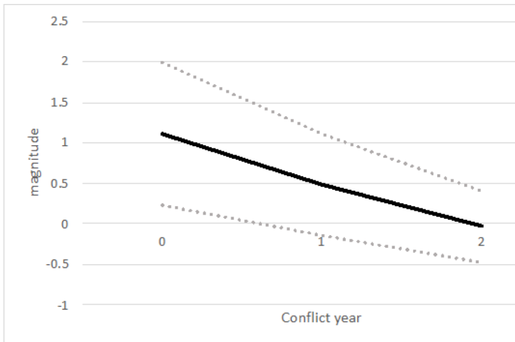
(2) Fatalities ≥ 100



(3) Fatalities ≥ 200



(4) Fatalities ≥ 500

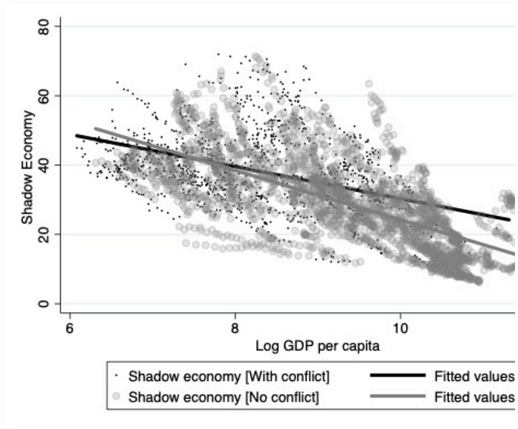


The black line represent the dynamic impact of conflict on the shadow economy for three periods, the contemporary year and the next two years, the four figures display this impact when if number of fatalities in a year ≥ 25 in (1), ≥ 100 in (2) ≥ 200 in (3) and ≥ 500 in (4).

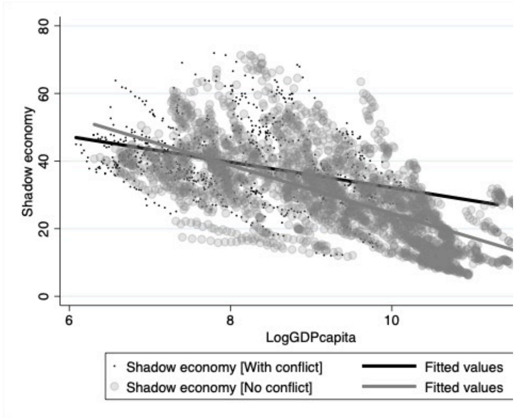
Source: author’s work, based on Table 3 results.

Figure 4: The relationship between shadow economy and GDP per Capita after moderating for conflict.

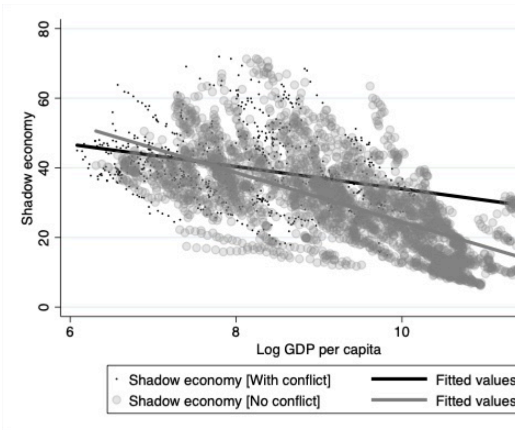
(1) Fatalities ≥ 25



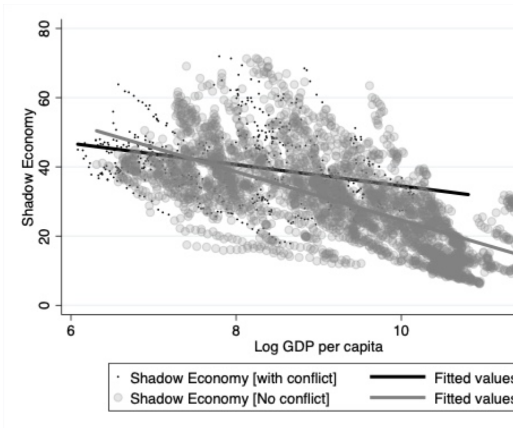
(2) Fatalities ≥ 100



(3) Fatalities ≥ 200



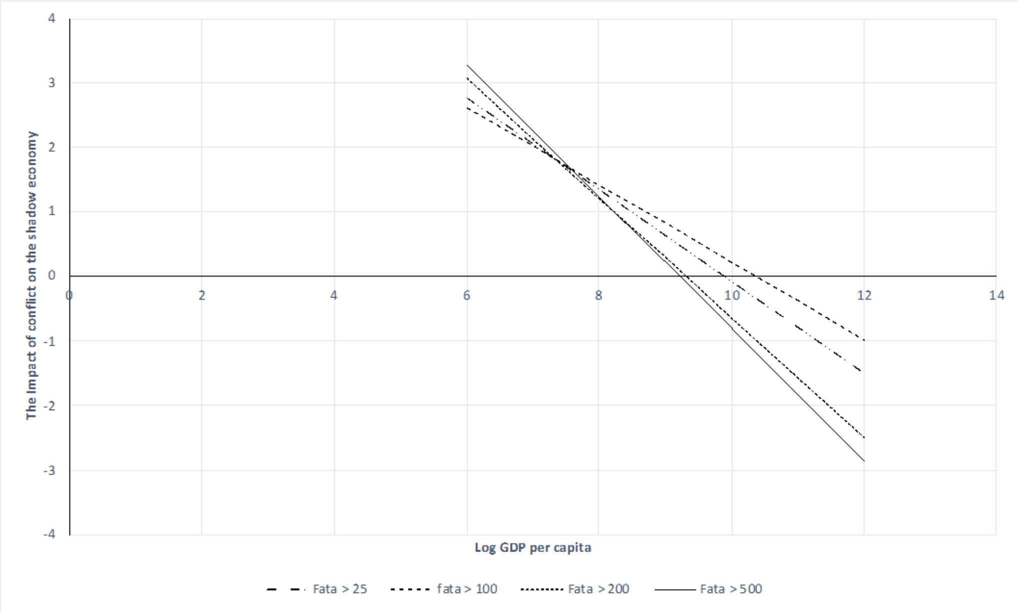
(4) Fatalities ≥ 500



The scatter diagram displays the observations that represent the relationship between the shadow economy on the y-axis and the GDP per capita on the x-axis, the black dots are those observations when conflict exist and the grey ones when conflict does not exist, the black and grey lines represent the fitted values of the relationship for each case.

Source: author’s work, based on Table 7 results

Figure 5: The marginal Impact of conflict on the shadow economy after interacting with GDP per capita



Source: author’s work, based on model (1) Table 7 results and Equation 5 calculations

2.7 Tables

Table 1: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Shadow Economy	3870	31.89	13.05	6.16	71.95
Fatalities	3875	215.54	1361.97	0	48666
GDP per capita	3781	16159.31	19058	438	124024
Self employed	3875	44.03	28.37	0.42	94.95
Unemployment	3875	7.79	5.87	0.16	37.94
Government expenditure	3492	15.73	6.10	0.91	76.22
Trade Openness % GDP	3615	83.10	52.65	0.17	442.62
Inflation	3786	41.05	549.24	-31.57	26765.86
Domestic credit provided by financial sector share of GDP	2982	46.37	45.28	0.19	308.98
Corruption	2,617	-.024	1.03	-1.77	2.47

Source: author's work

Table 2: Summary statistics on the size of shadow economy based on countries level of income

Variable	observations	Mean	Std. Dev.	Min	Max
World	3875	31.89	2.55	27.53	35.26
Low-income countries	650	40.19	2.2	36.05	43.42
Lower mid income countries	900	38.61	3.36	32.28	42.57
Higher Mid income countries	1125	34.65	2.99	29.64	38
High income countries	1200	19.81	1.88	17.18	22.95

Source: Author's calculations, based on Medina and Schneider (2018)

Table 3: Two-sample t-test, based conflict intensity

	Obs. (0)	Obs. (1)	Mean (0)	Mean (1)	Dif.	St. Err.	t-test	p-value
Fatalities No. ≥ 25	3063	802	30.062	38.813	-8.751	.498	-17.55	0.000
Fatalities No. ≥ 100	3312	558	30.617	39.422	-8.805	.58	-15.2	0.000
Fatalities No. ≥ 200	3403	467	30.774	39.995	-9.22	.627	-14.7	0.000

(0) Represents non-conflict observations, (1) Represents conflict observations

Table 4: Dynamic effect of conflict on the shadow economy size [without including corruption]

VARIABLES	(1)	(2)	(3)	(4)
L. Log GDP Capita	-9.823***	-9.664***	-9.678***	-9.698***
	(1.773)	(1.756)	(1.794)	(1.805)
L. Self-employed	-0.0179	-0.0207	-0.0154	-0.00938
	(0.0742)	(0.0720)	(0.0730)	(0.0746)
L. Unemployment	0.210***	0.214***	0.213***	0.204***
	(0.0732)	(0.0744)	(0.0736)	(0.0719)
L. Government exp. %GDP	0.127**	0.127**	0.127**	0.123**
	(0.0580)	(0.0589)	(0.0583)	(0.0573)
L. Trade Openness % GDP	-0.0140*	-0.0134*	-0.0137*	-0.0138*
	(0.00751)	(0.00742)	(0.00752)	(0.00750)
L. Inflation	5.83e-05	6.52e-05	5.16e-05	7.35e-05
	(4.08e-05)	(4.27e-05)	(4.25e-05)	(4.47e-05)
L. DCPS	0.0206***	0.0205***	0.0205***	0.0206***
	(0.00676)	(0.00672)	(0.00676)	(0.00681)
D_{t+1}	0.326	0.516	0.486	0.0111
	(0.267)	(0.405)	(0.469)	(0.372)
D_{t0}	0.692***	0.582*	0.848**	1.112**
	(0.232)	(0.333)	(0.428)	(0.446)
D_{t-1}	0.264*	0.522***	0.411*	0.482
	(0.151)	(0.194)	(0.220)	(0.322)
D_{t-2}	0.359**	0.389**	0.200	-0.0348
	(0.174)	(0.192)	(0.189)	(0.222)
D_{t-3}	-0.127	0.193	-0.0766	0.254
	(0.316)	(0.353)	(0.335)	(0.326)
Constant	118.1***	116.5***	116.8***	116.9***
	(18.62)	(18.50)	(18.85)	(18.97)
Observations	2,556	2,556	2,556	2,556
Number of ID	143	143	143	143
Robust	Yes	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Shadow economy size in all models, the key independent variable Conflict Dummy is a binary variable, in which equal 1 if number of fatalities in a year ≥ 25 in model (1), ≥ 100 in model (2) ≥ 200 in model (3) and ≥ 500 in model (4).

Table 5: The impact of conflict on the shadow economy in high and non-high-income countries

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L. Log GDP Capita	-9.324***	-10.06***	-9.426***	-9.786***	-9.465***	-9.787***	-9.465***	-9.780***
	(2.696)	(2.200)	(2.603)	(2.189)	(2.613)	(2.246)	(2.613)	(2.258)
L. Self-employed	0.104	-0.0568	0.104	-0.0603	0.106	-0.0545	0.106	-0.0471
	(0.146)	(0.0829)	(0.146)	(0.0801)	(0.145)	(0.0812)	(0.145)	(0.0831)
L. Unemployment	0.241*	0.148	0.236*	0.146	0.234*	0.147	0.234*	0.131
	(0.130)	(0.0929)	(0.134)	(0.0974)	(0.131)	(0.0933)	(0.131)	(0.0850)
L. Government exp. %GDP	0.142	0.143**	0.143	0.144**	0.146	0.144**	0.146	0.140**
	(0.0962)	(0.0651)	(0.0979)	(0.0667)	(0.0978)	(0.0660)	(0.0978)	(0.0648)
L. Trade Openness % GDP	0.00615	-0.0333***	0.00590	-0.0325***	0.00611	-0.0331***	0.00611	-0.0334***
	(0.00768)	(0.0104)	(0.00736)	(0.0103)	(0.00741)	(0.0104)	(0.00741)	(0.0102)
L. Inflation	0.0470*	3.40e-05	0.0459*	4.03e-05	0.0462*	2.60e-05	0.0462*	4.56e-05
	(0.0266)	(5.21e-05)	(0.0270)	(5.32e-05)	(0.0270)	(5.32e-05)	(0.0270)	(5.44e-05)
L. DCPS	0.0118	0.0313**	0.0119	0.0308**	0.0118	0.0305**	0.0118	0.0305**
	(0.0102)	(0.0151)	(0.0102)	(0.0149)	(0.0102)	(0.0154)	(0.0102)	(0.0155)
D_{t+1}	0.465	0.300	-0.106	0.548	-0.273	0.506	-0.273	0.0193
	(0.383)	(0.278)	(0.350)	(0.419)	(0.859)	(0.475)	(0.859)	(0.380)
D_{t0}	0.285	0.736***	0.162	0.629*	0.172	0.897**	0.172	1.176**
	(0.411)	(0.248)	(0.566)	(0.350)	(0.641)	(0.439)	(0.641)	(0.464)
D_{t-1}	-0.126	0.237	0.422	0.447**	-0.254	0.325	-0.254	0.400
	(0.340)	(0.160)	(0.641)	(0.205)	(0.459)	(0.229)	(0.459)	(0.312)
D_{t-2}	-0.253	0.346*	-0.700	0.363*	-1.935	0.204	-1.935	-0.0110
	(0.286)	(0.188)	(1.367)	(0.205)	(1.262)	(0.196)	(1.262)	(0.238)
D_{t-3}	-0.504	-0.181`	-1.014	0.207	-2.529	-0.0394	-2.529	0.329
	(0.499)	(0.343)	(1.862)	(0.364)	(2.014)	(0.329)	(2.014)	(0.328)
Constant	109.9***	123.6***	112.0***	121.1***	115.0***	121.3***	115.0***	120.9***
	(28.97)	(21.51)	(27.51)	(21.46)	(28.11)	(21.95)	(28.11)	(22.12)
Observations	791	1,765	791	1,765	791	1,765	791	1,765
Number of ID	46	97	46	97	46	97	46	97
Robust	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Shadow economy size in all models, the key independent variable Conflict Dummy is a binary variable, in which equal 1 if the number of fatalities in a year ≥ 25 in models (1) & (2), ≥ 100 in models (3) & (4) ≥ 200 in models (5) & (6), ≥ 500 in models (7) & (8), the odd columns represent the high income countries and the even columns represent the non-high income countries.

Table 6: Dynamic impact of conflict on the shadow economy size controlling for corruption

VARIABLES	(1)	(2)	(3)	(4)
L. Log GDP Capita	-9.323***	-9.198***	-9.243***	-9.333***
	(1.417)	(1.385)	(1.422)	(1.446)
L. Self-employed	-0.0218	-0.0275	-0.0209	-0.0133
	(0.0605)	(0.0581)	(0.0594)	(0.0611)
L. Unemployment	0.164**	0.167**	0.168***	0.159**
	(0.0638)	(0.0649)	(0.0642)	(0.0641)
L. Government exp. %GDP	0.108*	0.109*	0.109*	0.104*
	(0.0599)	(0.0603)	(0.0596)	(0.0588)
L. Trade Openness % GDP	-0.00941	-0.00845	-0.00892	-0.00897
	(0.00699)	(0.00679)	(0.00683)	(0.00695)
L. Inflation	-5.34e-05	-3.91e-05	-4.50e-05	-0.000167
	(0.000346)	(0.000349)	(0.000343)	(0.000332)
L. DCPS	0.0177***	0.0173**	0.0175***	0.0178***
	(0.00683)	(0.00675)	(0.00679)	(0.00685)
L. Corruption	-1.778***	-1.810***	-1.776***	-1.753***
	(0.568)	(0.572)	(0.568)	(0.571)
D_{t+1}	0.238	0.169	0.149	0.269
	(0.305)	(0.479)	(0.530)	(0.544)
D_{t0}	0.868***	0.961**	1.411***	1.011*
	(0.219)	(0.478)	(0.538)	(0.604)
D_{t-1}	0.121	0.291	-0.0923	0.425
	(0.216)	(0.394)	(0.415)	(0.327)
D_{t-2}	0.251	0.789**	0.568	-0.351
	(0.223)	(0.369)	(0.348)	(0.296)
D_{t-3}	-0.0200	0.141	-0.0651	0.361
	(0.286)	(0.376)	(0.337)	(0.394)
Constant	113.6***	112.7***	112.9***	113.6***
	(14.88)	(14.56)	(14.91)	(15.13)
Observations	1,891	1,891	1,891	1,891
Number of ID	142	142	142	142
Robust	Yes	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Shadow economy size in all models, the key independent variable is Conflict Dummy is a binary variable, in which equal 1 if number of fatalities in a year ≥ 25 in model (1), ≥ 100 in model (2) ≥ 200 in model (3) and ≥ 500 in model (4).

Table 7: the cumulative impact of conflict on the shadow economy

	(1)	(2)	(3)	(4)
VARIABLES	Fata>25	Fata>100	Fata>200	Fata>500
L. Log GDP Capita	-9.818***	-9.776***	-9.650***	-9.658***
	(1.735)	(1.714)	(1.779)	(1.789)
L. Self-employed	-0.0178	-0.0236	-0.0168	-0.0125
	(0.0739)	(0.0724)	(0.0730)	(0.0740)
L. Unemployment	0.222***	0.224***	0.227***	0.221***
	(0.0710)	(0.0717)	(0.0724)	(0.0721)
L. Government exp. %GDP	0.124**	0.123**	0.125**	0.121**
	(0.0563)	(0.0569)	(0.0578)	(0.0567)
L. Trade Openness % GDP	-0.0140*	-0.0142*	-0.0142*	-0.0140*
	(0.00753)	(0.00749)	(0.00753)	(0.00751)
L. Inflation	5.86e-05	6.06e-05	5.76e-05	5.59e-05
	(3.90e-05)	(3.88e-05)	(3.95e-05)	(3.99e-05)
L. DCPS	0.0205***	0.0203***	0.0201***	0.0206***
	(0.00675)	(0.00672)	(0.00673)	(0.00680)
Conflict interval $_{(1,5)}$	1.025***	1.324***	1.140**	1.141**
	(0.366)	(0.469)	(0.485)	(0.573)
Constant	118.3***	118.2***	116.8***	116.8***
	(18.27)	(18.03)	(18.62)	(18.74)
Observations	2,556	2,556	2,556	2,556
Number of ID	143	143	143	143
Robust	Yes	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Shadow economy size in all models, the key independent variable is (Conflict interval $_{(1,5)}$) which is a binary variable that equals 1 for the next five years if the number of fatalities in a year ≥ 25 in model (1), ≥ 100 in model (2) ≥ 200 in model (3) and ≥ 500 in model (4).

