OPERATIONS MANAGEMENT IN TIMES OF WAR

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With dozens of armed conflicts and billions of dollars in losses, war is a concern of the utmost importance for operations management. My dissertation has three chapters and studies the effect of war on the operational performance of humanitarian and commercial organizations. In the first chapter, I study how war influences the operational performance of humanitarian organizations by estimating how war affects rural public hospitals' total factor productivity, efficiency, and efficiency variability. Using panel data from 163 Colombian hospitals, I find that war has a positive effect on hospitals' total factor productivity, while it has a negative impact on hospital efficiency. Further, efficiency and total factor productivity increase in post-conflict times. In the second chapter, I investigate the effect of war on firms' inventory by gleaning data from 1,122 municipalities, 1,258 attacks, and 38,916 firms in Colombia. To obtain causal estimates, I study the 2012 peace process between the Colombian government and one of the two Colombian guerrilla groups. I find that firms hold less inventory in times of war: Firms decrease their inventory-to-assets ratio up to 3.65 percent points. Firms' proximity to battle zones intensifies this effect, whereas distance to trade centers moderates this effect. In the third chapter, I study the causal effect of social investments (in conflict zones) on firms' operational performance. I explore the impact of a law that obliged some firms in the Colombian oil industry to invest 1% of their budget in social investments. I find these investments lead, from every dollar in sales, to an increase of 23 cents in the firms' operating margin. Also, I study five firms in the Colombian oil industry and find their social investments decrease the frequency of war-related disruptions, which increases revenue and reduces costs.

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Introduction

With dozens of armed conflicts, thousands killed, and millions displaced every year, the threat of war is a concern of the utmost importance for operations management. Ensuring an adequate healthcare response to this humanitarian crisis is vital. However, episodes such as the bombing of the Doctors Without Borders hospital in Afghanistan—in 2015, which killed 30, shows that response organizations are on the frontlines of battle. Understanding how war affects the productivity and efficiency of healthcare organizations in war zones is essential to ensure an adequate humanitarian response. To that end, I study the following research question:

1. *How do armed conflicts affect the productivity and efficiency of healthcare response organizations?*

War is not only tragic; is expensive and increases supply uncertainty of commodities (produced in war countries) such as oil and agricultural goods. The cost of violence has been estimated at $13.3 trillion (18% the global production) (IEP, 2016). Although inventory is a buffer against supply uncertainty, firms' inventory decisions in war countries are difficult to predict. Firms can mitigate war-related disruptions by holding inventory. However, holding inventory is costly, and inventory can get damaged during war attacks. Thus, I investigate this question:

2. *How do armed conflicts affect firms' inventory?*

Finally, firms in war zones can provide aid to local communities via social investments. Although it is well understood social investments improve the well-being of communities, little is known on how these investments affect firms' operations. To investigate this, I formulate this question:

3. *How do social investments in conflict zones affect the firms' operational performance?*

Using unique qualitative and quantitative data, I explore the impact of war on the operational performance of commercial and humanitarian organizations. My dissertation spans two streams of literature in operations management: humanitarian operations and operations in emerging markets. In the first stream, authors have assessed the impact of conflict on humanitarian vehicle performance (Pedraza-Martinez & Van Wassenhove, 2013; Eftekhar & Van Wassenhove, 2016). In the second stream, authors have studied emerging-market operations without examining the effect of war on firms' operational performance (Han et al., 2013; Jain et al., 2013; Marquis & Raynard, 2015; Steven & Britto, 2016; Shou et al., 2016). To the best of my knowledge, no research has addressed the impact of war on the operational performance of humanitarian and commercial organizations or investigated how social investments in war zones affect firms' operational performance.

In the first chapter "Effect of Armed Conflicts on Humanitarian Operations: Total Factor Productivity and Efficiency of Rural Hospitals," I address the first research question. I study how war affects the operational performance of humanitarian organizations by examining the impact of war on their productivity and efficiency. Typically, war affects people in rural areas (developing countries) where care infrastructure is limited but critical to local communities. As a result, hospitals serving rural areas are one of the first layers of humanitarian response to conflicts. However, war puts their response at risk via abrupt demand changes, capital or labor destruction, unrest, and supply chain disruptions.