Table 8: Interaction between Conflict 5 years interval and GDP per Capita

VARIABLES	(1) Fata>25	(2) Fata>100	(3) Fata>200	(4) Fata>500
L. Log GDP Capita	-9.533***	-9.558***	-9.394***	-9.423***
	(1.725)	(1.723)	(1.769)	(1.768)
L. Self-employed	-0.0237	-0.0275	-0.0209	-0.0172
	(0.0722)	(0.0711)	(0.0712)	(0.0725)
L. Unemployment	0.223***	0.224***	0.232***	0.228***
	(0.0710)	(0.0719)	(0.0716)	(0.0716)
L. Government exp. %GDP	0.125**	0.125**	0.128**	0.125**
	(0.0573)	(0.0580)	(0.0589)	(0.0584)
L. Trade Openness % GDP	-0.0143*	-0.0143*	-0.0146**	-0.0142*
	(0.00748)	(0.00742)	(0.00744)	(0.00739)
L. Inflation	6.14e-05	6.34e-05*	6.38e-05*	6.49e-05*
	(3.84e-05)	(3.83e-05)	(3.84e-05)	(3.93e-05)
L. DCPS	0.0191***	0.0195***	0.0190***	0.0188***
	(0.00666)	(0.00668)	(0.00668)	(0.00673)
$\text{Conflict interval}_{(1,5)}$	7.021***	6.210**	8.620***	9.395**
	(1.899)	(2.432)	(3.074)	(3.667)
$\text{Conflict interval}_{(1,5)} \times GDP\ per\ capita$	-0.710***	-0.600**	-0.927**	-1.021**
	(0.211)	(0.299)	(0.379)	(0.440)
Constant	116.0***	116.5***	114.7***	114.9***
	(18.16)	(18.09)	(18.49)	(18.53)
Observations	2,555	2,555	2,555	2,555
Number of ID	143	143	143	143
Robust	Yes	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Shadow economy size in all models, the key independent variable is ($\text{Conflict interval}_{(1,5)}$) which is a binary variable that equals 1 for the next five years if the number of fatalities in a year ≥ 25 in model (1), ≥ 100 in model (2) ≥ 200 in model (3) and ≥ 500 in model (4).

2.8 Appendix

Appendix 1: List of countries

Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, The Bahamas, Bahrain, Bangladesh, Belarus, Belgium, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Canada, Central African Republic, Chad, Chile, China, Colombia, Comoros, Congo Dem. Rep., Congo, Rep., Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt Arab Rep., El Salvador, Equatorial Guinea, Eritrea, Estonia, Ethiopia, Fiji, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong, China, Hungary, Iceland, India, Indonesia, Iran Islamic Rep., Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea Rep., Kuwait, Kyrgyz Republic, Latvia, Lebanon, Lesotho, Liberia, Libya, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Palestine, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Rwanda, Saudi Arabia, Senegal, Sierra Leone, Singapore, Slovak Republic, Slovenia, Solomon Islands, South Africa, Spain, Sri Lanka, Suriname, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Tanzania, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe.

Appendix 2: nexus between corruption and conflict

Table 9: The impact of Corruption on Conflict

VARIABLES	(1)	(2)	(3)	(4)
Corruption	-0.0907***	-0.0674***	-0.0612***	-0.0199***
	(0.0221)	(0.0225)	(0.0192)	(0.00633)
Constant	0.225***	0.146***	0.106***	0.0454***
	(0.0316)	(0.0276)	(0.0240)	(0.0167)
Observations	2,617	2,617	2,617	2,617
Number of ID	154	154	154	154
Robust	Yes	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, The dependent variable is Conflict Dummy which is a binary variable, in equals 1 if number of fatalities in a year ≥ 25 in model (1), ≥ 100 in model (2) ≥ 200 in model (3) and ≥ 2000 in model (4).

Table 10: The impact of Conflict on Corruption

VARIABLES	(1)	(2)	(3)	(4)
Conflict	-0.0244	-0.0299	-0.0282	-0.0571
	(0.0280)	(0.0370)	(0.0362)	(0.0409)
Constant	-0.00403	-0.00517	-0.00654	-0.00695
	(0.0811)	(0.0815)	(0.0817)	(0.0818)
Observations	2,617	2,617	2,617	2,617
Number of ID	154	154	154	154
Robust	Yes	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, The dependent variable is corruption and the independent variable is Conflict Dummy which is a binary variable, in equals 1 if number of fatalities in a year ≥ 25 in model (1), ≥ 100 in model (2) ≥ 200 in model (3) and ≥ 2000 in model (4).

Appendix 3: Further analysis including more interaction terms

Table 11: Interaction between Conflict 5 years interval and Domestic credit to private sector

	(1)	(2)
VARIABLES	Fata>200	Fata>500
L. Log GDP Capita	-9.646***	-9.630***
	(1.803)	(1.813)
L. Self-employed	-0.0181	-0.0137
	(0.0727)	(0.0739)
L. Unemployment	0.225***	0.218***
	(0.0721)	(0.0717)
L. Government exp. %GDP	0.129**	0.124**
	(0.0592)	(0.0580)
L. Trade Openness % GDP	-0.0144*	-0.0140*
	(0.00755)	(0.00749)
L. Inflation	6.14e-05	5.90e-05
	(4.16e-05)	(4.19e-05)
L. DCPS	0.0198***	0.0200***
	(0.00674)	(0.00679)
Conflict interval $_{(1,5)}$	1.486**	1.672**
	(0.589)	(0.686)
Conflict interval $_{(1,5)} \times Inflation$	-0.0119*	-0.0173**
	(0.00689)	(0.00872)
Constant	116.7***	116.5***
	(18.84)	(18.96)
Observations	2,546	2,546
Number of ID	143	143
Robust	Yes	Yes
Country clustering	Yes	Yes
Year fixed effect	Yes	Yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Shadow economy size in all models, the key independent variable is (Conflict interval $_{(1,5)}$) which is a binary variable that equals 1 for the next five years if the number of fatalities in a year $\geq$ 200 in model (1) and $\geq$ 500 in model (2).

Table 12: Interaction between Conflict 5 years interval and inflation

VARIABLES	(1) Fata>25	(2) Fata>500
L. Log GDP Capita	-9.819***	-9.692***
	(1.739)	(1.797)
L. Self-employed	-0.0174	-0.0132
	(0.0740)	(0.0742)
L. Unemployment	0.221***	0.221***
	(0.0710)	(0.0721)
L. Government exp. %GDP	0.124**	0.122**
	(0.0567)	(0.0573)
L. Trade Openness % GDP	-0.0139*	-0.0140*
	(0.00752)	(0.00751)
L. Inflation	8.27e-05**	-3.66e-05
	(3.52e-05)	(5.92e-05)
L. DCPS	0.0212***	0.0205***
	(0.00697)	(0.00679)
Conflict interval $_{(1,5)}$	1.039***	1.070*
	(0.366)	(0.578)
Conflict interval $_{(1,5)} \times Inflation$	-0.00105**	0.00606*
	(0.000529)	(0.00361)
Constant	118.2***	117.1***
	(18.31)	(18.82)
Observations	2,555	2,555
Number of ID	143	143
Robust	Yes	Yes
Country clustering	Yes	Yes
Year fixed effect	Yes	Yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Shadow economy size in all models, the key independent variable is (Conflict interval $_{(1,5)}$) which is a binary variable that equals 1 for the next five years if the number of fatalities in a year ≥ 25 in model (1) and ≥ 500 in model (2).

3 The impact of Intifada on the shadow economy in Palestine: an empirical study using the Difference in Differences approach

3.1 Introduction

The previous chapter has presented an introduction to the impact of conflict on the shadow economy, and the results suggest that the impact could be dynamic, in other words, it not only affects the contemporaneous year but also the following years. Moreover, the results show that the there was no significant impact in high-income countries, unlike in the less wealthy countries.

This chapter mainly aims to examine the results obtained by studying a special case of prolonged conflict, and to test whether the findings in the previous chapter remain the same for this case. This study employs the Difference in Differences approach, to assess whether conflict had an impact on the shadow economy in Palestine during the period 1996-2015. The paper seeks to provide evidence with which to answer the question: "did the conflict which arose with the outbreak of the second Intifada have any impact on the shadow economy in Palestine?". Moreover, the study aims to estimate the size of the shadow economy in Palestine using the MIMIC approach.

The second Intifada witnessed a period of intensified Israeli–Palestinian conflict. The Palestinians describe Intifada as a rebellion against Israel, yet Israelis consider it an organized and prolonged terror campaign perpetuated by the Palestinian National Authority and several Palestinian militant groups. The general spark for the conflict was the collapse of the Camp David negotiations held in July 2000 with the intention of reaching a final agreement on the Israeli-Palestinian peace process (Pressman, 2003).

Intifada not only affected the Palestinian economy, but also harmed the Israeli economy (Fishelson, 1993; Fielding, 2003; Horiuchi & Mayerson, 2015). Consequently, this paper extends previous estimations to examine the impact of Intifada on the Israeli shadow economy. Furthermore, in the study, Jordan is selected to be included in Difference in Differences estimation as a placebo, assuming that the Intifada had no impact on the Jordanian shadow economy. This was done to ensure that there would be no spillover for the treatment on the outcome variable across neighbouring countries.

Intifada as an indicator of consecutive conflict events can be considered an exogenous variable on the outcome. The Israeli-Palestinian conflict started in 1948, and represents one of the most prolonged conflicts in the contemporary era. moreover, the size of the shadow economy in Palestine is above the worldwide average by 36%: thus, the above-stated reasons provide justification for this study's focus on investigating the Palestinian-Israeli conflict and its impact on the size of the shadow economy.

For better and more accurate estimates, the study starts investigating empirical evidence using the propensity score matching (PSM) method. The propensity score enables researchers to use vast datasets and complex statistical techniques to build up the best probable control group for a given treatment group (Gertler, et al., 2016).

Applying the Difference in Differences approach requires the fulfilment of several assumptions. First is the parallel trend assumption, which is considered the main assumption, and states that for the outcome variable of interest, both the treated and control groups would have charted the same time trend in the absence of the treatment (Card & Krueger, 1993; Card & Krueger, 2000; Stuart, et al., 2014). The Stable Unit Treatment Value Assumption (SUTVA) is another essential assumption, and identifies that there should be no spillover effects between the treatment and control groups, and alignment of treatment and comparison groups is stable for repeated cross-sectional design (Duflo, et al., 2007). The third assumption in the Difference in Differences approach is that the treatment is not determined by outcome: in other words, the treatment is exogenous in the model.

The rest of the paper is organized as follows: Section 2 discusses data collection and description; Section 3 introduces the Difference in Differences approach; Section 4 describes the model; Section 5 proposes the use of PSM to better serve the Difference in Differences approach; Section 6 satisfies the parallel trend assumption for treated countries; Section 7 tests reverse causality; and Section 8 provides the estimated results and a discussion of these. Finally, Section 9 is the conclusion.

3.2 Data collection

The required data for examining the causal impact of conflict on the shadow economy in Palestine using Difference in Differences were collected from different sources.

For the shadow economy data, the study employed the estimated results of the shadow economy for Israel, Jordan, and the control group, as obtained by Medina and schneider (2018) covering the period from 1995 to 2015. For data on the shadow economy's size in Palestine, the study depends on estimations made by the author, which will be provided in this chapter.

The set of control variables includes GDP per capita adjusted to Purchasing Power Parity (PPP), the share of self-employment to the total labour force (Dobre & Alexandru, 2009; Dell'Anno, 2007; Herwartz, et al., 2015), the unemployment rate (Gutmann, 1977; Tanzi, 1999; Dell'Anno & Solomon, 2008; Dobre & Alexandru, 2009), trade openness, which is measured by dividing the sum of imports and exports by GDP (Peksen & Early, 2019), inflation proxied by GDP deflator (Peksen & Early, 2019), and domestic credit provided by the financial sector as a share of GDP (Peksen & Early, 2019). These data were subtracted from World Bank development indicators.

In estimating the size of the shadow economy in Palestine for the period 1996-2017, the MIMIC approach uses the following set of variables:

Tax Burden: collected taxes divided by GDP, retrieved from the Palestinian Monetary Authority (PMA) annual reports.

Self-employment: the percentage of self-employed as a share of the total labour force. The data is collected from the Palestinian Central Bureau of statistics (PCBS).

Unemployment rate: the percentage of unemployed workers as a share of the labour force. The data is collected from the PCBS.

Size of government: represented by government expenditure as a share of GDP. Data are collected from PMA annual reports.

Control of corruption: this index was obtained from the World Bank dataset. It lies between the values -2.5 and 2.5, and the negative values indicate lower control of corruption and vice versa.

Gross Domestic Product: GDP was used as an indicator for the shadow economy, and data was collected from PMA annual reports.

Labour force participation rate: for the percentage of workforce share of the population that is eligible to work, data was collected from PCBS reports.

The descriptive statistics in Table 12 show that the average size of the shadow economy in Palestine is two times larger than in Israel, while Jordan witnesses the lowest average size among the three countries. However, fluctuations in the shadow economy's size in Palestine were very high, varying approximately by 11.5% annually, whereas the shadow economy in Israel was more stable than either Palestine or Jordan.

The data show that GDP per capita in Israel was 7 times larger than the Palestinian figure, and more than threefold of the Jordanian GDP per capita. Self-employment as a share of the total labour force and the unemployment rate in Palestine were the highest among the three countries, as more than one-third of the workforce was self-employed, and on average, around 22% of the labour force were unemployed. Furthermore, the standard deviations for the self-employment rate and unemployment rate were very high for Palestine compared with the other two countries.

3.3 Modelling the MIMIC

In a confirmatory analysis, structural equation models can be used to measure the effect of observable variables, which are the causes, on unobservable variables (Alañón & Gómez-Antonio, 2005).

Multiple indicators multiple causes (MIMIC) is a special case of SEM and was first used by Jöreskog and Goldberger (1975). The MIMIC approach consists of two equations: the structural equation, and the measurement equation (Dell'Anno & Solomon, 2008).

These two equations can be presented as follows:

$$\eta_t = \gamma' x_{it} + \epsilon_t \qquad \text{Equation 6}$$

$$y_{it} = \lambda \eta_t + \varepsilon_t \qquad \text{Equation 7}$$

Equation 6 is a structural equation that examines the relationships between the unobserved or latent variable (η_t) and a set of observable exogenous causes $x_{it,}$ in addition to the structural disturbance term ϵ_t. γ is the 1×c vector of structural parameters that illustrate the relationships between the latent variable η_t and the set of causes x_{it}.

Equation 7 is the measurement equation that connects a set of indicators y_{it} with the latent variable (η_t). λ is the d×1 vector of parameters that links the indicators y_{it} to the latent variable (η_t).

From Equation 6 and Equation 7, it is concluded that:

$$y_{it} = \lambda(\gamma x_{it} + \epsilon_t) + \varepsilon_t \qquad \text{Equation 8}$$

$$y_{it} = \Pi' X + \nu \qquad \text{Equation 9}$$

where $\Pi'$is the reduced form of coefficients $\Pi' = \lambda'\gamma$ and ν is the reduced form of disturbance vector $\nu = \lambda\epsilon_t + \varepsilon_t$, X is the matrix of the causes.

Hence, the estimated covariance matrix is

$$\mathrm{cov}(\nu\nu') = \mathbb{E}(\nu\nu') - \mathbb{E}(\nu)\,\mathbb{E}(\nu') \qquad \text{Equation 10}$$

The approach includes the following assumptions:

$\mathbb{E}(\nu) = 0$.

The residuals of the structural equation ϵ_t and the error term of the measurement equation ε_t are independent of each other $\mathbb{E}(\epsilon_t\varepsilon_t')=0$.

$\mathbb{E}(\epsilon_t^2) = \sigma^2$.

$\mathbb{E}(\varepsilon_t\varepsilon_t') = \Theta$, where Θ is a diagonal (p×p) matrix with the error variations.

Equation 10 may be rewritten as follows:

$$\mathrm{cov}(\nu\nu') = \mathbb{E}(\nu\nu') \qquad \text{Equation 11}$$

$$\mathrm{cov}(\nu\nu') = \mathbb{E}[(\lambda\epsilon_t + \varepsilon_t)(\lambda\epsilon_t + \varepsilon_t)'] \qquad \text{Equation 12}$$

$$\mathrm{cov}(\nu\nu') = \mathbb{E}[(\lambda\lambda'\epsilon_t\epsilon_t' + \lambda'\varepsilon_t\epsilon_t' + \lambda\epsilon_t\varepsilon_t' + \varepsilon_t'\varepsilon_t)] \qquad \text{Equation 13}$$

$$cov(\nu\nu') = \lambda\lambda'\sigma^2 + \Theta_\varepsilon \qquad \text{Equation 14}$$

For model identification, the necessary condition is that the number of structural parameters should equal the number of reduced-form parameters. If the necessary condition is not satisfied, then a sufficient condition should be implemented. The best way to satisfy the sufficient condition is to fix one of the coefficients of the vector-matrix which links the latent variable with the indicators to a constant value.

Thus, this model will consider $\lambda_1 = 1$, which means that the relationship between log GDP and the shadow economy is fixed.

Hence, the model can determine the structural parameters from Equation 6 and Equation 7, in which the structural model has *c* elements in γ, d elements in λ, two elements, one for each, in the variance of ϵ_t and ε_t respectively, and *c(c+1)/2* elements in the variance of x_t. However, for the reduced form, the number of reduced parameters from Equation 9 and Equation 14 can be estimated. There are *cd* elements in Π, *d(d+1)/2* elements in Θ_ε, and *c(c+1)/2* elements contained in the variance of X.

Therefore, the number of reduced form parameters is greater than the number of structural parameters; in this case, it is necessary to fulfil the sufficient condition, which means that this indicator is considered the basis for quantifying the other indicators' effects (Dell'Anno & Solomon, 2008).

As the sample size is relatively limited, the model uses the maximum likelihood method (MLE) in order to estimate the latent variable. MLE provides efficient estimations supposing there is multivariate normality, and is relatively robust if the series is not too far from the multivariate standard normal distribution (Alañón & Gómez-Antonio, 2005).

Figure 4 shows the variables chosen to represent the causes and indicators of the shadow economy in Palestine for the MIMIC approach.

Table 13 shows two different MIMIC models that illustrate the effect of set causes on the shadow economy. The two models lead to the same level of significance, in the same direction, and with roughly the same magnitude for the structural parameters. To estimate the size of the shadow economy, a set of restrictions are imposed on the model.

According to goodness of fit, it can be concluded that MIMIC(1) is more reliable than MIMIC2, as the Comparative Fit Index CFI and Normed Fit Index NFI are greater and the RMSEA is lower and more significant. Thus, this study depends on MIMIC(1) results to estimate the size of the shadow economy in Palestine for the period 1996-2017.

3.3.1 Estimating the size of the shadow economy

The measurement equation can be written as follows:

$$\frac{GDP_t - GDP_{t-1}}{GDP_b} = 7.245 + \frac{\tilde{\eta}_t - \tilde{\eta}_{t-1}}{GDP_b} \qquad \text{Equation 15}$$

where GDP_t is the current GDP, GDP_{t-1} is the last year's GDP, GDP_b is the GDP in the base year, $\tilde{\eta}_t$ is the estimated shadow economy for the current year and $\tilde{\eta}_{t-1}$ is the estimated shadow economy for the previous year.

The structural equation:

$$\frac{\tilde{\eta}_t}{GDP_b} = 1.115X_1 - 1.858X_2 + 0.779X_3 - 0.087X_5 - 1.218X_6 \qquad \text{Equation 16}$$

In order to estimate the size of the shadow economy, Dell'Anno and Solomon (2008) used a benchmark equation for estimation:

$$\frac{\tilde{\eta}_t}{GDP_b} * \frac{\eta_t^*}{GDP_b} * \frac{GDP_b}{\tilde{\eta}_b} * \frac{GDP_b}{GDP_t} = \frac{\hat{\eta}_t}{GDP_t} \qquad \text{Equation 17}$$

where: $\frac{\tilde{\eta}_t}{GDP_b}$ is the shadow economy index calculated by Equation 16, $\frac{\eta_t^*}{GDP_b}$ is an exogenous estimate for the shadow economy, $\frac{GDP_b}{\tilde{\eta}_b}$ is the value of the shadow economy in the base year according to Equation 16, $\frac{GDP_b}{GDP_t}$ is necessary to convert the index of changes of the base year of the shadow economy with respect to current GDP, and $\frac{\hat{\eta}_t}{GDP_t}$ is the estimated shadow economy share of GDP.

Therefore, to estimate the size of the shadow economy according to the previous benchmark Equation 17, it is necessary to specify a base year, and the size of the shadow economy of this base year should have been estimated previously.

This paper considers the year 1996 as the base year. It is one of the initial years of the establishment of the Palestinian Authority (PA) and is taken as the first year that official statistics were released. In addition to the base year, a value must be found for the size of the shadow economy at the base year. Unfortunately, a reliable source of information on the size of the shadow economy does not exist. Therefore, the study assumes that the size of the shadow economy in 1996 was equal to the size of the formal economy. Figure 5 shows the size of the shadow economy in line with the previous restrictions and assumptions using the MIMIC approach.

3.4 The Difference in Difference approach

The difference in difference approach is commonly used in evaluating the impact of policies that occurred at a specific point in time (Lechner, 2011; Stuart, et al., 2014). The method was used originally for assessing the effectiveness of after-school training programmes on earnings in the USA. Ashenfelter (1978) and Ashenfelter and Card (1984) estimated the effect of training programmes using the longitudinal structure of earnings. Pivotal applications of difference in differences were later conducted by various researchers (Card & Krueger, 1993; Meyer, et al., 1995; Eissa & Liebman, 1996; Blundell, et al., 1998).

Moreover, difference in difference can be used in its simplest form as a special case in which there are two observed groups only, in two time periods. Both groups are subjected to the control condition in the first period, whereas in the second period, the treatment is applied to only one group (Wing, et al., 2018).

Several assumptions must be fulfilled before using the difference in differences approach. The parallel trend assumption is considered the main assumption, and states that, for the outcome variable of interest, both the treated group and the control group would have charted the same time trend during the absence of the treatment: hence, the difference between the treated and control group is constant over time before the treatment (Card & Krueger, 1993; Card & Krueger, 2000), In other words, the control group serves as an effective reflection of the trends over time that the treatment group would have experienced if they had not been selected for the event of the study (Stuart, et al., 2014).

The Stable Unit Treatment Value Assumption (SUTVA) is another essential assumption, which holds that there should be no spillover effects between the treatment and control groups, and alignment of treatment and comparison groups is stable for repeated cross-sectional design (Duflo, et al., 2007)

The third assumption in the difference in differences approach is that the treatment is not determined by outcome: in other words, the treatment is exogenous in the model.

3.5 The model

The study is going to start with a difference in difference model without including the control variable as follows:

$$Y_{it} = \alpha + Y_{it-1} + \delta + \beta_1 Tr_i + \beta_2 C_i + \beta_3 (Tr_i * C_i) + \varepsilon_{it} \quad \text{Equation 18}$$

where Y_{it} is the outcome variable for country i and time t, which is the shadow economy size share of GDP, δ stands for the time trend, the model controls for time trend as a global trend of the shadow economy, and estimations are negative over time. Furthermore, it enables the model to eliminate bias in comparisons over time in the treatment group which are unrelated to the treatment. Furthermore, the model includes a one-lag dependent variable, assuming that the contemporaneous size of the shadow economy depends on the previous period as well (Card, 1992; Bertrand, et al., 2004).

C_i is a binary variable which equals one when country i is treated and equals zero when country i is in the control group. Tr_i is a binary variable which equals one when it reflects the period after the treatment, and zero otherwise: thus, $Tr_i = 1$ for years from 2000 and above. The parameter β_3 is the coefficient of interest which represents the difference in difference estimator for the interaction between the treated country C_i and the treatment Tr_i.

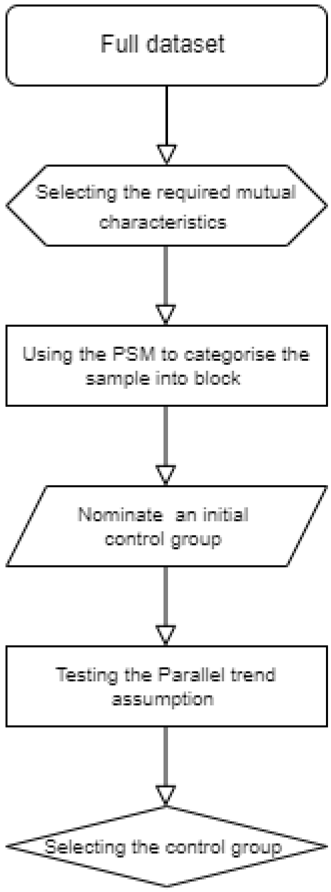
The previous model can be modified by including control variables to gain more reliable and consistent results. The common way to adjust controlling variables, covariates, in the difference in difference model is to introduce them linearly in the model (Abadie, 2005), with the covariates explained previously. Therefore, the estimation equation will be as follows after controlling for a set of explanatory variables:

$$Y_{it} = \alpha + Y_{it-1} + \delta + \gamma X'_{it-1} + \beta_1 Tr_i + \beta_2 C_i + \beta_3 (Tr_i * C_i) + \varepsilon_{it} \quad \text{Equation 19}$$

where Y_{it-1} stands for the lagged dependent variable, δ is the time trend, γ is the vector of covariates' coefficients, and X is the covariates matrix, which represents GDP per capita adjusted to Purchasing Power Parity (PPP), the share of self-employment to the total labour force, unemployment rate, trade openness measured by dividing the sum of imports and exports by GDP, and domestic credit provided by the financial sector as a share of GDP.

Before running difference in differences estimates, two actions must be satisfied. The first is to find control countries to build up a control group for effective comparison in casual studies. To do so, it is necessary to use matching methods which involve solid assumptions of no clear difference in both treatment and control groups. Matching methods are typically most useful in combination with one of the other casual effect models: e.g., Gertler et al. (2016) used propensity score matching (PSM) to select for control countries. The second action that must be satisfied is the main assumption of the difference in differences approach: that is, the control and treatment groups must show parallel trends across time in the absence of the treatment (Stuart, et al., 2014). For the parallel trend assumption fulfilment see Figure 8, Figure 9 and Figure 10.

The following flowchart illustrate how the control group is selected



Source: Author’s work

3.6 Propensity score matching

At its early application, PSM has been applied with two groups: the treatment, and the control group. However, some authors promote the “generalized propensity score” for treatments within multi levels (Imai & Van Dyk, 2004; Imbens & Wooldridge, 2009), whereas McCaffrey et al. (2013) extend the approach to include multiple treatment groups.

PSM is regularly used to minimize selection bias in non-experimental studies. It is also used to balance treatment and control groups on a vector of baseline features (Rosenbaum & Rubin, 1983). Ho et al. (2007) argue that PSM minimizes inference and is successive in outcome model features, and thus more robust inferences can be reached. Another benefit of using the method is that PSM condenses the vector of control variables into an ordinal summary, making these matches more understandable. PSM differentiates between the study design and the study analysis, as the approach process is applied without using the outcome variable (Rosenbaum, 2010; Rubin, 2007).

Rosenbaum and Rubin (1983) define the propensity score as the conditional propensity for receiving a treatment given pre-treatment characteristics:

$$pr(\mathrm{X}) \equiv pr(\mathrm{D} = 1|\mathrm{X}) = \mathrm{E}(\mathrm{D}|\mathrm{X})$$

where X is the multidimensional vector of pre-treatment characteristics and D = {0, 1} is the indicator for being involved in treatment. The following algorithm, which was introduced by Becker and Ichino (2002), is used to estimate the propensity score and to satisfy the balancing hypothesis, which argues that observations with the same propensity score must have the same distribution of observable and unobservable characteristics independently from treatment status.

1. Fitting the Probit model:

$$pr(D_i = 1|\, X_i) = \Phi\{h(\, X_i)\}$$

where Φ refers to the cumulative distribution function and $h(\, X_i)$ is the function of covariates. This model includes one covariate, which is GDP per capita, to simply satisfy the test of balancing property.

1. splitting the sample into k equal intervals of the propensity score, where k is suggested by the researcher. Here, the study assumes k=10.
2. The average propensity score of treated and control groups should be tested to ensure that they do not differ within each interval.

3. Divide the interval in half and test again if the test fails in one interval, then continue until the average propensity score of treated and control groups does not vary for all intervals.
4. Finally, the algorithm tests that the means of each characteristic which do not differ between treated and control groups within each interval. The last step is a necessary condition for the balancing hypothesis.

Noting that the covariate function must be linear and with no higher-order terms or interactions.

The previous equation can be written as follows:

$$pr(Y_{it}) = \begin{cases} Conflict = 1, \beta_0 + \beta_1 GDP\ per\ Capita_{it} + \varepsilon_{it} \\ Conflict = 0, otherwise \end{cases}$$

where conflict is binary, in which take 0 if the years are before the year 2000 and 1 otherwise. The error terms are independent and identically distributed, in which they have a zero mean and standard deviation, besides, they are uncorrelated with any of the covariates.

The results of propensity score classified countries into eight blocks. Out of 154 countries, the mean propensity score of 18 countries is not different from Palestine, while the mean propensity score of 77 countries is not different from Israel and Jordan.

3.7 Satisfying the parallel assumption:

As mentioned earlier, the difference in difference approach assumes that the control and treatment groups must have parallel trends across time in the absence of the treatment. In other words, the control group serves as an effective reflection of the trends at the time where the treatment group has not experienced any treatment yet (Stuart, et al., 2014).

The parallel assumption must be checked three times: the first time is for Palestine, the second is for Israel, and the last is for Jordan. The parallel assumption allows the elimination of more countries from the control group and only keeps those that show a parallel trend with the treatment country before being treated.

3.8 Testing for reverse causality:

After matching each country treated with its control group, and satisfying the parallel trend assumption before treatment, there is one last issue to consider before running the Difference in Differences estimations using Equation 18 and Equation 19 that is to mitigate the reverse causality problem.

Reverse causality is described as a phenomenon in which the outcome affects and causes the independent variable (Flanders & Augestad, 2008; Flegal, et al., 2011) and it is considered as one of the causes of endogeneity problem.

To check if the model is suffering from the reverse causality problem, several strands of literature were checked to examine whether there were any reverse causalities between the shadow economy, the outcome variable, and the covariates. To the best of the researcher's knowledge, there are two studies that test the causal relationship between the shadow economy and unemployment rate, using Toda and Yamamoto's approaches for the USA and Tunisia. Both found unidirectional causality from the unemployment rate to the shadow economy (Alexandru, et al., 2011; Saafi & Farhat, 2015).

Other studies have investigated the causal relationship between the shadow economy and official GDP for New Zealand and Canada and identify clear evidence that there is Granger causality from official GDP to the shadow economy, while for the reverse direction, there is only mild evidence (Giles, 1997a; Giles, 1999a; Giles, et al., 2002).

No studies were found which had tried to test the causal relationship between self-employment and the other controlling variables with the shadow economy.

Therefore, based on the above-mentioned studies, there is insufficient evidence of a bidirectional relationship between the shadow economy and each covariate separately. Besides, it is argued here that the determinants of the formal economy have the potential to contribute to the size of the shadow economy: particularly as activities in the shadow mainly depend on the available fixed capital that has already accumulated in the official economy.

Therefore, Table 16 presents two models. The first model represents a simple model, without including any controlling variable, as shown in Equation 18, whereas the second model includes controlling variables with a one period lag to reduce the effect of reverse causality problems.

The model uses the ordinary least square method for estimating the unknown parameters. OLS assumes that errors are both independent and identically distributed: therefore, the model, in the absence of this assumption, suffers from heteroscedasticity which produces biased standard errors. To resolve the inconsistent variance bias and to ensure that error terms are independent of each other, the model includes Huber-White's Heteroscedasticity-consistent standard errors, which are used to allow for fitting models that contain heteroscedastic residuals (White, 1980). Huber-White's standard errors do not change the magnitude of the coefficient estimates, yet the test statistics will produce more accurate p-values as a result of changing the standard errors and relaxing the assumption that the errors are identically distributed (Williams, 2012).

3.9 Results and discussion

The average treatment effect of Intifada on the shadow economy in Palestine is given by the coefficient of the difference in difference dummy. The coefficient of interest in Table 16 is statistically significant and positive in both models: this indicates a strong inference that the Intifada increased the size of the shadow economy in Palestine. Nevertheless, the magnitude of the treatment effect depends on the specifications of the difference in differences model.

In model 1, Table 16, the results show that the Intifada increased the size of the shadow economy by 4.2%. However, paying greater attention to the reverse causality problem by including one lag for each controlling variable delivers a higher impact, and based on this, the outbreak of the Intifada increased the size of the shadow economy in Palestine by 10.8%.

Results in model 2, Table 16, can be illustrated in more detail, and Table 17 distinguishes between differences in outcome variable in both the control group and the treated country before and after the treatment.

Therefore:

$$E[Y|X] = \alpha + \beta_1 Tr_i + \beta_2 C_i + \beta_3 (Tr_i * C_i) \qquad \text{Equation 20}$$

- In the absence of treatment for the control group, $Tr = 0$ and $C = 0$, and the expected value of Y = α = (- 4.598). This can be explained as follows:

$$E[Y|X] = \alpha + \beta_1[0] + \beta_2[0] + \beta_3([0] * [0]) = \alpha$$

- In the absence of treatment for the treated country, $Tr = 0$, and $C = 1$

$$E[Y|X] = \alpha + \beta_1[0] + \beta_2[1] + \beta_3([0] * [1]) = \alpha + \beta_2$$

- After the outbreak of the Intifada for the control group, $Tr = 1$, and $C = 0$

$$E[Y|X] = \alpha + \beta_1[1] + \beta_2[0] + \beta_3([1] * [0]) = \alpha + \beta_1$$

- After the outbreak of Intifada for the treated country, $Tr = 1$, and $C = 1$

$$E[Y|X] = \alpha + \beta_1[1] + \beta_2[1] + \beta_3([1] * [1]) = \alpha + \beta_1 + \beta_2 + \beta_3$$

The results in Table 17 show that there is a minor difference between the average size of the shadow economy before and after the treatment for the control group. This difference is (-0.882%), which implies that the shadow economy trend had a downward slope over time for the control group, whereas for Palestine, the difference across time is (9%).

The overall impact when applying the Difference in Difference approach is around (9.882%). In other words, Intifada as an indicator of conflict affected the shadow economy's size in Palestine positively, increasing it by around 10.8%s after removing cross-country and time-invariant influences.

After concluding a positive impact from the Intifada on the size of the shadow economy in Palestine, an important question evolves, since the outbreak of Intifada has affected both Palestinian and Israeli economy (Fishelson, 1993; Fielding, 2003; Horiuchi & Mayerson, 2015). Therefore, did Intifada affect the size of the shadow economy in Israel?

To test this end, the previous steps and specifications were repeated to satisfy this parallel assumption. Figure 7 shows that the trend in shadow economy size in Israel before the year 2000 was parallel to the trends of Vietnam and Sri Lanka. Paying attention to the propensity score results, these suggest that the mean propensity score of GDP per capita in Vietnam and Sri Lanka was not different from Israel.

The results in Table 18 demonstrate that the Difference in Difference approach failed to conclude any significant impact of Intifada on the shadow economy in Israel. This result is consistent with the previous chapter's findings, which reveal that conflict in high-income countries has no impact.

Furthermore, the study’s investigations were extended by including Jordan as a placebo test, it is expected that the outbreak of Intifada would have no impact on the Jordanian shadow economy. Again, the fulfilment of the parallel trend assumption before the treatment found that Bangladesh can be considered as a control country.

As expected, the results (shown in Table 19) failed to conclude any significant impact for Intifada on the shadow economy in Jordan, this result serves to support the model’s reliability and to suggest that the impact does not spill over.

3.10 Conclusion

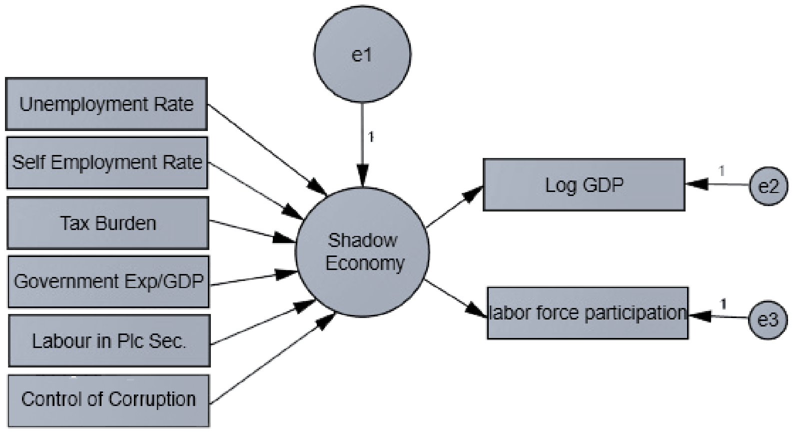
The study in this chapter has examined how conflict affects the size of the shadow economy. Conflict was proxied by the Intifada, which was a period of intensified Israeli–Palestinian conflict, described by Palestinian sources as a rebellion against Israel, while Israeli commentary frames it as an organized and prolonged terror campaign perpetuated by the Palestinian National Authority and several Palestinian militant groups. The general spark for the conflict is proposed as the collapse of the Camp David negotiations for the Israeli-Palestinian peace process, which were held in July 2000 (Pressman, 2003). Therefore, conflict can be considered as an exogenous variable on the outcome.

The study employed the Difference in Differences approach to investigate whether the outbreak of Intifada had an impact on the shadow economy's size in Palestine. Furthermore, the study extended its investigations to include Israel and Jordan. The Israeli economy was also affected by the Intifada (Horiuchi & Mayerson, 2015), and thus, the aim here was to assess the impact of the Intifada on the informal sector. Additionally, Jordan was chosen as a placebo.

The results suggest that the Intifada had a positive impact on the shadow economy in Palestine, with its outbreak increasing the size of the shadow economy by 9.882%. Nevertheless, Intifada had no impact on the shadow economy in Israel, and such a result is consistent with the pervious findings, which emphasise that the shadow economy in highly developed countries is not affected by outbreaks of conflict. Moreover, Jordan as the control country was not affected, making the investigations more reliable.