To obtain evidence of the impact of war's impact on hospital productivity and efficiency, I study rural hospitals in Colombia. To measure productivity, I examine total factor productivity, which explains hospital managerial ability and input quality. To measure efficiency, I calculate hospitals ratio between outputs (inpatients) and inputs (e.g., beds, wages, etc.) to populate a Data Envelopment Analysis with variable returns to scale. To study productivity and efficiency, I use panel data from 2007 to 2011 with 163 rural public hospitals in Colombia. I combine this information with conflict data at the municipality level. Finally, I span the operational performance estimations over severe, medium, low, and post-conflict regions.

In the second chapter 'Inventory in Times of War," I address the second research question. In this chapter, I estimate the effect of war on firms' inventory. This effect is not clear ex-ante due to opposing effects taking place amidst war: higher holding and higher ordering costs.

I estimate the ultimate effect of war on firms' inventory using a dataset from 38,916 firms, 1,122 municipalities, and 1,258 attacks in Colombia. To obtain causal estimates, I study a peace process between the Colombian government and one of the two guerrillas groups in the country. I study firms' inventory before and after the peace-process announcement in municipalities where one of the two guerrillas groups dominates. Then, I implement a Difference-in-Differences model to estimate the Average Treatment Effect on the Treated.

In the third chapter: "Communities in the Crossfire: How Companies Can Do Well by Doing Good," I address the third research question by using a natural experiment and dataset from the Colombian oil industry. The oil industry in Colombia comprises two types of firm: exploration and production firms, and oil service firms. In 2003, the Colombian government obliged all oil exploration and production firms to invest 1% of their budgets in social investments. While firms in the exploration and production sector were subject to the requirement, firms in the oil service sector were not. I study this regulation by collecting a panel with all 252 firms in the Colombian oil industry: 114 firms from the oil exploration and production sector and 138 from the oil service sector.

I implement a Difference-in-Difference model to obtain causal estimates of the effect of social investments on firm performance. Also, to understand the effect of social investments on firm performance, I collected qualitative data from the Colombian oil industry. I conducted two field visits and thirteen interviews.

My doctoral dissertation opens a new stream of research in operations management by studying the effect of war on commercial and non-profit operations. My contribution is threefold. First, I show that war affects both productivity and efficiency of first-layer response organizations. I find that conflict has a positive effect on productivity, while it has an adverse impact on efficiency. Interestingly, efficiency and productivity both increase in post-conflict times. Second, I provide evidence that firms hold less inventory in times of war. Firms decrease their inventory-to-assets ratio up to 3.65 percent points. This implies war exposes firms to higher risks of shortages and delays and that firms should adjust their safety stocks or implement alternative mitigation strategies to cope with lower product availability. Also, firms' proximity to battle zones intensifies this effect, whereas distance to trade centers moderates it. Third, I provide evidence that social investments increase firms' operating margin. As a response of investing 1% of their budgets in social investments, firms observe, from every dollar in sales, an increase of 23 cents in their operating margin. I find the larger the firm, the higher the yield from social investments. Finally, I find that social investments affect processes of workforce, sourcing, and logistics management. These processes improve firms' operating margins via fewer war-related disruptions, which increases revenue and decreases costs

Chapter 1

Effect of Armed Conflicts on Humanitarian Operations: Total Factor Productivity and Efficiency of Rural Hospitals

1.1 Introduction

In this paper we study an important but widely neglected topic in humanitarian operations: armed conflicts. As stated by Uppsala Universitet, 24 developing countries experienced active armed conflicts in 2013. Each of these armed conflicts (henceforth referred to as conflicts) caused at least 25 deaths and affected millions of people worldwide (Uppsala-Universitet, 2014). Common characteristics of the 24 developing countries suffering conflicts in 2013 were a gross national income per capita below US$11,905 as determined by the World Bank as well as their economic dependence on mining, hydrocarbons, or agricultural activities. Such economic activities took place in rural areas and the conflicts these countries faced were also mostly rural. This is why hospitals that serve rural areas, henceforth referred to as either rural hospitals or simply hospitals, are one of the first layers of humanitarian response to conflicts. As a result of conflicts, rural hospitals face a series of challenges that may include abrupt demand changes, capital or labor destruction, unrest, violence and fear experienced by medical personnel, transportation problems and disruptions in the supply of medical items.