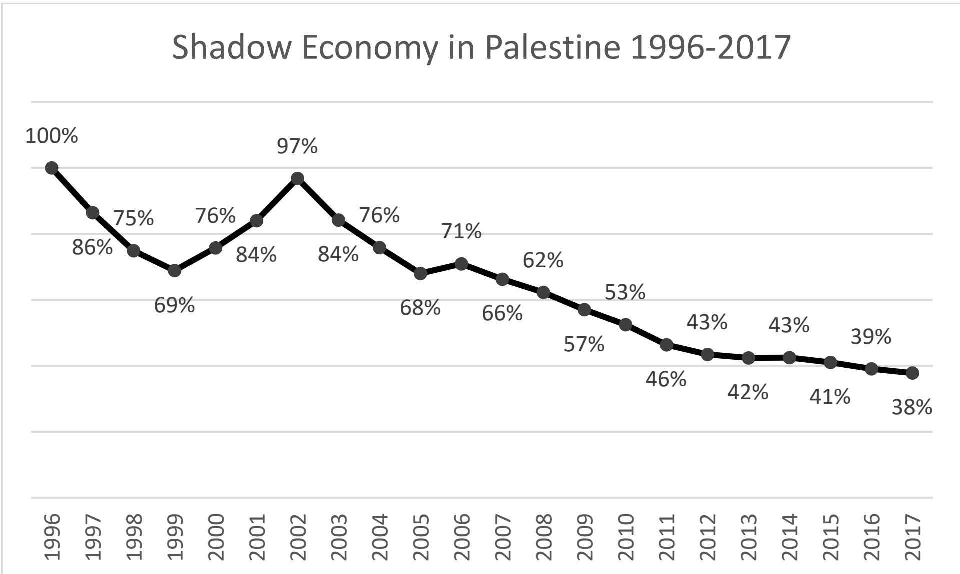
3.11 Figures

Figure 6: MIMIC Path diagram



Source: based on Author's work

Figure 7: The Shadow Economy in Palestine as a percentage of GDP 1996-2017



Source: based on the Author's calculations by using MIMIC approach in AMOS

Figure 8: Controlled shadow economy trend (1997-2015) for Palestine, Sierra Leone, Chad, Benin and Bosnia and Herzegovina

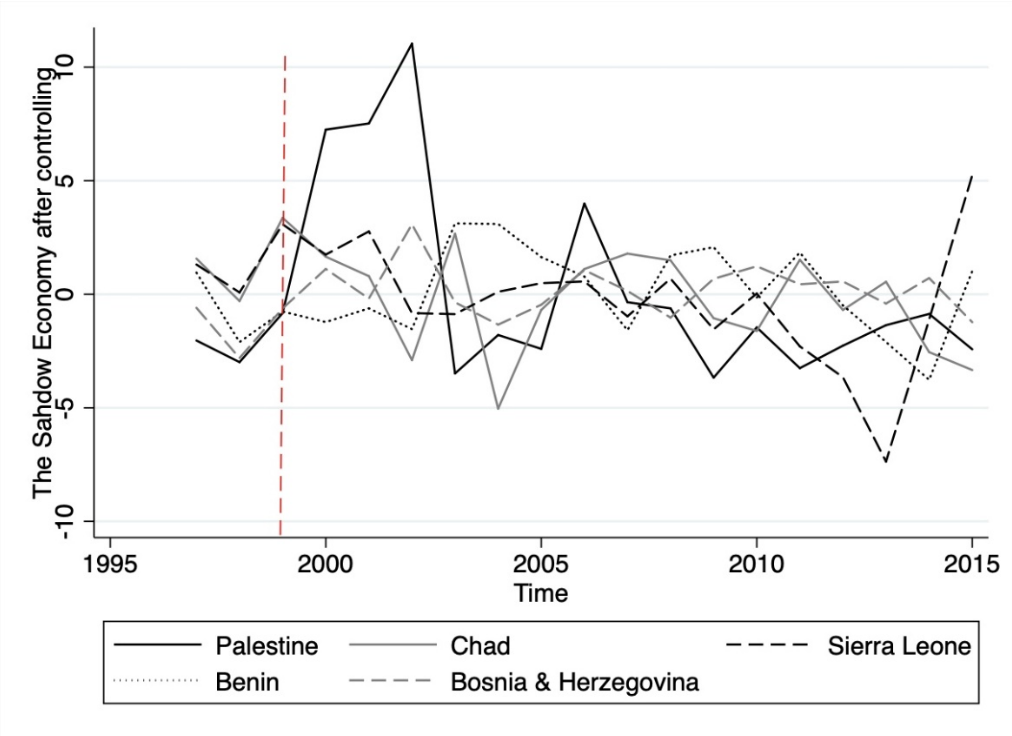


Figure 9: Controlled shadow economy trend (1996-2015) for Israel, Vietnam and Sri Lanka

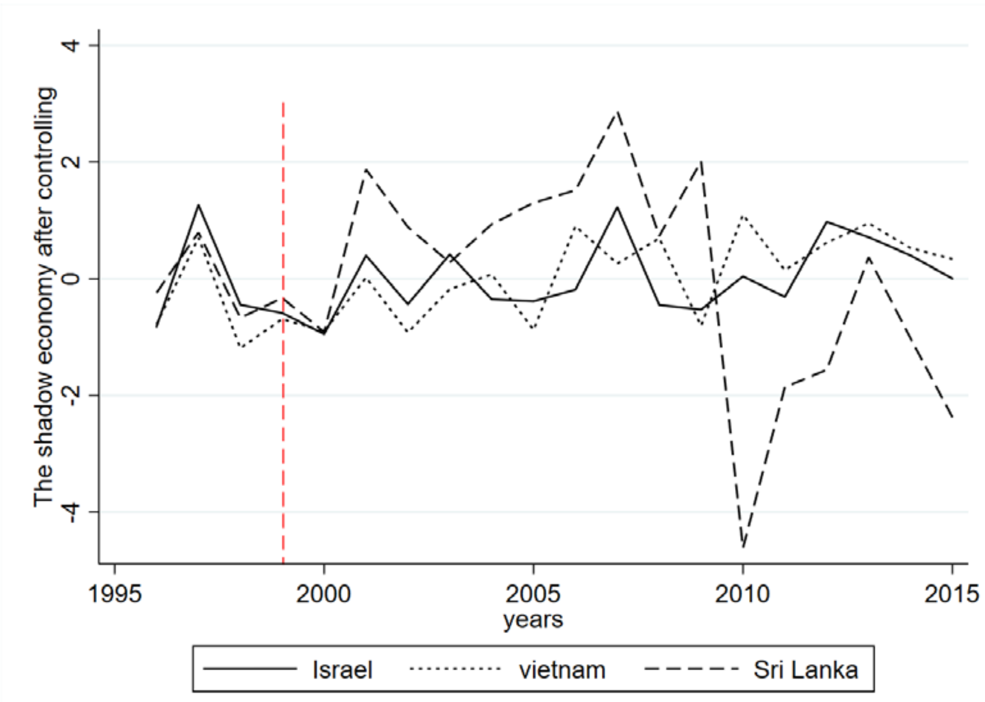
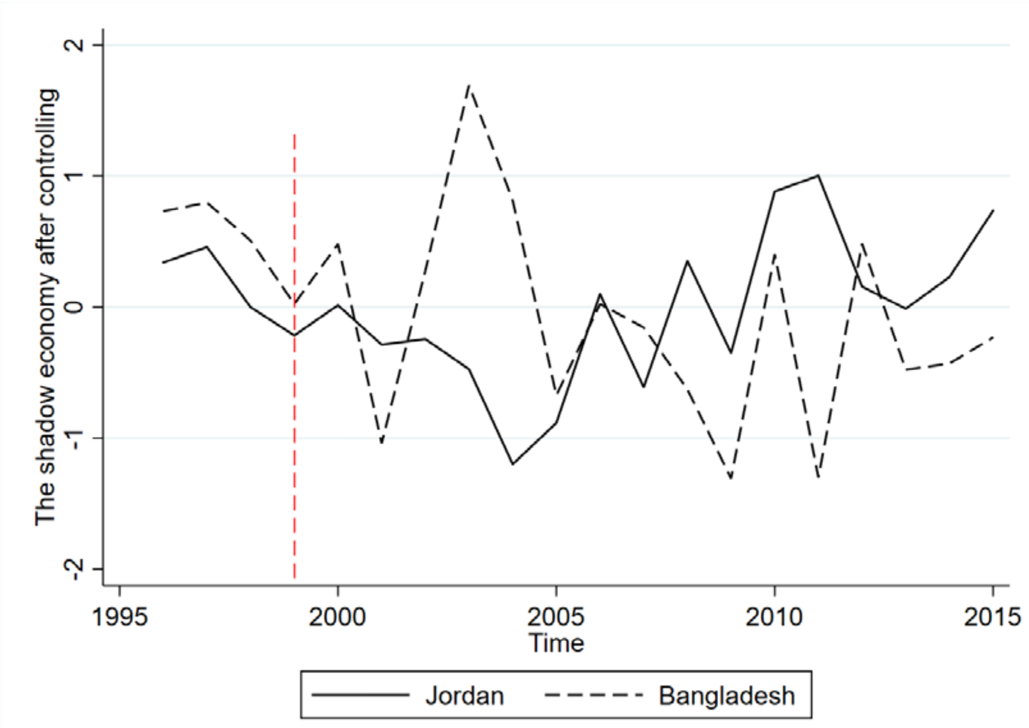


Figure 10: Controlled shadow economy trend (1996-2015) for Jordan and Bangladesh



3.12 Tables:

Table 13: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Palestine					
Shadow economy size % GDP	20	42.4	11.4	26.24	62.55
GDP per capita	20	3764.7	535.4	2781.3	4568.5
Self-employment % total labor force	20	36.4	4.0	31.2	43.5
Unemployment	20	22.1	5.3	13.5	31.2
Trade Openness % GDP	20	83.1	8.2	71.1	97.1
Domestic Credit to private sector % GDP	20	23.3	5.3	11.9	35.9
Israel					
Shadow economy size % GDP	20	21.4	1.4	19.18	23.3
GDP per capita	20	27911.3	2433.8	24775.5	31989.4
Self-employment % total labor force	20	11.8	.25	11.3	12.2
Unemployment	20	9.5	2.4	5.2	13.5
Trade Openness % GDP	20	69.3	7.4	59.3	81.8
Domestic Credit to private sector % GDP	20	70.4	4.7	62.6	79.8
Jordan					
Shadow economy size % GDP	20	16.64	2.4	13.44	19.93
GDP per capita	20	8394.6	987.3	6896.60	9782.37
Self-employment % total labor force	20	14.9	.35	14.45	15.33
Unemployment	20	13.54	.95	11.9	15.3
Trade Openness % GDP	20	119.7	14.2	96.7	144.8
Domestic Credit to private sector % GDP	20	73.9	7.1	67.5	90.3

Table 14: Estimated coefficients of the MIMIC models and Goodness of fit

Variable / Specification	Symbol	MIMIC1 5-1-2	MIMIC2 5-1-2
Causes			
Tax Burden	X_1	1.115***	1.332***
Self-Employment	X_2	-1.858***	-1.187***
Unemployment	X_3	0.779***	0.564***
Government Expenditure	X_4	-	-0.309***
Control of Corruption	X_5	-0.087*	-0.12***
Labour in Public Sector	X_6	-1.218*	-
Indicators			
LogGDP	Y_1	1	1
Intercept		7.245***	6.945***
Labour Participation rate	Y_2	0.196***	0.197**
Intercept		.298***	.239***
Goodness of Fit			
Chi-square		28.387	30.489
DF		14	14
CFI		.873	.863
NFI		.799	.794
RMSEA		.221***	.237**

Source: based on author's calculations. Notes: *** means the parameters are significant at 1% level, ** significant at 5% and * significant at 10%

Table 15: Propensity score summary

Treatment	Freq.	Percent	Cum.
0	776	23.84	23.84
1	2,479	76.16	100
Total	3,255	100	

Table 16: The Probit regression estimation of the Propensity score

Variables	Coef.
Log GDP per Capita	.0619541 ***
	(.0124035)
Constant	-.8243879 ***
	(.3100698)
Number of obs.	3216
Pseudo R2	0.0072
Log-likelihood	-1741.2026
Number of blocks [a]	8
Test of balancing property	Satisfied

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is a binary variable which take 1 if the years are from 2000 and above, zero otherwise, [a] number of blocks ensures that the mean propensity score is not different for treated and controls in each block

Table 17: Difference in Difference estimation of the impact of Intifada on the shadow economy size in Palestine

VARIABLES	(1) Naive estimation	(2) After controlling
$Shadow\ economy_{t-1}$	0.973***	1.054***
	(0.0206)	(0.0571)
Time trend	1.95e-05	0.000831
	(0.000145)	(0.000657)
$GDP\ per\ capita_{t-1}$		0.00158
		(0.00156)
$Self\ employed_{t-1}$		-0.108
		(0.155)
$\text{Unemployment}_{t-1}$		-0.493***
		(0.0474)
$\text{Trade Openness}_{t-1}$		0.0111
		(0.0203)
DCPS $_{t-1}$		-0.122*
		(0.0511)
Time Dummy	-0.0438	-0.882
	(1.098)	(1.053)
Country Dummy	-5.719***	-8.710
	(0.768)	(4.319)
DiD	5.241***	9.882***
	(0.966)	(1.419)
Constant	0.542	5.549
	(1.442)	(17.95)
Observations	99	86
R-squared	0.906	0.927
Robust	Yes	Yes
Country clustering	Yes	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is the shadow economy, the models used the Huber-White's Heteroscedasticity-consistent standard errors. Model (1) is a simple model without controlling for covariates, while model (2) controls for covariates.

Table 18: Expected value of the change in the shadow economy size before and after the treatment.

Shadow economy Trend	Before treatment $Tr = 0$	After treatment $Tr = 1$	Difference
Control group $C = 0$	α (5.549)	$\alpha + \beta_1$ (5.549) + (-0.882)	β_1 (-0.882)
Treatment group $C = 1$	$\alpha + \beta_2$ (5.549) + (-8.710) = (-3.161)	$\alpha + \beta_1 + \beta_2 + \beta_3$ (5.549) + (-0.882)+ (-8.710) + (9.882) = (5.839)	$\beta_1 + \beta_3$ 9
	Difference in Difference		β_3 9.882

Table 19: Difference in Difference estimation of the impact of Intifada on the shadow economy size in Israel

VARIABLES	(1)	(2)
	Naive estimation	After controlling
$Shadow\ economy_{t-1}$	0.925***	0.747***
	(0.0365)	(0.0556)
Time trend	-0.00445	-0.0516*
	(0.00270)	(0.0172)
$GDP\ per\ capita_{t-1}$		-0.000485
		(0.000379)
$Self\ employed_{t-1}$		0.164
		(0.130)
$\text{Unemployment}_{t-1}$		-0.377
		(0.263)
Trade Openness $_{t-1}$		0.0579
		(0.0334)
DCPS $_{t-1}$		-0.000375
		(0.0126)
Time Dummy	-0.0990	-0.530**
	(0.195)	(0.111)
Country Dummy	-6.491	-52.67*
	(4.208)	(15.74)
DiD	-0.0889	1.662
	(0.163)	(1.322)
Constant	14.42	142.0*
	(8.889)	(43.67)
Observations	60	60
R-squared	0.990	0.992
Robust	Yes	Yes
Country clustering	Yes	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is the shadow economy, the models used the Huber-White's Heteroscedasticity-consistent standard errors. Model (1) is a simple model without controlling for covariates, while model (2) controls for covariates.

Table 20: Difference in Difference estimation of the impact of Intifada on the shadow economy size in Jordan

VARIABLES	(1) Naive estimation	(2) After controlling
$Shadow\ economy_{t-1}$	0.865*	0.530
	(0.0985)	(0.162)
Time trend	-0.0532	-0.0940
	(0.122)	(0.153)
$GDP\ per\ capita_{t-1}$		-1.74e-05
		(7.83e-05)
$Self\ employed_{t-1}$		0.358
		(0.632)
$\text{Unemployment}_{t-1}$		-0.0875
		(0.828)
Trade Openness $_{t-1}$		-0.0261
		(0.0224)
DCPS $_{t-1}$		-0.0230*
		(0.00362)
Time Dummy	-0.452	0.957
	(0.932)	(0.547)
Country Dummy	66.99	138.1
	(157.7)	(175.8)
DiD	0.199	-1.734
	(0.0787)	(0.840)
Constant	15.69	13.12
	(28.31)	(69.50)
Observations	40	40
R-squared	0.992	0.994
Robust	Yes	Yes
Country clustering	Yes	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is the shadow economy, the models used the Huber-White's Heteroscedasticity-consistent standard errors. Model (1) is a simple model without controlling for covariates, while model (2) controls for covariates.

4 Conflict & Greenfield FDI in the Mining sector: An investigation for the dynamic and spillover impact

4.1 Introduction:

Trade trends in the several last decades have been directed by multinational corporations which activate this influence in the form of foreign direct investments. These trends have led to considerable concern by economists to examine the structural factors that determine foreign direct investment (FDI) behaviour (Blonigen, 2005).

FDI is one of the main pillars of development policies in resource-abundant countries and is able to enhance the development process in developing countries also, as it can diversify economic activities, open up access to new markets through exports, and attract new technologies (De Ferranti, et al., 2002).

The determinants in attracting foreign direct investment have developed over time. Dunning (1998) argues that in the 1970's, some of the variables that influenced the location of productive activities by multinational corporations (MNCs) were the resources available, and the cost of these resources, in addition to their quality. Moreover, MNCs have paid attention to the necessity of infrastructure for exploitation and exportation. Finally, the Government may place restrictions on FDI and/or on capital and dividends cutbacks. However, in the 1990s, Dunning (1998) added local opportunities for renovating the quality of resources and processing and transportation, besides the readiness of homegrown partners to cooperatively endorse capital and/or knowledge-intensive resource utilization.

Summarizing the preceding discussion, the so-called OLI paradigm of Dunning's demonstrates that FDI takes place if ownership-specific benefits, "O", like privately-operated technology exist alongside location-specific benefits, “L”, in host countries: e.g., a low cost of factors of production; and potential advantages for internalization, “I”, of the exporting of production (Frenkel, et al., 2004)

Recently, different strands of economic growth literature have proposed that greater economic growth is linked to more qualified institutions which encourage investment and allocate resources efficiently (Acemoglu & Johnson, 2005). Furthermore, domestic and foreign investment can be motivated to penetrate markets when information asymmetries are lesser, and information about markets, products, and participants are provided. However, an economy requires high-quality institutions to provide the preceding efficiencies (WTO, 2004).

The quality of institutions affects political governance and stability, and various researchers conclude that political risks deter foreign investments (Busse & Hefeker, 2007; Wei, 2000; Asiedu, 2013; Mina, 2012), while others identify no significant evidence of a link between political stability and FDI (Asiedu, 2002; Harms & Ursprung, 2002; Balakrishnan, et al., 2013). In contrast, Li (2003) and Shan et al. (2018) conclude a negative relationship between political stability and FDI.

Conflict is one important cause of political instability and a consequence of poor institutional quality and governance. Wars destroy physical capital, human capital, and social capital. All three have a significant impact in the long run. Physical infrastructure is crucial for development if destructions have a lasting impact. However, one should consider that, given the resources, bridges and roads and other similar physical infrastructure can be rebuilt quickly. It is harder, and takes much longer, to rebuild social and human capital.

From an economic theoretical perspective there is no consensus about the impact of conflict on economic performance. Neoclassical growth theory predicts that an economy recovers relatively quickly and converges to its steady state. Alternative models argue that catch up may take a long time, for instance because human capital recovers only slowly (see Barro and Sala-i-Martin (2004)), or that countries can be trapped in a low-level equilibrium where conflict and poor performance coexist (Sachs, 2005).

Barro and Sala-i-Martin (2004) predict that the speed of recovery depends on the type of destroyed capital, with a slower recovery if it is human capital, rather than physical capital, is destroyed, this is because the human capital has a higher adjustment cost. Endogenous growth models, as well as poverty trap models, predict that conflict has a direct effect on an economy's steady state, and as a result otherwise similar economies do not converge. (Azariadis & Drazen, 1990; Rodrik, 1999; Collier, 1999)

The exposure of conflict sparks heterogeneous behaviours of foreign investors, and thus, the characteristics of a firm's overseas investments arise as moderator factors in the relationship between conflict and FDI flows. However, these decisions are subject to investment in non-physical, capital-intensive investments and location substitutability. (Mihalache, 2011)

For example, copper in Afghanistan has attracted the Chinese smelters, JCCL one of the giant Chinese smelters prefers to own copper fields instead of buying them from other producers to diminish its exposure to upstream raw material risk. (Downs, 2012)

The Chinese companies were not the only interested investors in copper mining in Afghanistan, companies from USA, Kazakhstan, Canada, and Cyprus were interested in investing in Aynak Copper Mine field in Afghanistan.