We analyze empirically the effect of armed conflicts on the operational performance of rural hospitals, and use total factor productivity and efficiency as measures of hospital performance. We investigate three research questions: (i) What is the effect of conflicts on hospital total factor productivity? (ii) What is the effect of conflicts on hospital efficiency? and (iii) What is the effect of conflicts on hospital efficiency variability? First, we examine total factor productivity (TFP), which incorporates unobservable aspects such as managerial ability and input quality that are not explained by the mix of capital and labor. According to Solow (1957), TFP includes slowdowns, speedups and improvements in training of the labor force. While limited literature has found both positive and negative effect of conflicts on TFP, we ultimately propose that conflicts have a positive effect on TFP. Second, we look at efficiency, which is modeled as the ratio between outputs (inpatients) and inputs used for healthcare provision at the hospital level. We conjecture that conflicts have a negative effect on efficiency. Finally, we propose that efficiency variability is lower in hospitals that are located in conflict regions compared to hospitals located in peaceful regions.

To examine our research questions, we use a panel data set with information on 163 rural public hospitals in Colombia during the period 2007-2011. The data set contains information at the hospital level and is combined with cross-sectional data on conflict at the municipality level. We also include socio-economic control variables at the municipality level obtained from different government organizations in Colombia. In addition, we complete the data with field visits to rural hospitals and six semi-structured interviews with staff from the Ministry of Health and rural hospitals in different conflict zones in Colombia. It is important to remark that gathering this unique data set was difficult. Even though hospital information is public, there were many challenges and barriers for collecting both quantitative and qualitative data, which are explained in Section 5.

Based on the data, we obtain TFP as the residual of a Cobb-Douglas production function using a fixed effect model for years 2007-2011 and estimate the relative efficiency of hospitals using data envelopment analysis. We find that conflict has a positive effect on TFP while it has a negative effect on efficiency. The results also show that efficiency variability is higher in peace and post-conflict hospitals and lower in medium and severe-conflict hospitals. In addition, we find that both TFP and efficiency increase in post conflict. These results lead to operations management implications and opportunities for future research related to sourcing decisions, supply chain and workforce flexibility, behavioral impacts on the workforce, and humanitarian response to conflicts.

1.2 Brief typology of disasters

This section presents a brief typology of disasters with the aim of positioning our research in the humanitarian operations management literature. To begin with, the disaster cycle is composed of preparedness, response, rehabilitation and mitigation (Tomasini & Van Wassenhove, 2009). Preparedness focuses on reducing the expected impact of a disaster. Response addresses the urgent needs of the affected population. Rehabilitation aims at attaining or increasing the quality of life of the affected community relative to what it was before the disaster. Mitigation considers how to avoid and reduce the risk of future disasters. Our research studies the response stage.

Disasters range from natural to man-made (Van Wassenhove, 2006). According to the International Federation of Red Cross and Red Crescent Societies (IFRC, 2014), natural disasters can be biological (outbreaks of epidemic diseases, animal plagues and infestation), climatological (heat/cold waves, wildfire), meteorological (hurricanes, typhoons), hydrological (flood, wet mass movement), or geophysical (earthquakes, tsunami). The location and intensity of natural disasters is uncertain and its response is urgent but its timeline is relatively short compared to the entire disaster cycle. The operations management literature has focused on the study of preparedness and response to natural disasters (Starr & Van Wassenhove, 2014; Altay & Green III, 2006). Some examples of recent research on natural disasters include the Ekici et al. (2013) study of food distribution planning and influenza pandemic and the Pedraza-Martinez et al. (2011) research on field vehicle fleet management for disaster response.