Jiangxi Copper Co Ltd and Metallurgical Corp of China (MCC) took on a 30-year lease for the Aynak Copper Mine in 2008, which has an approximate reserve of 11.08 million tonnes of copper. However, Due to the unstable situation in Afghanistan, the Mes Aynak copper mine invested by the company has not yet undergone substantial construction. (Min & Shivani, 2021)

Conflict in Iraq is another example that has attracted FDI in mining sector even during the conflict time, USA, United Kingdom, France, Iran, Lebanon, Turkey, United Arab Emirates, and other countries have started investing in exploiting Coal, Oil and Natural Gas in addition to Metals in Iraq. Data from the Financial Times shows that the largest greenfield investment in the mining sector in Iraq during the period 2003-2016 was from Lebanon for the interest of Make oil company with an investment of 3 billion US dollars and directed to the Petroleum refineries sub-sector in Dahuk. Moreover, around 45 percent of investments in greenfield FDI have taken place at the first 5 years of the war that surge in 2003.

As a result, the impact of conflict on FDI is still ambiguous. Therefore, the purpose of this study is to investigate the impact of conflict on greenfield FDI. In other words, the study attempts to identify the existence of an impact, its direction and magnitude. Furthermore, to test whether the impact and direction differs among diverse areas around the world. Unlike other works, this paper focuses on testing two impacts: first, dynamic impact, which investigates the impact of conflict on FDI over the contemporary and following periods; and second, the paper investigates spillover impact in three directions, namely the expected spillover impact of the outcome variable in one country on its neighbours' outcome, the spillover impact of conflict, and the spillover impact of any unobserved variables.

The data on conflict employed was obtained from the One-sided Violence dataset of Uppsala Conflict Data Program (Eck & Hultman, 2007; Pettersson, et al., 2019). The unique greenfield FDI data was obtained from the Financial Times, and tracks FDI inflow in the mining sector from 2003 to 2017. Both conflict and greenfield FDI data were aggregated on a quarterly basis.

To fulfill the paper's aims and to avoid the problem of endogeneity, the methodology used for this paper consists of three parts, the first part is designed to obtain a valid instrument for conflict, and this instrument is then used to test the dynamic impact of conflict on FDI in the mining sector. The last part concerns the spatial models used to test the spillover impact.

The key contributions of this paper are four-fold. Firstly, to the best of the researcher's knowledge, this study is amongst the pioneering empirical works that test the conflict-FDI nexus. Most of the previous studies focused on terrorism and foreign firms. Secondly, the majority of empirical studies on conflict and FDI have tested the impact using aggregated data: however, this study utilizes disaggregated data on a quarterly basis, and exclusively for the mining sector. Thirdly, the estimation depends on the event study approach to determine the dynamic impact of conflict on greenfield FDI over the 4 quarters following any conflict event breakout, and uses spatial econometrics to infer spillover impact. Fourthly, this study uses a unique dataset on sectorial greenfield FDI.

This chapter consists of five sections. First is the introduction, which clarifies the main objectives, research questions, and discusses the novelty of this chapter. In the second section, the study reviews the literature that discusses possible links between conflict and FDI, while the methodology, data collection, and models are discussed in the third section. The subsequent section presents the results and the discussion, and finally, the last section is the conclusion.

4.2 Literature review

In the Keynesian model of economic growth, Harrod–Domar suggests that an economy's growth rate depends on the level of capital and savings (Harrod, 1939; Domar, 1946). Moreover, the neoclassical economic growth theory states that capital stock shocks and labour are the main factors that affect economic growth (Acemoglu, 2012). Thus, several studies have attempted to investigate the determinants of capital stock flow.

In this section, the study presents a state-of-the-art discussion on the impact of institutional quality, political instability, and finally terrorism and conflict on FDI.

4.2.1 Political instability and FDI

Previous investigations and various theoretical articles have revealed that foreign investment may be vigorously impacted by a country's degree of political risk.

For example, Basi (1963) concluded that political instability and the extent of its market potential were the most vital determinants for FDI. However, other studies find that the political considerations are second-order factors when compared with economic factors (Levis, 1979).

Different studies have focused on the impact of political instability and FDI and found that political risk is a major factor that MNC's CEOs consider when they make new international investment decisions (Aharoni, 1966; Bass, et al., 1977).

Nevertheless, the relationship between political instability and FDI was found to be significant and negative: e.g., Kobrin (1978) endorsed the existence of a negative impact from political instability towards FDI. Economic variables are included in Kobrin's model, yet Root and Ahmed (1979), in their attempt to explore the determinants of FDI in developing countries' manufacturing sector found that only the frequency of regular changes in government heads was significant and had a negative impact. Moreover, frequent changes in government discourage foreign direct investment, but this relation does not hold in the primary sector.

Green (1972) finds an insignificant relationship between FDI and political instability. Moreover, Robinson (1969) and Vernon and Wells (1981) suggest that political instability is not an effective determinant for FDI, as CEOs do not take political instability into account when making investment decisions.

In summary, the impact of political instability or political risk on FDI has been founded inconsistent across different studies: this could be for one or more reasons, as follows. Political instability and risk have different definitions, and variations in the definition of political risk and how it relates to instability could be part of the problem with previous studies (Sethi & Luther, 1986). Furthermore, investments are likely more related to the policy shifts and decisions of the host country than to political events (Brewer, 1985; Yu, 1987). In other words, corruption could play a mediating role in the relationship between political instability and FDI.

Nonetheless, Aharoni (1966) claimed that evaluating the political risk of a country depends on oversimplifications rather than in-depth and intensive investigation for the potential host country. Root (1968) and Robock (1971) report that executives' attitudes play the foremost role in profitability and risk appraisal for any international investment opportunity. Besides, the directors who are responsible for multinational cross-border operations rarely depend on methodical environmental investigations (Keegan, 1974).

4.2.2 FDI and conflict

Capital stock is an accumulation of investments, and therefore, when a state comes to be involved in an armed conflict, capital stock is considered to be affected in two directions (Zafeer, 2015).

The first direction is the destructive nature of conflict, which diminishes capital stock when armed forces and rebels target infrastructure which is either damaged or demolished. In terms of the second direction, Solow (1956) suggests that the amount of accumulated capital depends on new investments and existing capital adjusted to depreciation. Therefore, armed conflict increases the depreciation rate, and moreover encourages capital flight, deters new investment opportunities, and accelerates loss for businesses.

Different studies have attempted to investigate the impact of terrorism on FDI, yet this relationship is ambiguous. Various strands of research conclude the negative impact of terrorism on FDI (Enders & Sandler, 1996; Abadie & Gardeazabal, 2003; Agrawal, 2011; Abadie & Gardeazabal, 2008). Others found an insignificant relationship (Enders, et al., 2006; Li, 2006; Powers & Choi, 2012; Ouyang &

Rajan, 2017), while few streams of research suggest the positive impact of terrorism on FDI (Lutz & Lutz, 2017).

Enders and Sandler (1996) investigated the impact of terrorism on FDI during the period from 1975 to 1991, and the results show that, on average, terrorism reduced the net inflow of FDI to Spain by 13.5% and Greece by 11.9%. Conversely, Abadie and Gardeazabal (2008) do not conclude a direct negative impact but find an indirect one. As the authors assumed that terrorism had caused a negative investment reputation in Spain, impact was inferred using the synthetic control method, which measures the opportunity cost if a treatment did not exist.

Moreover, Agrawal's (2011) results support a negative relationship: the author measured economic significance and points out that a one standard deviation change in terrorist risk changes net FDI by 5% in the opposite direction.

Bezić et al. (2016) report that, in developed countries, transnational terrorism affects the total inflow of FDI negatively, and the same result has been ascertained for developing countries (Abadie & Gardeazabal, 2003; Alomar & El-Sakka, 2011).

Enders, et al. (2006) point to a negative impact from terrorist attacks against U.S. interests on U.S. FDI in OECD countries. However, this impact becomes insignificant for non-OECD countries. Moreover, Powers and Choi (2012) reveal that terrorism which targets multinational corporations harms FDI, while contrariwise, the impact becomes insignificant if terrorists attack non-business targets. Ouyang and Ramkishen (2017) claim that terrorist events do not alter mergers and acquisitions (M&A): however, the frequency and intensity of terrorist events significantly affects brownfield FDI. Moreover, Efobi et al. (2015)

identified an insignificant impact of terrorism on FDI except for in highly developed countries.

Terrorism is a clear phase of conflict, and the difference is narrow; however, terrorism is less frequent compared to conflict, and correspondingly, conflict is broader and more prolonged. Besides, a critical difference is that, in legal issues, armed conflict is a condition in which specific event of violence are considered legal and others are illegal, while any event of violence termed as "terrorist" is always unlawful. The fundamental target of an armed conflict is to prevail over the enemy's armed forces. When the USA declared war against the Taliban in Afghanistan, The US forces aimed to damage the power of Taliban. However, Euskadi Ta Askatasuna (ETA) was an armed Basque nationalist and separatist terrorist organization engaged in a violent campaign of bombing, assassinations, and kidnappings in the Southern Basque Country and throughout Spanish territory. Its goal was gaining independence for the Basque Country. Between 1968 and 2010, it killed 829 people (including 340 civilians) and injured thousands more, The actions of ETA was considered as a terrorist events. (CICR, 2015)

Ouyang and Ramkishen (2017) support the idea that terrorist events do not alter M&A. However, the frequency and intensity of terrorist events significantly affect brownfield FDI.

Khayat (2016) tested the impact of several components of risk and reveals that the impact of internal and external conflict on FDI is insignificant.

However, Schöllhammer and Nigh (1984) find that the German flow of capital to less developed countries is affected negatively by internal conflict in the host state. In addition, Nigh (1985) argues that conflict affects the flow of U.S. manufacturing direct investments to developing countries in both inter and intrastate conflict. In contrast, this relationship holds for developed countries when they witness inter-state conflict only. Moreover, Biglaiser and Staats (2010) include conflict as one of the determinants of foreign direct investment in developing countries during the period 1976-2004, and the authors find a negative impact from lagged conflict on FDI.

Mihalache (2011) reveals that the exposure of conflict sparks heterogeneous behaviours of foreign investors, and thus, the characteristics of a firm's overseas investments arise as moderator factors in the relationship between conflict and FDI flows. However, these decisions are subject to investment in non-physical, capital-intensive investments and location substitutability. The author argues that the ratio of high intensity of non-physical assets to high location substitutability, high intensity of non-physical assets to low location substitutability, and low intensity of non-physical assets to low location substitutability lean towards being less sensitive to political conflict. Moreover, FDI would not be affected by conflict occurrence in low capital intensive FDI such as agriculture, footloose manufacturing industries, and finance sectors. Conversely, investments in sectors that rely heavily on physical assets, such as mining and manufacturing and tertiary industries, decline considerably during conflict.

Although Depetris & Rohner (2009) support the vast majority of literature in finding that conflict diminishes the share of the manufacturing sector in GDP, they also find that it increases the exploitation of natural resources (e.g., forestry).

As discussed earlier, the key contributions of this paper are four-fold. Firstly, to the best of the researcher's knowledge, this study is amongst the pioneering empirical works to test the conflict-FDI nexus, while most previous studies focus on terrorism and foreign firms. Secondly, the majority of empirical studies of conflict and FDI test impact using aggregated data, while this study utilizes disaggregated data on a quarterly basis and exclusively for the mining sector. Thirdly, the estimation depends on the event study approach to infer the dynamic impact of conflict on greenfield FDI over the 4 quarters following any conflict event breakout, and on spatial econometrics to infer spillover impact. Fourthly, this study uses a unique dataset on sectorial greenfield FDI.

4.3 Methodology

As mentioned in the introduction section, this study aims to investigate the impact of conflict on greenfield FDI in the mining sector, and focuses on testing two different impacts: first, dynamic impact, which investigates the impact of conflict events on FDI over the contemporary and following periods. Second, the paper investigates the existence of spillover impact in three directions, the expected spillover impact of the outcome variable in one country on its neighbours' outcome, the spillover impact of conflict, and the spillover impact of any unobserved variables.

To fulfill the paper's aims and avoid the problem of endogeneity, the methodology consists of three steps. The first part is designed to mitigate the endogeneity problem and to obtain a valid instrument for conflict. Then, this instrument is used to serve as a valid proxy for conflict to test the dynamic impact of conflict on FDI in the mining sector. The last part is designed to test spillover impact using spatial models.

The methodology section includes two sub-sections. The first introduces the data, justifying its use and identifying sources, and the next section presents how this paper mitigates the endogeneity problem. The next sub-section introduces the models that test dynamic impact, and finally, the last section illustrates the spatial models that designed to test spillover impact.

4.3.1 Data Collection

4.3.1.1 Dependent variable

The dependent variable employed in this study is greenfield FDI in the mining sector, which is defined as investment projects that entail the establishment of new production facilities, such as offices, buildings, plants and factories, as well as the movement of intangible capital (Liu & Zou, 2008). The greenfield FDI data encompasses the 1st quarter of 2003 until the 3rd quarter of 2017, across 151 countries, and data on greenfield FDI is transformed into (1+ the natural logarithmic form) following (Feenstra and Sasahara, 2018).

4.3.1.2 Key independent variable

Conflict is the treatment variable in this model, and this represents the quarterly number of fatalities during the armed conflict. The data was obtained from the One-sided violence[4] dataset of the Uppsala Conflict Data Program (UCDP) (Eck & Hultman, 2007; Pettersson, et al., 2019). The Uppsala dataset has three different estimations for one-sided violence, and this study uses the "best estimate"[5].

[4] One-sided violence is the use of armed force by the government of a state or by a formally organized group against civilians which results in at least 25 deaths. Extrajudicial killings in custody are excluded. (Pettersson, 2019)

[5] Best estimate: The UCDP Best estimate consists of the aggregated most reliable numbers for all incidents of one-sided violence during a year. If different reports provide different estimates, an examination is made as to what source is most reliable. If no such distinction can be made, UCDP as a rule includes the lower figure given. (Pettersson, 2019)

Conflict is a binary variable D that equals 1 if the number of fatalities in year $t \geq$ 25 in model 1, $\geq$ 100 in model 2, and $\geq$ 200 in model 3. Moreover, the quarter q had witnessed at least one fatality, and this is applied for all of the estimations which follow.

4.3.1.3 Explanatory variables

Following the literature, the model controls for different factors that can determine FDI, including total natural resource rents (% of GDP), inflation rate, official exchange rate, and control of corruption.

Total natural resources rents (% of GDP) includes the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents. Estimates of natural resources rents are calculated as the difference between the price of a commodity and the average cost of producing it. Data on natural resources rents was retrieved from the World Bank data.

Control of corruption was another controlling variable, for which data was obtained from the Worldwide Government indicators, with the estimate of corruption ranging from -2.5 (weak) to 2.5 (strong) control of corruption (Kraay, et al., 2010).

The previous studies have emphasised that inflation and exchange rate are crucial determinants for FDI (Alam, Shah, 2013). Inflation and GDP deflator (annual %), measured by the annual growth rate of the GDP implicit deflator, shows the rate of price change in the economy. The GDP implicit deflator is the ratio of GDP in current local currency to GDP in constant local currency. (Banerji & Sugata, 1992; Sayek, 2009)

The official exchange rate refers to the exchange rate determined by national authorities or to the rate determined in the legally sanctioned exchange market. It is calculated as an annual average based on monthly averages (local currency units relative to the U.S. dollar). (Froot & Stein, 1991; Grubert & Mutti, 1991; Swenson, 1994)

The human capital is an important determinant of FDI. However, the case is not the same when it comes to greenfield FDI in the mining sector, for example, investors become motivated to invest when the natural resources rent is competitive, the exchange rate is stable at low levels, no inflation that depreciate their profits, and when political situation protect their investments. The development of the human capital index in the host country is not that critical for them.

4.3.2 Mitigating the endogeneity problem

In econometrics, endogeneity generally cause biased estimated results, and it denotes circumstances in which an explanatory variable is correlated with the error term. Endogeneity may arise from three sources: omitted variables, measurement error, or simultaneity.

The omitted variables arise when there is a need to adjust for one or more extra variables, but it is not possible to do so in a regression model due to the lack of data. To mitigate the omitted variables problem, the model includes different explanatory variables in addition to controlling the model for unobserved time and country heterogeneities. Measurement error is the difference between a determined value of a variable and its actual value. Measurement error is not a mistake, but variability is an in-built component of the outcomes of measurements and the measurement process. Simultaneity is an issue which arises when one of the explanatory variables is simultaneously determined along with the outcome variable (Wooldridge, 2015). One of the aims for this research is to test the impact of conflict on greenfield FDI in the mining sector: however, in some cases, FDI could be the cause of a conflict's outbreak, and therefore, the model includes at least one explanatory variable that could be correlated with the error term. By excluding this assumption, none of the proofs of consistency for using the OLS estimation will hold up.

4.3.3 Instrument selection

One of the most effective available approaches for dealing with endogeneity problems is the 2SLS approach, as it allows for consistent estimation of the simultaneous equation with endogenous predictors.

The method is built over the following common extension of the estimation approach at typical regression models.

Assume that in the standard model,

$$y_i = x_i'\beta + u_i$$

However, the K variables x_i could be associated with ε_i. In addition, assume that a set of L variables z_i are available, that L is at least as large as K, and that z_i is associated with x_i but not with the error term u_i. Therefore, a consistent estimator of β is constructed using the following relation among x_i, z_i, and u_i (Greene, 2003).

$$x_i = z_i\beta + \varepsilon_i$$

The idea behind using the 2SLS method is to run the regression using an instrument(s) that can serve as a proxy for the endogenous variable(s). In other words, the instrument has the property that changes in z_i are correlated with changes in x_i but do not lead to a change in y_i. Nevertheless, several conditions must be satisfied to choose a valid instrument.

z_i is called an instrumental variable for x_i in a regression model $y_i = x_i'\beta + u_i$ if:

(1) z_i is not correlated with the error u_i, this assumption eliminates the instrument z_i from being a regressor for y_i.

(2) z_i is associated with the regressor x_i. This assumption holds that there is some relationship between the instrument and the variable being instrumented (Cameron & Trivedi, 2005).

Moreover, the factors to consider when selecting a valid instrument are not only subject to statistical intuition but should meet the economic intuition as well. Hence, this paper uses conflict in neighbouring countries as an instrument for conflict. The suggested instrument is considered not to have a spillover impact on FDI in neighbouring countries. Besides this, conflict in country i is assumed to have a spillover impact on neighbouring countries' conflict. To satisfy this first assumption, the study uses the spatial Durbin model to test the existence of the spatial effect of conflict on FDI:

$$Y_{it} = \rho W Y_{it} + \propto \iota_n + \mathrm{X}_{it}\beta + W\mathrm{X}_{it}\theta + W\mathrm{z}_{it}\tau + \mathcal{E}_t$$

The spatial methodology is explained in more detail in Section 4.3.4. For instance, the expectation is to find an insignificant relationship between Y_{it}: FDI inflow in the mining sector for country i and time t and $W\mathrm{z}_{it}$: the spatial matrix of conflict.

To satisfy the second assumption, the study uses the Spatial Autoregressive (SAR) model to capture the effect of conflict in one country on conflict in its neighbours.

$$z_{it} = \rho W z_{it} + \propto \iota_n + \mathrm{X}_{it}\beta + \mathcal{E}_t$$

In the preceding, the expectation is to find ρ significant, and then the model would be ready to predict the fitted values of z_{it} that serve as an instrument for conflict.

4.3.4 Testing the dynamic impact

To examine the dynamic impact of exogenous conflict variation on greenfield FDI, the study follows Karafiath's (1998) model representing the event study by using dummies:

$$\mathrm{Y_{iqt}} = \alpha + \varphi \mathbf{X}_{\mathrm{iqt}} + \sum_{\mathrm{j}=1}^{-3} \beta \, \mathrm{D_{tq+j}} + \delta_i + \varepsilon_{\mathrm{it}} \qquad \text{Equation 21}$$

Where, $\mathrm{Y_{it}}$ is greenfield FDI in the mining sector, i, and t represent country and time respectively, q $\in (1,4)$ represents a quarter, γ_t is the year fixed effect which controls for any fixed unobserved heterogeneity for year-specific, or for any other shocks that affect greenfield FDI, and δ_i is the country fixed effect and captures any fixed country-specific unobserved heterogeneity.

$\mathrm{D_{qt+j}}$ denotes the treatment effect if the instrumented conflict breaks out at year t and quarter $q + j$, $j \in (1, -3)$, where D is a binary measure that represents instrumented conflict in which the total number of fatalities is equal to or above 25 persons in a certain year and country. Later, for a robustness check, this identification will be replaced, to define the binary variable as the aggregate number of fatalities equal to or greater than 100, and then 200 persons. The dummies reflect the dynamic effect of conflict events on FDI during five periods. The first period is a placebo, since it is a one leaded dummy to test if the treatment has any impact on the outcome before its outbreak. In other words, the purpose of this step is to test if the current conflict event has any effect on the greenfield FDI of the last quarter: therefore, it can be expected that the coefficient of this dummy should be insignificant. The second dummy D_0 represents the contemporaneous quarter to the conflict event, and the other dummies represent the three quarters following the contemporary quarter. This enables the model to test the dynamic impact of conflict on FDI.

The statistical precision of the binary measure coefficients $\beta's$ are the main coefficients of interest that capture the dynamic impact of conflict on greenfield FDI.

$\boldsymbol{X_i}$: a set of covariates of different controlling factors, including control of corruption, total natural resources rents (% of GDP), inflation GDP deflator, and official exchange rate. φ is a vector of coefficients. ε_{it} is the error term.

4.3.5 Testing the spatial impact

The specific-to-general approach suggests starting the analysis with non-spatial linear regression, to test whether the model should incorporate spatial interaction effects. The following model sets out a taxonomy of linear spatial dependence models:

$$Y_{it} = \propto \iota_n + \mathrm{X}_{it}\beta + \mathcal{E}_{it}$$

Where Y represents an $N \times 1$ vector consisting of one observation on the dependent variable, which will be greenfield FDI in the mining sector, for each country ($\mathrm{i} = 1, \ \dots, \mathrm{N}$). In this study, N equals 196 countries, ι_n is an $N \times 1$ vector of those associated with the constant term parameter $\propto$, and X represents an $N \times K$ matrix of exogenous explanatory variables, where K is the number of exogenous explanatory variables and equals 5, including natural resources rent, inflation rate, exchange rate, control for corruption and conflict. More discussion of the explanatory variables and the dependent variable has already been introduced in the data collection section. The explanatory variables are associated with a set of parameters β which are represented in a $K \times 1$ vector. $\mathcal{E}$ is a vector of disturbance term for country i and time t, where $\mathcal{E}$ is independently and identically distributed.

However, changes in observations tend to be affected by changes in closer observations rather than observations of more distant units. In other words, it has become generally acknowledged that observations from geographically close entities are not independent but spatially correlated (Tobler, 1970).

Spatial associations are often observed for socio-demographic and economic determinants (Moscone & Knapp, 2005; Kostov, 2009; Elhorst & Fréret, 2009; Moscone, et al., 2012), and empirically, spatial panel-data models have become a well-known tool for determining the existence of spatial spillovers.

Therefore, Manski (1993) reports three types of interaction effects that may help in explaining why changes in observations tend to be affected by changes in neighbourhood units: first, when the behaviour of the dependent variable relies on the decision taken by other spatial dependent variables, in so-called endogenous interaction effects. Second are the exogenous interaction effects, and these may happen when the behaviour of the dependent variable depends on the decision of independent explanatory variables taken by other spatial units: and third are the correlated effects, where similar unobserved environmental characteristics result in similar behaviour.

For the above-noted reasons, Manski (1993) suggests the following model:

$$Y_{it} = \rho W Y_{it} + \propto \iota_n + \mathrm{X}_{it}\beta + W\mathrm{X}_{it}\theta + \mathrm{u}_t$$

$$u_t = \lambda W u_t + \varepsilon_t$$

where W is an $N \times N$ matrix which refers to the spatial composition of the spatial units included in the sample. Each element of the matrix is binary and equal to one when two units are neighbours, and no unit can be a neighbour on its own. Therefore, the diagonal elements of the matrix are set to zero. Lee (2004) shows that W should be a non-negative matrix of known constants. Non-negative matrix factorization (NMF) delivers profound explanations of complicated latent relationships (Gao, et al., 2019).

WY represents the endogenous interaction effects for the dependent variable, WX is the exogenous interaction effects among the independent variables, Wu is the interaction effects among the disturbance terms of the different spatial units. ρ is the spatial autoregressive coefficient, λ the spatial autocorrelation coefficient, and θ denotes a $K \times 1$ vector of fixed but unknown parameters.

Manski's model, also known as the general nesting spatial (GNS), suffers from an identification problem, as it commonly leads to an overparameterized model that will ultimately lower the level of significance for parameters (Elhorst, 2014) and it will not give accurate clarifications of the reasons for using the spatial models discussed in this section previously see (Manski, 1993) Therefore, Elhorst's (2010) taxonomy implies that by imposing some restrictions, the models can explain how to gain more explanations of how spatially interacting observations can affect each other. Figure 9 introduces Elhorst's taxonomy of spatial dependence models.

Different approaches have been suggested as to which model to start with. Kelejian and Prucha (1999) suggest starting with spatial autocorrelation models (SAC): however, as mentioned earlier, Anselin (2013) suggests starting from the specific and moving to the general approach, which implies commencing analysis with a non-spatial linear regression such as OLS, and then to conduct tests to identify the need to add spatial terms. Nevertheless, this study follows LeSage and Pace (2009) stating that by starting with the Spatial Durbin Model (SDM) and imposing restrictions, it will be easy to obtain the Spatial Autoregressive model (SAR) and the Spatial Error Model (SEM) models. This paper uses the maximum likelihood approach to infer the spatial impacts.

4.3.5.1 The Spatial Durbin Model (SDM)

Imposing a restriction on Manski's Model by letting $\lambda = 0$ leads to the Spatial Durbin Model.

$$Y_{it} = \rho W Y_{it} + \propto \iota_n + \mathrm{X}_{it}\beta + W\mathrm{X}_{it}\theta + \mathcal{E}_t$$

The Spatial Durbin Model enables the researcher to infer the impact of greenfield FDI in the mining sector in neighbouring countries on a specific country's greenfield FDI, at the same time, it assesses the impact of the exogenous explanatory variables of both the country and its neighbours on the dependent variable. Table 38 presents the results of the SDM models. Model 1 includes the country fixed effects, model 2 includes the time fixed effect, and model 3 includes both.

However, to only capture the effect of greenfield FDI in the mining sector in one country on its neighbourhood countries, the Spatial Lag model or so-called spatial autoregressive model can be used for this purpose.

The SAR model is a special case for the SDM model and is obtained by introducing some restriction to the model by making $\theta = 0$. Therefore, the model would be as follows:

$$Y_{it} = \rho W Y_{it} + \propto \iota_n + X_{it}\beta + \mathcal{E}_t$$

Table 39 presents the results of the SAR models. Model 1 includes the country fixed effects, model 2 includes the time fixed effect, and model 3 includes both.

Moreover, by imposing different restrictions on Manski's model by making $\theta = 0$ and $\rho = 0$, the impact of unobserved variables can be obtained, which is represented by the error term on the error term for neighbouring countries. By imposing restrictions, the Spatial Error Model (SEM) can be obtained. The following equations represent the SEM model.

$$Y_{it} = \propto \iota_n + X_{it}\beta + u_t$$

$$u_t = \lambda W u_t + \mathcal{E}_t$$

Table 40 presents the results of the SEM models. Model 1 includes the country fixed effects, model 2 includes the time fixed effect, and model 3 includes both.

Direct and Indirect effect:

The interpretation of the parameters grows deeper and more sophisticated in models with spatial lags for the explanatory or dependent variables. Several econometricians have pointed out that models with spatial lags in the dependent variable necessitate unique explanations of the parameters (Le Gallo, et al., 2003; Kim, et al., 2003; Kelejian, et al., 2006; Anselin & Le Gallo, 2006).

Moreover, spatial regression models take advantage of the complex interdependence structure between units, and thus a change in an explanatory variable for one unit will have an indirect influence on all other units. This means that there are both direct and indirect marginal effects, as well as total marginal effects (Belotti, et al., 2017).

The average direct effect is similar to that of the β coefficients of a non-spatial linear model calculated using the OLS method. In other words, the impact is simply represented by the effect of explanatory factors on the dependent variable for a specific country. However, the indirect effect represented the impact of explanatory variables on the dependent variables of other countries. Moreover, by using dynamic models such as SDM and SAR, it is possible to obtain the direct effect, indirect effect, and the total effect in both the short-term and the long-term.

The idea of short-term effects and long-term effects was developed when the spatial Durbin model with dynamic effects was considered in several pieces of research. The focus of these pieces of research is on growth and convergence among countries or regions (Ertur & Koch, 2007; Elhorst, 2010).

Typically, these analyses regress the dependent variable of a specific country on the following:

- The dependent variable in neighbouring territories.
- The initial values (lagged values) of the dependent variable in the country and neighbouring economies.
- And on a set of explanatory variables in the country and neighbouring countries.

Table 41 and Table 42 show the dynamic spatial Durbin model and the dynamic spatial autoregressive model, which illustrate direct, indirect, and total effects in both the short and long term.

4.3.5.2 The Weighting Matrix

Data on the world countries map were extracted from the GADM database (www.gadm.org), and then GeoDa software was used to generate the Weighting Matrix. Finally, Stata software was used for analysis.

4.4 Results and discussion

The analysis starts with an assessment of the dynamic impact of conflict on greenfield FDI in the mining sector for the full sample. Further investigations have been conducted in this paper to examine the spatial impact of FDI in greenfield FDI in the mining sector. Table 38 shows the estimation results of the fixed effect Spatial Durbin Model (SDM). As discussed earlier, this estimation allows the impact of greenfield FDI in the mining sector in neighbouring countries on a specific country's greenfield FDI to be inferred, while at the same time, it assesses the impact of the exogenous explanatory variables of a specific country on its neighbour's outcome variable. The results show that a spatial impact on greenfield FDI in the mining sector exists and follows a negative direction: in other words, the inflow of greenfield FDI in the mining sector for country i decreases the same investments in neighbourhood countries. The same results have been obtained from the Spatial Autoregressive Model in Table 39. However, the spillover impact of conflict in country i on FDI in neighbourhood countries was insignificant. Table 40 shows the estimation results of the Fixed effect Spatial Error Model (SEM). The model investigates the impact of unobserved variables, which is represented by the error term on the error term for neighbouring countries. The results show that the unobserved variables in country i can affect the greenfield FDI in a neighbouring country.

4.4.1 The dynamic and one-year aggregate models

Table 20 shows that the placebo dummy successfully satisfies the preceding assumption; the upcoming conflict event should not have any impact on the current value of FDI. This assumption has been fulfilled for the suggested three models.

A common mistake is made when interpretating the coefficients of dummy variables in semilogarithmic regression models. Usually, analysts multiply the coefficient by 100. Consequently, they assume this equal to the percentage effect of that dummy variable on the outcome variable. However, it is easily shown that this interpretation, while correct for continuous variables, is not correct for dummy variables and can result in substantial errors in the reporting of results.

To calculate the impact of dummy conflict on logarithmic greenfield FDI, the study uses the following equation suggested by (Halvorsen & Palmquist, 1980)

$$100\%\ \Delta Y = 100 \times (e^{\beta} - 1)$$

In model 1 (Table 20), when conflict fatalities ≥ 25, the dynamic impact is significant over three periods and has a negative direction. Generally, the event of conflict outbreak decreases the contemporaneous FDI by a 24.8 percent. However, the results in model 1 show that conflict does not has any impact on the next quarter, yet the impact exists for the following two quarters and decreases FDI by 21.6 and 35 percent respectively. Nevertheless, the impact exists for the contemporaneous and the fourth quarters only in model 2, where lower conflict cases are excluded, the magnitude of the impact has in fact increased in its absolute value, yet the increase is not statistically significant, as it still lies within the confidence interval of the same coefficients in model 1. Moreover, the dynamic impact is no longer exists when the model retains highly intense conflict events, as model 3 shows. However, FDI flies out in the fourth quarter only: thus, when a highly intense conflict event occurred, greenfield FDI in the mining sector declined by a 63.7 percent.

Table 26 shows the one-year aggregate impact of conflict on greenfield FDI in the mining sector across world countries. The one-year aggregate impact exists only for the low and medium scales of conflict; however, it has no impact for the highly intensive events of conflict on FDI. When conflict is defined to be >25 fatalities, the existence of conflict event decreases greenfield FDI in mining sector by 35.5% (see model 1-Table 26). This impact increases to 41% in model 2 where the one-year aggregate conflict dummy is re-defined and restricted to cases above 100 fatalities.

Table 32 shows the interaction between the natural resources and the one-year aggregate conflict events, results show that the interaction terms were insignificant among the different levels of conflict intensity.

The absence of significant impact in model 3 Table 26 and Table 32 could be due to the heterogeneity between countries across world which witnessed highly intensive conflict events. Therefore, the study extended its analysis and the discussion by estimating the impact across sub-samples as follow.

The study has divided the full sample into sub-samples, including the Sub-Saharan, South Asian, MENA, and Oil producing countries, to provide more in-depth analysis and to test if the preceded results hold.

Table 21 shows the dynamic impact of conflict on greenfield FDI in the mining sector across Sub-Saharan countries, the impact is significant for the first two quarters, and it is -29% and -32% respectively, and only when conflict is defined as having a total number of fatalities which exceeds 100. However, the one-year aggregate impact shown in Table 27 reveals that aggregate impact for the first four quarters is significant and negative for low and medium intensities of conflict, and it was -39.6% and 45% respectively.

Table 33 shows that the interaction between natural resources and one-year aggregate conflict has an impact on greenfield FDI in the mining sector across Sub-Saharan countries, the impact of c conflict on FDI is negative in all models. However, interaction with natural resources rents decreases the negative impact in more conflict intensive events (see model 2 and 3- Table 33). In model 2, the one-year aggregate impact of conflict on greenfield FDI becomes positive when the natural resources rent is 28.75, in other words when the difference between the price of the natural resource and the average cost of producing it is 28.75 US dollar. Nonetheless, when conflict becomes more intensive on Sub-Saharan countries, the negative impact disappears when the natural resources rent is above 10.95 US Dollar. in summary, FDI in mining sector flies less when profit opportunities become more likely in Sub-Saharan countries.

In contrast, the dynamic impact of conflict on greenfield FDI in the mining sector across South Asian countries is inconsistent. Table 22, model 1, reveals a negative impact, and thus when a conflict event arises, greenfield FDI declines by a 0.795 percentage change. However, in model 2, when the model excludes low scale conflict cases, the outbreak of conflict decreases FDI by 1 percentage point change, yet the following quarter witnesses an inverse impact. However, the results in Table 27 show a positive impact of conflict in terms of one-year aggregate impact on FDI when the conflict event is low or medium only. More confusing results are presented in Table 34, as the impact no longer exists in any model.

In MENA countries, dynamic impact does not exist. In Table 23, model 1 shows that the impact is limited within the third quarter and in model 2, is limited within the fourth quarter. However, one-year aggregate impact is only significant and negative when conflict intensity becomes greater. Additionally, the opportunity to achieve profit from natural resources rents in conflict areas may exist, but not in medium and high-intensity conflict models. Table 24 shows the dynamic impact of conflict on greenfield FDI in the mining sector across oil-producing countries. This dynamic impact only exists in high-intensity conflict cases: however, the impact is inconsistent. In the first quarter, the impact of conflict on FDI is negative, and it becomes positive in the third and fourth quarter. However, the aggregate impact is negative.

4.4.2 The spatial models

Further investigations have been conducted in this paper to examine the spatial impact of greenfield FDI in the mining sector. Table 38 shows the estimation results of the Fixed effect Spatial Durbin Model. as discussed previously, this estimation enables inference of the impact of greenfield FDI in the mining sector in neighbouring countries on a specific country's greenfield FDI. At the same time, it assesses the impact of the exogenous explanatory variables of a specific country on its neighbour's outcome variables. The results show that a spatial impact on greenfield FDI in the mining sector is exists and has a negative direction. In other words, the inflow of greenfield FDI in the mining sector in country i decreases the same investments in neighbouring countries. The same results have been obtained from the SAR model in Table 39. However, the spillover impact of conflict in country i on FDI in neighbourhood countries is insignificant. Table 40 shows the estimation results of the Fixed effect SEM, the model investigates the impact of unobserved variables, represented by the error term on the error term in neighbouring countries. The results show that unobserved variables in country i can affect greenfield FDI in neighbouring countries.

Table 41 and Table 42 show the estimation results for Direct, Indirect, Total, and short- and long-term SDM and for Direct, Indirect, Total, and short- and long-term SAR respectively. Neither model's results demonstrated any spatial impact for greenfield FDI and conflict in the mining sector. Thus, including lags for the dependent variable was not statistically significant, and this demonstrates that economic intuition as the concept of greenfield investments is limited to new investments only, which in most cases do not depend on previous ones.

Most of the results obtained from the previous models which revealed a negative impact of conflict on greenfield FDI matched previous literature findings (Enders & Sandler, 1996; Abadie & Gardeazabal, 2003; Agrawal, 2011; Abadie & Gardeazabal, 2008). However, Robinson (1969) and Vernon & Wells (1981) suggest that the inconsistency in results exist as political instability could not be an effective determinant for FDI, as CEOs do not take political instability into account when making investment decisions.

It is recommended that future research focuses on studying single cases and use quasi-experimental designs, the difference in difference and regression discontinuity design may form a valid technique to use for this manner, conflict may arise in a specific country but not in surrounding areas, single cases could tell researchers more about the association between conflict and FDI. In summary, the outbreak of conflict events is a vital determinant of FDI flows as it has a negative impact, and this effect can be extended to include subsequent periods as well.

4.5 Conclusion

The aim of this study was to investigate the impact of conflict on greenfield FDI in the mining sector. Unlike other works, this paper focuses on testing two impacts. First is dynamic impact, which investigates the impact of conflict on FDI on the contemporary and subsequent quarters, and second, the paper investigates the spillover impact in three directions: the expected spillover impact of the outcome variable in one country on its neighbours' outcome; the spillover impact of conflict on FDI; and the spillover impact of any unobserved variables on FDI.

The data employed on conflict was obtained from the One-sided Violence data set of the Uppsala Conflict Data Program (Eck & Hultman, 2007; Pettersson, et al., 2019), whereas the unique greenfield FDI data was obtained from the Financial Times, and tracks the FDI inflow in the mining sector from 2003 to 2017. both conflict and greenfield FDI data were aggregated on a quarterly basis.