Man-made disasters include armed conflicts, industrial accidents and transport accidents (IFRC, 2014). The term conflict can be defined as "*a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths in one calendar year*" (Themnér & Wallensteen, 2013). Conflict's duration may extend for years and their intensity may change over time between different regions in the same affected country. In the operations management community man-made disasters have been studied much less than natural disasters. Pedraza-Martinez & Van Wassenhove (2013) are the first to empirically investigate the impact of conflicts on operations management. They study vehicle replacement at the International Committee of the Red Cross and build a conflict index to test whether conflict impacts replacement decisions. They did not find a significant relationship between conflict and vehicles' salvage value and highlight the need for more research on the impact of conflicts on operations management. Eftekhar & Van Wassenhove (2016) elaborate on the impact of conflicts on last mile fleet management in humanitarian operations. We contribute to the nascent research on man-made disasters in operations management by investigating the impact of armed conflicts on service-oriented organizations such as rural hospitals.

In this paper we study the impact of conflict across four stages (peace, medium conflict, severe conflict, and post conflict). The use of these four stages comes from the fact that conflict dynamics are mainly characterized by processes of escalation and de-escalation of the conflict intensity (Dudouet, 2013). Conflict escalation is described by the increase in the intensity and frequency of violent actions (Mitchell, 2011). Typically a de-escalation process described as going from armed to unarmed resistance follows the escalation stage. The subsequent demilitarization or post-conflict stage can be achieved through mechanisms such as decapitation of the structure (capture/killing leader), success/failure (any party succeeds/fails in the objective), repression (use of force), negotiation or reorientation to other ways of resistance (Cronin, 2009). Although data limitations do not allow us to directly investigate the transition of each hospital from one stage to the other, we study hospital performance under each conflict stage and compare it to hospital performance in other conflict stages. Armed conflicts can range from short-rapidly changing ones that last one year or less (as in Rwanda in 2009) to steady-state slow-changing ones (as in Colombia, Myanmar, Thailand) that continue active for decades (Kreutz, 2010). While in the first transitions between stages such as peace, medium conflict and severe conflict occur rapidly, in the second transitions between stages occur slowly. In both cases rural hospitals are key response organizations that face complex situations. In case of long-term conflicts response and rehabilitation stages may occur during conflicts (Crost et al., 2014). Therefore, aid providers face challenges to keep safe both their staff and civilians (UN-Assembly, 2015). We study steady-state slow-changing conflict.

Complex disasters include shocks like natural disasters in conflict-prone areas that increase humanitarian logistics challenges (Starr & Van Wassenhove, 2014). For instance, last mile distribution of aid in conflict areas in the aftermath of disasters may be disrupted due to security reasons. Moreover, conflicts may create demand mobility in the form of internally displaced people, which increases demand uncertainty. Complex disasters also include escalating disasters such as the tsunami and nuclear disaster in Fukushima, Japan in 2010, and the cholera outbreak in Haiti following the 2010 earthquake. We include complex disasters in this brief typology for completeness. Although the area of complex disasters remains mostly unexplored, it is not the focus of our research.

Finally, disasters can also be classified according to their magnitude and required level of response. Small to medium disasters can be handled by means of local or national response that often involves the local government, local NGOs, as well as the National Society of The Red Cross and other volunteer organizations. On the other hand, megadisasters (Simchi-Levi, 2011) or catastrophes cannot be handled locally. Instead, these require national or international participation that involves international organizations such as IFRC and the United Nations

Office for the Coordination of Humanitarian Affairs. Our paper contributes to the humanitarian operations literature on local response to armed conflicts.

1.3 Hypotheses on conflict

We propose three hypotheses on how armed conflicts trigger a series of direct and indirect effects that impact hospitals' total factor productivity and efficiency.

1.3.1 Conflicts and total factor productivity (TFP)

We are interested in capturing the managerial aspects of hospitals' operations and in analyzing how these are affected by conflicts. As opposed to labor or capital productivity, our approximation is commonly known as total factor productivity (TFP). TFP is exogenous to the hospitals' inputs composition, so that it explains output differences not attributable to labor, capital or material expenses. Instead, TFP incorporates unobservable aspects of hospitals' operations, such as managerial ability and inputs quality (Grieco & McDevitt, 2012). Solow (1957) presented the theoretical foundations of TFP, which he describes as a pure scale effect that is exogenous to the inputs' marginal rates of substitution that are incorporated in the production function. Although TFP is widely used in economics, it is not as common as other measures of productivity such as throughput rates in operations management. However, in the case of conflict hospitals' TFP has an important role describing unobservable aspects of their service process. Some of these aspects may include the organization's behavior and knowledge, managerial ability and the intrinsic capacity to respond to the operational challenges raised by conflicts.

It is reasonable to expect that conflicts may have a negative effect on TFP. Capital is affected by attacks on medical facilities including shooting, bombing or deprivations of basic utilities like water or electricity. Capital also suffers via attacks on ambulances or on transport of medical equipment or supplies (González & Lopez, 2007). Capital availability may be affected by improper use of facilities or emblems which include using facilities for military purposes (Rubenstein & Bittle, 2010). Human resources such as medical staff may also suffer attacks that include arrests, detentions, kidnapping, intimidations or killing (Collier, 1999). Moreover, fighters may use patients or medical staff as human shields, or may attack wounded or sick individuals by interfering, obstructing or interrupting the medical care to patients (Rubenstein & Bittle, 2010). As illustrated above, human resources may experience directly the impact of conflict. Thus, we could expect that the hospitals' capacity to increase their knowledge, specialization and managerial ability would decrease as a result of the negative impact of conflict on the availability of supplies and labor.

Interestingly, it is also reasonable to expect that conflicts may have a positive effect on TFP. Different authors have illustrated advances in medical and managerial practices as a response to healthcare challenges during war. For example, it has been suggested that advances in medical department administration, staff management, emergency care practices, disease prevention, trauma and surgical techniques have improved as a consequence of innovations made during conflicts (Manring et al., 2009). Some of these advances in practice might be attributable to the stress that emergency care conditions pose to medical doctors. In particular, the response to patients' life-threatening situations triggers stress and certain physiologic reactivity on medical staff (Sluiter et al., 2003). Reactions to stress may lead to split up of the staff into two groups: stress impaired and non-stress impaired physicians. If stress adaptation is successful (in the case of non-impaired physicians), adaptations to unalterable stress of medicine may be productive and actually improve the quality of medical care (McCue, 1982). Adaptations include speed-up, rush or even multi-tasking for a period of time as a consequence of a peak in the demand (Batt & Terwiesch, 2012; Chan et al., 2014; KC & Terwiesch, 2009). We argue that in the case of steady-state slow-changing conflicts that we study, the medical staff will develop practices to mitigate the negative effect of conflicts on capital and labor, which will result in a net positive effect of conflicts on TFP.

Furthermore, conflicts may impact hospitals' knowledge via workforce training and shifts in the learning curve (Adler & Clark, 1991). As conflicts may have short and medium term effects on the prevalence of some diseases and consequently on the demand for specific healthcare services, we expect that hospitals in these areas will gain specialization and knowledge by treating these diseases more frequently. In Colombia, tropical diseases such as Leishmaniasis are a good example of the aforementioned effect (Vélez & Zuleta, 2014). Thus, we formulate the following hypothesis.

HYPOTHESIS 1 *Conflicts have a positive effect on hospital total factor productivity.*

1.3.2 Conflicts and efficiency

We are interested in comparing the operational performance of hospitals in peace, medium conflict, severe conflict, and post conflict. We use overall operational efficiency—simply efficiency henceforth—expressed as an output/input ratio to determine the relative performance of hospitals.

The concept of efficiency, as defined above, was popularized by Farrell (1957) and can be expressed in terms of technical and allocative efficiency. Efficiency implies the best possible allocation of resources given a set of market prices (allocative efficiency), where the resources are transformed using the best technique/technology available (technical efficiency). We implement data envelopment analysis (DEA) to estimate efficiency. This method is explained in detail in Section 4.

Technical efficiency can be described as the state in which the best production technology available is used. In terms of healthcare it implies the use of the best practices and resources to meet demand, which are elements present in TFP as described above. Any production structure below the efficient frontier, i.e. with less TFP, is suboptimal because it requires more inputs to produce a given amount of output (Farrell, 1957). Therefore, TFP and efficiency are expected to have a positive relationship.