To fulfil the paper's aims and to avoid the problem of endogeneity, the methodology of this paper consisted of three parts: the first part was designed to obtain a valid instrument for conflict; then this instrument was used to test the dynamic impact of conflict on FDI in the mining sector; and the last part involved applying spatial models to test the spillover impact.

For dynamic impact, the results showed inconsistency across different groups of countries. For example, while this impact exists for the full sample in particular when conflict is defined to be an event if the total number of fatalities during the year is greater than 25 cases, unlike the oil-producing countries, dynamic impact exists for high-intensity conflict, while in Sub-Saharan and South Asian countries dynamic impact only exists for two periods when regression excludes low-intensity conflict cases. However, in MENA countries, the dynamic impact did not exist at all. Table 25 shows a summary of the dynamic impact of conflict on greenfield FDI in the mining sector.

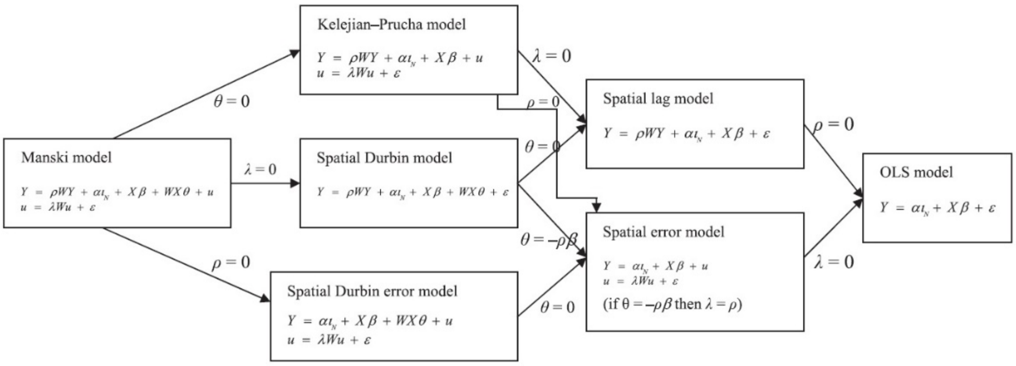
Table 31 presents a summary of the one-year aggregate impact of conflict on greenfield FDI in the mining sector, and the results show that a negative and significant impact exists across global, Sub-Saharan, MENA, and Oil countries: however, the impact is positive in South Asian countries.

Further investigations have been conducted in this paper to examine the spatial impact of FDI on greenfield FDI in the mining sector. Table 38 shows the Spatial Durbin Model, enabling evaluation of the impact of greenfield FDI in the mining sector in neighbouring countries on a specific country's greenfield FDI. At the same time, it infers the impact of the exogenous explanatory variables of both the country and its neighbours on the dependent variable.

The study concludes a significant but negative spillover impact for greenfield FDI in the mining sector: however, this impact does not exist when the model includes the lag dependent variable as an additional explanatory variable. Moreover, the conflict has no spillover impact on FDI in neighbouring countries.

4.6 Figures

Figure 11: The relationships between different spatial dependence models for cross-section data



source: (Elhorst, 2010)

4.7 Tables

Table 21: The dynamic impact of conflict on Greenfield FDI in mining sector cross-world countries

VARIABLES	(1) Fatalities ≥ 25	(2) Fatalities ≥ 100	(3) Fatalities ≥ 200
Inflation	0.00513**	0.00528**	0.00566**
	(0.00257)	(0.00259)	(0.00261)
Exchange Rate	1.55e-10***	1.45e-10***	1.39e-10***
	(0)	(0)	(0)
Control of Corruption	0.266*	0.325**	0.319**
	(0.141)	(0.139)	(0.136)
Natural resources Rent	0.00386	0.00946	0.0137**
	(0.00764)	(0.00687)	(0.00636)
D_{tq+1}	0.0414	0.158	0.457
	(0.112)	(0.210)	(0.586)
D_{tq}	-0.248*	-0.419**	-0.674
	(0.130)	(0.200)	(0.499)
D_{tq-1}	0.147	0.163	-0.209
	(0.123)	(0.228)	(0.514)
D_{tq-2}	-0.216**	-0.168	0.498
	(0.106)	(0.152)	(0.338)
D_{tq-3}	-0.350***	-0.449**	-1.013*
	(0.113)	(0.198)	(0.547)
Constant	1.148***	1.319***	1.524***
	(0.247)	(0.329)	(0.558)
Observations	11,564	11,564	11,564
Number of countries	196	196	196
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3); besides, the quarter q had witnessed at least one fallen fatality.

Table 22: The dynamic impact of conflict on Greenfield FDI in mining sector cross Sub-Saharan countries

VARIABLES	(1) Fatalities ≥ 25	(2) Fatalities ≥ 100	(3) Fatalities ≥ 200
Inflation	0.00227	0.00118	0.00144
	(0.00448)	(0.00437)	(0.00434)
Exchange Rate	1.49e-10***	1.35e-10***	1.27e-10***
	(0)	(0)	(0)
Control of Corruption	0.547**	0.660**	0.653**
	(0.275)	(0.270)	(0.269)
Natural resources Rent	0.00706	0.0149	0.0200
	(0.0132)	(0.0139)	(0.0124)
D_{tq+1}	-0.0659	0.466	0.845
	(0.247)	(0.394)	(0.929)
D_{tq}	-0.211	-0.342**	-0.204
	(0.237)	(0.154)	(0.183)
D_{tq-1}	0.0366	-0.386**	-0.787
	(0.340)	(0.171)	(0.912)
D_{tq-2}	-0.169	0.141	0.790
	(0.253)	(0.115)	(0.915)
D_{tq-3}	-0.218	-0.392	-0.740
	(0.256)	(0.248)	(0.935)
Constant	1.173***	4.744***	4.249***
	(0.272)	(0.696)	(0.377)
Observations	2,301	2,301	2,301
Number of countries	39	39	39
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3); besides, the quarter q had witnessed at least one fallen fatality.

Table 23: The dynamic impact of conflict on Greenfield FDI in mining sector cross South Asian countries

	(1)	(2)	(3)
VARIABLES	Fatalities ≥ 25	Fatalities ≥ 100	Fatalities ≥ 200
Inflation	-0.00577	-0.00286	-0.00410
	(0.0141)	(0.0126)	(0.0126)
Exchange Rate	-0.0188*	-0.0161	-0.0144
	(0.0112)	(0.0114)	(0.0107)
Control of Corruption	0.683	0.619	0.561
	(0.725)	(0.688)	(0.688)
Natural resources Rent	-0.0953	-0.0822	-0.0849
	(0.0819)	(0.0686)	(0.0709)
D_{tq+1}	0.180	0.788	1.781*
	(0.894)	(0.717)	(0.958)
D_{tq}	-0.795***	-0.523	0.0196
	(0.220)	(0.325)	(1.716)
D_{tq-1}	0.538	-1.003***	-1.042
	(0.976)	(0.340)	(0.762)
D_{tq-2}	0.160	0.700***	0.359
	(0.138)	(0.210)	(0.229)
D_{tq-3}	0.295	0.162	0.233
	(0.307)	(0.353)	(0.681)
Constant	1.945	1.927	0.545*
	(1.569)	(1.502)	(0.302)
Observations	472	472	472
Number of countries	8	8	8
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3); besides, the quarter q had witnessed at least one fallen fatality.

Table 24: The dynamic impact of conflict on Greenfield FDI in mining sector cross MENA countries

VARIABLES	(1) Fatalities ≥ 25	(2) Fatalities ≥ 100	(3) Fatalities ≥ 200
Inflation	-0.00480	-0.00470	-0.00591
	(0.00976)	(0.00778)	(0.00847)
Exchange Rate	2.73e-10	1.87e-10	0
	(2.61e-10)	(2.66e-10)	(4.38e-10)
Control of Corruption	0.444	0.445	0.358
	(0.763)	(0.758)	(0.741)
Natural resources Rent	0.0253	0.0239	0.0278**
	(0.0179)	(0.0159)	(0.0133)
D_{tq+1}	0.353	0.122	-0.672
	(0.277)	(0.222)	(0.701)
D_{tq}	-0.142	-0.130	-0.255
	(0.407)	(0.308)	(0.935)
D_{tq-1}	0.207	0.425	0.891
	(0.326)	(0.371)	(1.028)
D_{tq-2}	-0.379*	-0.286	0.0895
	(0.230)	(0.243)	(0.375)
D_{tq-3}	-0.460	-0.776**	-1.835
	(0.288)	(0.350)	(1.304)
Constant	1.589	1.874	3.646**
	(1.779)	(1.553)	(1.536)
Observations	1,121	1,121	1,121
Number of countries	19	19	19
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3); besides, the quarter q had witnessed at least one fallen fatality.

Table 25: The dynamic impact of conflict on Greenfield FDI in mining sector cross Oil producers

	(1)	(2)	(3)
VARIABLES	Fatalities ≥ 25	Fatalities ≥ 100	Fatalities ≥ 200
Inflation	0.00568	0.00424	0.00434
	(0.00410)	(0.00389)	(0.00422)
Exchange Rate	-1.51e-09***	-1.70e-09***	-1.71e-09***
	(2.48e-10)	(3.67e-10)	(3.79e-10)
Control of Corruption	-0.340	-0.340	-0.297
	(0.439)	(0.469)	(0.460)
Natural resources Rent	0.0308**	0.0265***	0.0346***
	(0.0155)	(0.00919)	(0.00925)
D_{tq+1}	0.324	0.0534	0.225
	(0.264)	(0.314)	(0.308)
D_{tq}	-0.126	-0.260	-0.177***
	(0.412)	(0.273)	(0.0188)
D_{tq-1}	0.280	0.0782	-0.0293
	(0.330)	(0.338)	(0.0330)
D_{tq-2}	-0.210	-0.220	0.102***
	(0.222)	(0.202)	(0.0261)
D_{tq-3}	-0.436	-0.0288	0.336*
	(0.268)	(0.216)	(0.190)
Constant	1.414	1.422	1.334
	(0.901)	(0.964)	(0.945)
Observations	1,593	1,593	1,593
Number of countries	27	27	27
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3); besides, the quarter q had witnessed at least one fallen fatality.

Table 26: summary of the dynamic impact of conflict on Greenfield FDI in mining sector

	Conflict > 25	Conflict > 100	Conflict > 200
World countries			
D_{tq+1}	0.0414	0.158	0.457
D_{tq}	-0.248*	-0.419**	-0.674
D_{tq-1}	0.147	0.163	-0.209
D_{tq-2}	-0.216**	-0.168	0.498
D_{tq-3}	-0.350***	-0.449**	-1.013*
Sub-Sahara countries			
D_{tq+1}	-0.0659	0.466	0.845
D_{tq}	-0.211	-0.342**	-0.204
D_{tq-1}	0.0366	-0.386**	-0.787
D_{tq-2}	-0.169	0.141	0.790
pD_{tq-3}	-0.218	-0.392	-0.740
South Asia countries			
D_{tq+1}	0.180	0.788	1.781*
D_{tq}	-0.795***	-0.523	0.0196
D_{tq-1}	0.538	-1.003***	-1.042
D_{tq-2}	0.160	0.700***	0.359
D_{tq-3}	0.295	0.162	0.233
MENA countries			
D_{tq+1}	0.353	0.122	-0.672
D_{tq}	-0.142	-0.130	-0.255
D_{tq-1}	0.207	0.425	0.891
D_{tq-2}	-0.379*	-0.286	0.0895
D_{tq-3}	-0.460	-0.776**	-1.835
Oil Countries			
D_{tq+1}	0.324	0.0534	0.225
D_{tq}	-0.126	-0.260	-0.177***
D_{tq-1}	0.280	0.0782	-0.0293
D_{tq-2}	-0.210	-0.220	0.102***
D_{tq-3}	-0.436	-0.0288	0.336*

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1,

Table 27: The one-year aggregate impact of conflict on Greenfield FDI in the mining sector across world countries

	(1)	(2)	(3)
VARIABLES	Conflict > 25	Conflict > 100	Conflict > 200
Inflation	0.00493*	0.00513**	0.00561**
	(0.00258)	(0.00257)	(0.00260)
Exchange Rate	1.51e-10***	1.45e-10***	1.40e-10***
	(0)	(0)	(0)
Control of Corruption	0.273*	0.328**	0.329**
	(0.142)	(0.140)	(0.138)
Natural resources Rent	0.00563	0.00966	0.0140**
	(0.00758)	(0.00705)	(0.00668)
One -year Interval	-0.438***	-0.527***	-0.443
	(0.107)	(0.194)	(0.309)
Constant	0.993***	1.160***	1.071***
	(0.242)	(0.268)	(0.395)
Observations	11,564	11,564	11,564
Number of countries	196	196	196
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq$ 25 in model (1), $\geq$ 100 in model (2), and $\geq$ 200 in model (3).

Table 28: The one-year aggregate impact of conflict on Greenfield FDI in the mining sector across Sub-Saharan countries

	(1)	(2)	(3)
VARIABLES	Conflict > 25	Conflict > 100	Conflict > 200
Inflation	0.00248	0.00117	0.00150
	(0.00448)	(0.00437)	(0.00433)
Exchange Rate	1.46e-10***	1.39e-10***	1.27e-10***
	(0)	(0)	(0)
Control of Corruption	0.544*	0.651**	0.659**
	(0.279)	(0.268)	(0.269)
Natural resources Rent	0.00900	0.0124	0.0200
	(0.0129)	(0.0139)	(0.0124)
One -year Interval	-0.505***	-0.598**	0.0564
	(0.162)	(0.299)	(0.0531)
Constant	1.169***	1.066***	4.114***
	(0.277)	(0.264)	(0.334)
Observations	2,301	2,301	2,301
Number of countries	39	39	39
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3).

Table 29: The one-year aggregate impact of conflict on Greenfield FDI in the mining sector across South Asian countries

	(1)	(2)	(3)
VARIABLES	Conflict > 25	Conflict > 100	Conflict > 200
Inflation	-0.00285	-0.00330	-0.00325
	(0.0131)	(0.0129)	(0.0129)
Exchange Rate	-0.0162	-0.0165	-0.0164
	(0.0118)	(0.0118)	(0.0118)
Control of Corruption	0.630	0.565	0.568
	(0.742)	(0.703)	(0.701)
Natural resources Rent	-0.0702	-0.0647	-0.0646
	(0.0671)	(0.0614)	(0.0613)
One -year Interval	0.416***	0.288***	1.399
	(0.0792)	(0.100)	(1.623)
Constant	1.623	1.668	0.556*
	(1.493)	(1.447)	(0.315)
Observations	472	472	472
Number of countries	8	8	8
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3).

Table 30: The one-year aggregate impact of conflict on Greenfield FDI in the mining sector across MENA countries

	(1)	(2)	(3)
VARIABLES	Conflict > 25	Conflict > 100	Conflict > 200
Inflation	-0.00693	-0.00738	-0.00561
	(0.00922)	(0.00771)	(0.00804)
Exchange Rate	3.14e-10	2.32e-10	3.17e-10
	(2.92e-10)	(2.38e-10)	(2.52e-10)
Control of Corruption	0.500	0.500	0.471
	(0.782)	(0.788)	(0.766)
Natural resources Rent	0.0293	0.0239	0.0292*
	(0.0190)	(0.0166)	(0.0161)
One -year Interval	-0.163	-0.500	-0.615**
	(0.327)	(0.321)	(0.247)
Constant	1.237	1.853	2.651
	(1.916)	(1.541)	(1.714)
Observations	1,121	1,121	1,121
Number of countries	19	19	19
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3).

Table 31: The one-year aggregate impact of conflict on Greenfield FDI in the mining sector across Oil producers

	(1)	(2)	(3)
VARIABLES	Conflict > 25	Conflict > 100	Conflict > 200
Inflation	0.00432	0.00398	0.00433
	(0.00424)	(0.00385)	(0.00421)
Exchange Rate	-1.71e-09***	-1.69e-09***	-1.71e-09***
	(3.88e-10)	(3.60e-10)	(3.79e-10)
Control of Corruption	-0.298	-0.332	-0.302
	(0.441)	(0.474)	(0.459)
Natural resources Rent	0.0350**	0.0236***	0.0346***
	(0.0155)	(0.00873)	(0.00924)
One -year Interval	0.0118	-0.454*	-0.210***
	(0.304)	(0.276)	(0.0464)
Constant	1.335	1.407	1.344
	(0.907)	(0.975)	(0.944)
Observations	1,593	1,593	1,593
Number of countries	27	27	27
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3).

Table 32: The summary of one-year aggregate impact of conflict on Greenfield FDI in the mining sector across

	Conflict > 25	Conflict > 100	Conflict > 200
World			
one year Interval	-0.438***	-0.527***	-0.443
	(0.107)	(0.194)	(0.309)
Sub-Saharan			
one year Interval	-0.505***	-0.598**	0.0564
	(0.162)	(0.299)	(0.0531)
South Asia			
one year Interval	0.416***	0.288***	1.399
	(0.0792)	(0.100)	(1.623)
MENA			
one year Interval	-0.163	-0.500	-0.615**
	(0.327)	(0.321)	(0.247)
Oil Countries			
one year Interval	0.0118	-0.454*	-0.210***
	(0.304)	(0.276)	(0.0464)

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 33: The impact of the interaction between natural resources and one-year aggregate conflict on Greenfield FDI in the mining sector across world countries.

	(1)	(2)	(3)
VARIABLES	Conflict > 25	Conflict > 100	Conflict > 200
Inflation	0.00509**	0.00515**	0.00559**
	(0.00260)	(0.00258)	(0.00260)
Exchange Rate	1.57e-10***	1.48e-10***	1.37e-10***
	(0)	(0)	(0)
Control of Corruption	0.247*	0.320**	0.336**
	(0.142)	(0.138)	(0.139)
Natural resources Rent	0.00120	0.00809	0.0154**
	(0.00640)	(0.00620)	(0.00636)
One -year Interval	-0.659***	-0.671**	-0.163
	(0.118)	(0.271)	(0.508)
One -year Interval X Natural Resources Rent	0.0186**	0.0102	-0.0121
	(0.00830)	(0.0163)	(0.0193)
Constant	1.166***	1.287***	0.807
	(0.252)	(0.320)	(0.539)
Observations	11,564	11,564	11,564
Number of countries	196	196	196
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3).

Table 34: The impact of the interaction between natural resources and one-year aggregate conflict on Greenfield FDI in the mining sector across Sub-Saharan countries.

	(1)	(2)	(3)
VARIABLES	Conflict > 25	Conflict > 100	Conflict > 200
Inflation	0.00231	0.00103	0.00134
	(0.00434)	(0.00436)	(0.00435)
Exchange Rate	1.53e-10***	1.42e-10***	1.30e-10***
	(0)	(0)	(0)
Control of Corruption	0.534*	0.656**	0.658**
	(0.284)	(0.269)	(0.269)
Natural resources Rent	0.00468	0.0106	0.0183
	(0.0136)	(0.0137)	(0.0125)
One -year Interval	-0.736***	-1.216**	-0.735***
	(0.261)	(0.473)	(0.153)
One -year Interval X Natural Resources Rent	0.0159	0.0423**	0.0671***
	(0.0104)	(0.0200)	(0.0153)
Constant	1.191***	1.067***	3.987***
	(0.280)	(0.264)	(0.317)
Observations	2,301	2,301	2,301
Number of countries	39	39	39
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3).