Man-made disasters such as conflicts increase risk in the supply chain (Simchi-Levi, 2011). Risk mitigation strategies include capacity redundancy, prepositioned inventory (Duran et al., 2011; Rawls & Turnquist, 2010), and speed of sensing and responding (Simchi-Levi, 2011). However, risk mitigation strategies are costly because they involve extra capacity, inventory buffers, and expedited transportation (Stauffer et al., 2016). Additionally, market prices may increase during conflicts as a consequence of illegal groups imposing "taxes" (fixed amount of money charged per unit of output), extortion and kidnapping (Suárez, 2000). We illustrate in Section 6 that not only is access to market affected in conflict regions, but oftentimes the healthcare service costs are increased due to attacks on ambulances and medical staff, and as a consequence of robbery and improper use of medical supplies. As a result, the set of inputs used in the service process of hospitals in conflict areas might not be optimal when compared to non-conflict regions with normal market prices and standard input availabilities. It is expected that, everything else constant, hospitals in areas without conflict can provide the same output at lower costs compared to hospitals in conflict areas. Thus, we propose the following hypothesis.

HYPOTHESIS 2 *Conflicts have a negative effect on hospital efficiency.*

1.3.3 Conflicts and efficiency variability

We study the impact of conflicts on hospital efficiency variability at each conflict stage. To undertake this goal, we build upon the fact that conflicts cause disruptions to the hospitals' supply chain. We expect each conflict stage to have a different risk of disruption and demand characteristics, which lead to differences in demand variability. In addition, we build upon the idea that conflict will lead to more standardized delivery of healthcare.

It is reasonable to expect that conflict will increase efficiency variability of rural hospitals. As a consequence of a violent episode severe-conflict hospitals might not receive medical supplies or human resources on time. During disruptions hospitals may not have the ability to perform operations properly. However, once the disruption ends, hospitals would eventually recover their previous level of efficiency. These efficiency changes would increase the overall efficiency variability. Moreover, more complex supply chains are related to states of higher frequency of disruption events (Bode & Wagner, 2015). If no disruption mitigation strategies are carried out at the hospital level, we should expect rural hospitals' operation to be volatile due to the high complexity of the medical supply chain, especially in conflict areas where access to suppliers is more difficult. Therefore, conflict hospitals may experience an increase in efficiency variability via the direct impact caused by supply chain disruptions.

On the other hand, it can be argued that conflict will decrease the efficiency variability of rural hospitals. Managerial ability is a mechanism available to detect and prevent disruptive events, which can be used to cope with a higher frequency of disruptions (Bode et al., 2011). The literature on supply disruptions (Chopra & Sodhi, 2004; Tomlin, 2006), single versus multiple sourcing (Burke et al., 2007; Yu et al., 2009), and supply chain flexibility (Tang & Tomlin, 2008) discusses several strategies for reducing supply chain risk of the type faced by rural hospitals during armed conflict. Thus, if hospitals, especially those experiencing disruptions in severe-conflict regions, implement disruption mitigation strategies we should expect efficiency variability to decrease. Moreover, organizations' workforce flexibility plays an important role in coping with events of disruption and peaks of demand in healthcare institutions (Campbell, 1999; Pinker & Shumsky, 2000). If hospitals have the ability to handle the uncertainty in medical supply availability and also be flexible enough to handle wide variations in the number and type of patients needing medical care we could expect efficiency variability to decrease.

Instead of allowing more variation in medical practices, medical personnel turn to more standardized healthcare delivery as a consequence of conflict. Blaisdell (1988) explains that the accumulation of reports and the standardization of processes during the US civil war led to a major systematization of hospitals' procedures. New standards and knowledge led to the publication of the "Medical and Surgical History of the War of the Rebellion". This work was recognized in Europe as the first major academic accomplishment by US medicine. In addition, Blaisdell (1988) suggests that logistics and management practices were standardized to handle mass casualty events that later were applied in World War I, World War II, and the Korean War.