Table 35: The impact of the interaction between natural resources and one-year aggregate conflict on Greenfield FDI in the mining sector across South Asian countries.

VARIABLES	(1) Conflict > 25	(2) Conflict > 100	(3) Conflict > 200
Inflation	-0.00361	-0.00386	-0.00377
	(0.0129)	(0.0127)	(0.0126)
Exchange Rate	-0.0158	-0.0159	-0.0158
	(0.0119)	(0.0119)	(0.0118)
Control of Corruption	0.614	0.567	0.575
	(0.729)	(0.708)	(0.709)
Natural resources Rent	-0.232	-0.237	-0.265
	(0.340)	(0.327)	(0.326)
One -year Interval	0.202	0.0251	0.613
	(0.318)	(0.445)	(1.685)
One -year Interval X Natural Resources Rent	0.204	0.222	0.261
	(0.342)	(0.344)	(0.344)
Constant	1.773	1.876	1.291
	(1.576)	(1.583)	(1.054)
Observations	472	472	472
Number of countries	8	8	8
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3).

Table 36: The impact of the interaction between natural resources and one-year aggregate conflict on Greenfield FDI in the mining sector across MENA countries.

	(1)	(2)	(3)
VARIABLES	Conflict > 25	Conflict > 100	Conflict > 200
Inflation	-0.00397	-0.00740	-0.00717
	(0.0107)	(0.00815)	(0.00818)
Exchange Rate	4.67e-10	2.28e-10	0
	(3.89e-10)	(3.33e-10)	(4.69e-10)
Control of Corruption	0.380	0.503	0.567
	(0.814)	(0.797)	(0.769)
Natural resources Rent	0.0115	0.0241*	0.0417***
	(0.0150)	(0.0135)	(0.0113)
One -year Interval	-0.696***	-0.493	0.538
	(0.213)	(0.344)	(0.777)
One -year Interval X Natural Resources Rent	0.0268**	-0.000417	-0.0313
	(0.0126)	(0.0177)	(0.0225)
Constant	1.143	1.861	2.504*
	(2.098)	(1.708)	(1.421)
Observations	1,121	1,121	1,121
Number of countries	19	19	19
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3).

Table 37: The impact of the interaction between natural resources and one-year aggregate conflict on Greenfield FDI in the mining sector across Oil producers.

	(1)	(2)	(3)
VARIABLES	Conflict > 25	Conflict > 100	Conflict > 200
Inflation	0.00489	0.00396	0.00427
	(0.00367)	(0.00387)	(0.00425)
Exchange Rate	-1.59e-09***	-1.69e-09***	-1.71e-09***
	(2.88e-10)	(3.62e-10)	(3.79e-10)
Control of Corruption	-0.345	-0.339	-0.304
	(0.457)	(0.472)	(0.460)
Natural resources Rent	0.0299**	0.0241***	0.0346***
	(0.0138)	(0.00907)	(0.00926)
One -year Interval	-0.792***	-0.543*	-0.212***
	(0.155)	(0.314)	(0.0473)
One -year Interval X Natural Resources Rent	0.0456***	0.00559	1.372**
	(0.0112)	(0.0166)	(0.618)
Constant	1.430	1.421	1.349
	(0.940)	(0.971)	(0.946)
Observations	1,593	1,593	1,593
Number of countries	27	27	27
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Country fixed effect	yes	yes	yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the key independent variable is instrumented Conflict which is a binary variable D that equals 1 if the number of fatalities in a year $t \geq 25$ in model (1), ≥ 100 in model (2), and ≥ 200 in model (3).

Table 38: Summary of the impact of the interaction between natural resources and one-year aggregate conflict on Greenfield FDI in the mining sector across Oil producers.

	Conflict > 25	Conflict > 100	Conflict > 200
World			
One -year Interval	-0.659***	-0.671**	-0.163
One -year Interval X Natural Resources Rent	0.0186**	0.0102	-0.0121
Sub-Saharan			
one year Interval	-0.736***	-1.216**	-0.735***
One -year Interval X Natural Resources Rent	0.0159	0.0423**	0.0671***
South Asia			
one year Interval	0.202	0.0251	0.613
One -year Interval X Natural Resources Rent	0.204	0.222	0.261
MENA			
one year Interval	-0.696***	-0.493	0.538
One -year Interval X Natural Resources Rent	0.0268**	-0.000417	-0.0313
Oil Countries			
one year Interval	-0.792***	-0.543*	-0.212***
One -year Interval X Natural Resources Rent	0.0456***	0.00559	1.372**

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1,

Table 39:The estimation results of Fixed effect Spatial Durbin Model (SDM)

	(1)	(2)	(3)
VARIABLES	SDM FE	SDM FE	SDM FE
Conflict	5.135	56.95***	4.865
	(14.44)	(19.08)	(14.83)
Inflation	-1.424	-0.497	-1.383*
	(0.956)	(0.750)	(0.824)
Exchange rate	1.04e-08*	-7.70e-10	5.67e-09
	(5.44e-09)	(6.91e-09)	(6.77e-09)
Control of Corruption	9.490	24.78	9.631
	(19.55)	(20.64)	(20.07)
Natural Resources Rent	-1.110	0.158	-1.175
	(1.609)	(0.741)	(1.543)
Rho	-0.00752***	-0.0129***	-0.0175***
	(0.00264)	(0.00382)	(0.00261)
sigma2_e	220,594**	228,112**	219,511**
	(95,285)	(97,638)	(94,538)
W (Conflict)	36.69	-16.54	34.90
	(47.78)	(37.37)	(46.75)
W (Inflation)	6.675	4.521	6.971
	(6.233)	(4.805)	(6.678)
W (Exchange rate)	-7.81e-09	-3.10e-08	-2.47e-08
	(3.22e-08)	(2.79e-08)	(3.49e-08)
W (Control of Corruption)	-1.400	-6.692	-1.729
	(55.99)	(19.82)	(56.16)
W (Natural Resources Rent)	0.624	2.415***	0.0196
	(1.344)	(0.832)	(1.518)
Observations	11,564	11,564	11,564
R-squared	0.005	0.009	0.004
Number of Countries	196	196	196
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Year fixed effect	No	Yes	Yes
Country fixed effect	Yes	NO	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the independent variable Conflict is a binary variable that equals 1 if the number of fatalities in a year $t \geq 25$, besides, the quarter q had witnessed at least one fallen fatality.

Table 40:The estimation results of Fixed effect Spatial Autoregressive Model (SAR)

	(1)	(2)	(3)
VARIABLES	FE SAR	FE SAR	FE SAR
Conflict	2.649	61.36***	2.292
	(13.76)	(18.03)	(14.15)
Inflation	-0.314	0.187	-0.682*
	(0.361)	(0.284)	(0.352)
Exchange rate	9.94e-09**	-4.18e-09	2.20e-09
	(4.76e-09)	(6.10e-09)	(6.10e-09)
Control of Corruption	9.299	15.41	9.101
	(19.91)	(10.25)	(20.47)
Natural Resources Rent	0.451	1.645**	-0.260
	(0.757)	(0.694)	(0.731)
rho	-0.00926***	-0.00962***	-0.0183***
	(0.00330)	(0.00358)	(0.00290)
sigma2_e	221,657**	228,921**	220,300**
	(97,052)	(98,940)	(96,085)
Observations	11,564	11,564	11,564
R-squared	0.001	0.003	0.000
Number of Countries	196	196	196
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Year fixed effect	No	Yes	Yes
Country fixed effect	Yes	No	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the independent variable Conflict is a binary variable that equals 1 if the number of fatalities in a year $t \geq 25$, besides, the quarter q had witnessed at least one fallen fatality.

Table 41:The estimation results of Fixed effect Spatial Error Model (SEM)

VARIABLES	(1) FE SEM	(2) FE SEM	(3) FE SEM
Conflict	2.772	60.97***	2.469
	(13.77)	(18.01)	(14.15)
Inflation	-0.293	0.211	-0.635*
	(0.373)	(0.290)	(0.352)
Exchange rate	9.93e-09**	-4.27e-09	2.09e-09
	(4.76e-09)	(6.17e-09)	(6.22e-09)
Control of Corruption	9.272	15.32	9.045
	(19.95)	(10.14)	(20.56)
Natural Resources Rent	0.457	1.651**	-0.252
	(0.756)	(0.693)	(0.725)
lambda	-0.00898***	-0.0167***	-0.0198***
	(0.00346)	(0.00519)	(0.00448)
sigma2_e	221,658**	229,063**	220,301**
	(97,053)	(99,062)	(96,084)
Observations	11,564	11,564	11,564
R-squared	0.001	0.003	0.000
Number of Countries	196	196	196
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Year fixed effect	No	Yes	Yes
Country fixed effect	Yes	No	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the independent variable Conflict is a binary variable that equals 1 if the number of fatalities in a year $t \geq 25$, besides, the quarter q had witnessed at least one fallen fatality.

Table 42:The estimation results of Direct, Indirect, Total, and short- and long-term Spatial Durbin Model (SDM)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Main	W(X)	SR_Direct	SR_Indirect	SR_Total	LR_Direct	LR_Indirect	LR_Total
L. Greenfield FDI	-0.00464							
	(0.00938)							
L.W (Greenfield FDI)	0.0176							
	(0.0185)							
Conflict	5.281	38.73	7.594	28.71	36.30	7.697	29.04	36.74
	(23.10)	(34.36)	(22.08)	(25.43)	(33.27)	(21.97)	(25.63)	(33.64)
Inflation	-1.493**	6.837***	-1.511***	5.310***	3.799***	-1.479***	5.333***	3.854***
	(0.590)	(0.988)	(0.572)	(0.740)	(0.835)	(0.569)	(0.744)	(0.845)
Exchange rate	1.07e-08	-8.18e-09	1.06e-08	-3.82e-09	6.77e-09	1.05e-08	-3.71e-09	6.82e-09
	(3.42e-08)	(8.17e-08)	(3.29e-08)	(6.23e-08)	(6.95e-08)	(3.27e-08)	(6.28e-08)	(7.03e-08)
Control of Corruption	9.311	0.356	10.58	-0.855	9.727	10.53	-0.719	9.811
	(22.05)	(49.08)	(21.86)	(36.69)	(41.43)	(21.75)	(36.97)	(41.92)
Natural Resources Rent	-1.167	0.516	-1.162	0.434	-0.728	-1.155	0.422	-0.733
	(1.140)	(1.709)	(1.191)	(1.341)	(1.430)	(1.183)	(1.346)	(1.446)
Rho	0.00731							
	(0.0137)							
sigma2_e	227,974***							
	(2,973)							

Observations	11,368	11,368	11,368	11,368	11,368	11,368	11,368	11,368
R-squared	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
Number of Countries	196	196	196	196	196	196	196	196
Robust	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the independent variable Conflict is a binary variable that equals 1 if the number of fatalities in a year $t \geq 25$, besides, the quarter q had witnessed at least one fallen fatality.

Table 43:The estimation results of Direct, Indirect, Total, and short- and long-term Spatial Autoregressive Model (SAR)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Main	SR Direct	SR in Direct	SR Total	LR Direct	LR in Direct	Total
L. Greenfield FDI	0.000168						
	(0.00895)						
L.W (Greenfield FDI)	0.0132						
	(0.0139)						
Conflict	2.921	4.374	-0.0301	4.344	4.374	0.0143	4.389
	(14.03)	(13.41)	(0.101)	(13.32)	(13.41)	(0.0542)	(13.45)
Inflation	-0.344	-0.355	0.00198	-0.353	-0.355	-0.00162	-0.356
	(0.389)	(0.383)	(0.00254)	(0.381)	(0.383)	(0.00216)	(0.385)
Exchange rate	1.01e-08**	9.90e-09**	-7.04e-11*	9.83e-09**	9.91e-09**	0	9.94e-09**
	(4.67e-09)	(4.33e-09)	(0)	(4.30e-09)	(4.33e-09)	(0)	(4.34e-09)
Control of Corruption	9.129	10.21	-0.0680	10.15	10.21	0.0357	10.25
	(20.93)	(20.96)	(0.154)	(20.82)	(20.96)	(0.0920)	(21.03)
Natural Resources Rent	0.404	0.399	-0.00288	0.396	0.399	0.00117	0.400
	(0.792)	(0.825)	(0.00625)	(0.819)	(0.825)	(0.00332)	(0.828)
Rho	-						
	(0.00333)						
sigma2_e	229,137**						
	(98,646)						

Observations	11,368	11,368	11,368	11,368	11,368	11,368	11,368
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Number of Countries	196	196	196	196	196	196	196
Robust	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, the dependent variable is Greenfield FDI in all models, the independent variable Conflict is a binary variable that equals 1 if the number of fatalities in a year $t \geq 25$, besides, the quarter q had witnessed at least one fallen fatality.

Table 44:Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
(1) Number of fatalities quarterly	11564	46.477	295.34	0	7407
(2) FDI inflow quarter	11564	136.059	727.581	0	36800
(3) Inflation	11564	6.042	9.374	-27.632	174.858
(4) Exchange Rate	11564	1446449.5	1.336e+08	-3.995e+08	6.723e+09
(5) Control of Corruption	11564	-.022	.996	-2.222	2.586
(6) Natural Resources Rent	11564	7.34	11.544	-17.032	81.95

Table 45: Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Number of fatalities quarterly	1.000					
(2) FDI inflow quarter	0.011	1.000				
(3) Inflation	0.023	0.037	1.000			
(4) Exchange Rate	0.001	0.001	-0.007	1.000		
(5) Control of Corruption	-0.171	-0.010	-0.273	-0.028	1.000	
(6) Natural Resources Rent	0.068	0.068	0.249	0.020	-0.376	1.000

5 Conclusion

This thesis implemented three empirical studies to investigate the relationships between contemporary topics, including conflict, the shadow economy and greenfield FDI. The study was designed to test the dynamic and causal impacts of conflict on the shadow economy, and besides this, to investigate whether a dynamic and spatial impact exists for conflict on greenfield FDI in the mining sector.

The main aims for the second chapter were three-fold: firstly, to examine the causal effect of exogenous conflict on the shadow economy and test its dynamism; secondly, to assess whether this impact, if it exists, differs according to the countries' level of income; and finally, to investigate the impact of conflict intensity on the informal sector, the study used the event study approach (Karafiath, 1998). The results show that conflict has a dynamic impact on the shadow economy that remains statistically significant over three periods, starting from the contemporaneous year, and encompassing the following two years. Also, the study found that lower intensity conflict events increase the size of the shadow economy by less than one percent for each following year, whereas high-scale conflict events increase the impact by 1.3 percent for the contemporary year and 1.2% for the next year only. Investigations conclude that there is a statistically significant difference between high and non-high-income countries on the impact of conflict on the shadow economy, the impact becomes insignificant in high-income countries, unlike other. Moreover, the suggested technique failed to show any dynamic impact once the model controlled for corruption. Both strands of literature and further applied simple investigations assume that there is a possibility of multicollinearity when considering conflict and corruption in the same model. This study has extended the analysis by moderating the model by the level of income of each country, and the results reveal that the interaction between conflict and GDP per capita can better interpret the relationship between conflict and the shadow economy. Thus, more economic growth is required to decrease the size of the shadow economy when conflict exists. Additionally, more intensified conflict events steepen the marginal impact of conflict on the shadow economy.

The third chapter mainly aimed to support the results obtained in Chapter 2 by studying a special case of prolonged conflict, and tested whether the findings in the previous chapter applied for this case. Here, the study employed the Difference in Difference approach to assess whether the Intifada, as an event of conflict, had an impact on the shadow economy in Palestine during the period 1996-2015. Moreover, the size of the shadow economy in Palestine was estimated using the MIMIC approach. The study found that the size of the shadow economy in Palestine was between one hundredth share of GDP in the benchmark year and 38% in 2017. Moreover, the study concluded that the Intifada had exerted a positive impact on the shadow economy in Palestine, and that the outbreak of conflict had increased the size of the shadow economy by 10.8%. Nevertheless, Intifada has no impact on the shadow economy in Israel, and this result is consistent with Chapter One’s findings, which emphasise that the shadow economy in highly developed countries was not affected by the outbreak of conflict event. Moreover, the size of the shadow economy in Jordan was not affected by Intifada, which makes the investigations more reliable.

Finally, the purpose of the third empirical study was to investigate the impact of conflict on greenfield FDI, and to test whether the magnitude and direction of impact differ among diverse areas around the world. This study focused on testing two impacts: first, dynamic impact, or the impact of conflict on FDI on the contemporary and following periods; and second, the paper investigated the spillover impact in three directions, which were the expected spillover impact of the outcome variable in one country on its neighbours’ outcome, the spillover impact of conflict, and the spillover impact of any unobserved variables. The results showed inconsistency across different groups of countries for dynamic impact. For example, this impact exists for the full sample in particular when the conflict is defined to be an event if the total number of fatalities during the year is greater than 25 cases. Conversely, in oil-producing countries, dynamic impact exists for high-intense conflict only, while in Sub-Saharan and South Asian countries, the dynamic impact only exists for two periods when regression excludes the low-intense conflict cases. However, in MENA countries dynamic impact was not found to exist at all. Additionally, the study concluded a significant but negative spillover impact for greenfield FDI in the mining sector. However, this impact does not exist when the model includes the lag dependent variable as an additional explanatory variable, and moreover, the conflict has no spillover impact on FDI in neighbourhood countries.

5.1 Policy implications

It is important for policymakers to realise the size and growth of the shadow economy and the structure of its labour force. Besides this, they should investigate the real reasons behind the engagement of individuals in shadow economy activities. Otherwise, policies designed based on the official statistics without considering the shadow economy and its consequences will be ineffective.

Further, the findings encourage researchers and policymakers to consider conflict as one of the determinants of the shadow economy when they conduct research and policy programmes for less developed countries.

International donors and policymakers would be advised to pay attention to the need to support economic institutions in order to increase the level of income in the least developed countries. This strategy will directly reduce the impact of conflict on the shadow economy.

Conflict resolution should be practised not only based on international and national pressure levels, but among regional efforts as well, countries' FDI may be affected negatively by a neighbour's conflict, and therefore, these countries should play a significant role in solving or reducing the scale of conflict in the surrounding area.

5.2 Research limitations

Considering the limitations of the research is as important as underlining the significance of the study, and it is recognised that the restrictions encountered in research can limit the contributions of any study. This section, therefore, summarizes the crucial limitations of the study. This allows the research results and implications to be explained within the context of these research limitations.

The analysis of the dynamic impact of conflict on the shadow economy size which was conducted in the first empirical chapter was bounded within the period 1991-2015, due to the availability of data for the shadow economy.

Moreover, in the second empirical chapter, estimation of the shadow economy's size in Palestine depended mainly on an assumed benchmark value at the year 1996, as the MIMIC approach relies on this step. However, none of the available local studies is sufficiently reliable to use.

Furthermore, the third empirical chapter investigated the impact of conflict on the greenfield FDI, yet the study could have included more sectors, and it would be useful to make comparisons among different sectors. Nevertheless, the only data available for this research was on the mining sector.

5.3 Future Research

Future studies in the area of the informal economy are recommended, to focus on in-depth investigations of how the interaction between conflict and other shadow economy determinants can disrupt, in particular, the quality of government and the rule of law. The same recommendation can be applied to the case of the Israeli-Palestinian conflict, and future research could focus on the mechanisms through which this conflict may affect the shadow economy when conflict interacts with other economic and financial variables, such as financial inclusion. Last but not least, other studies should focus on the environmental impacts of conflict, the shadow economy, and FDI in the mining sector.

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