As discussed above, there are arguments in favor and against the increase of efficiency variability in conflict hospitals. However, in steady-state slow-changing conflict, where healthcare delivery has become more standardized and supply chain disruptions have been taking place for a long period of time, we conjecture that hospitals would have eventually adapted by implementing mechanisms to cope with disruptions. Thus, we conjecture that the net effect of conflicts on efficiency variability is negative, i.e., conflicts decrease efficiency variability.

HYPOTHESIS 3 *Let EV represent Efficiency Variability.*
EV(peace) > EV(post conflict) > EV(medium conflict) > EV(severe conflict).

In summary, we propose that conflicts have a positive effect on TFP due to the better managerial and medical practices developed throughout the conflict stages. We conjecture that conflicts have a negative effect on efficiency due to the increase in costs that result from disruptions. Finally, we expect that efficiency variability decreases as conflict severity increases as a result of the implementation of strategies that aim to mitigate supply chain disruptions and as a result of more standardized healthcare delivery.

1.4 Empirical model

1.4.1 Conflicts and hospital performance

We build econometric models to test the impact conflicts have on TFP (Hypothesis 1) and efficiency (Hypothesis 2). See Appendix A.1 for additional details on the analysis of the models used in this section. We test the difference in efficiency variability (Hypothesis 3) using t-tests between conflict stages.

Model 1.1 tests Hypothesis 1. It uses $\text{TFP}_{i,j}$ as the dependent variable. The independent variables include conflict and social and economic controls (see Table 1.2 in Section 5.1).

$$\text{TFP}_{i,j} = \beta_0 + \beta_1 \text{Conflict}_j + \beta_x X_j + \epsilon_{i,j}, \tag{1.1}$$

where $\text{TFP}_{i,j}$ is the TFP for hospital i in municipality j, Conflict_j is a variable that categorizes the conflict in municipality j, X_j is the set of economic and social control variables that potentially impact TFP, and $\epsilon_{i,j}$ is the error term for hospital i in municipality j.

Model 1.2 tests Hypothesis 2. It uses efficiency as the dependent variable. A specific functional form for TFP is used (see Section 4.2.1) to capture nonlinear effects and the strong relationship between TFP and efficiency discussed in Section 3. The functional form of our model is further discussed in Appendix A.1. This model also includes the conflict variable as well as social and economic controls (see Table 1.2 in Section 5.1). We do not include variables controlling for the severity of patients or the type of services provided by the hospitals since, as we explain in Section 5.2, our sample includes mostly level 1 or low-complexity hospitals. Then, we formulate this model as:

$$\begin{aligned} \text{Efficiency}_{i,j} = \beta_0 + \beta_1 \text{Conflict}_j + \beta_2 \text{TFP}_{i,j} + \beta_3 \text{TFP}^2_{i,j} + \beta_4 \text{TFP}^3_{i,j} \\ + \beta_5 \text{TFP}_{i,j} \text{Conflict}_j + \beta_x X_j + \epsilon_{i,j}, \end{aligned} \tag{1.2}$$

where $\text{Efficiency}_{i,j}$ is the efficiency estimation for hospital i in municipality j, X_j is the set of economic and social control variables that potentially impact the efficiency scores, and $\epsilon_{i,j}$ is the error term for hospital i in municipality j.

Since the efficiency values are bounded between zero and one, ordinary least square (OLS) will yield biased estimates (Scheraga, 2004). Tobit regressions have been used to asses the determinants of hospital efficiency (Kirigia & Asbu, 2013; Sikka et al., 2009). Therefore, a Tobit regression is used to implement (1.2) as it provides unbiased and more efficient estimates (Färe et al., 2006).

1.4.2 Estimations of efficiency and total factor productivity

Total Factor Productivity

The empirical estimation of TFP is obtained through the so-called Solow Residual. Grieco & McDevitt (2012) have been one of the latest to apply this concept in the study of the relationship between productivity and quality in healthcare. We estimate TFP as a fixed term, TFP_i, for every hospital in the sample, which is obtained as the residual of a Cobb-Douglas production function (1.3). This production form using capital, labor and materials has shown empirical support in the literature (Berndt & Christensen, 1973; Van Beveren, 2012). This representation also allows us to assume Variable Returns to Scale (consistent with the DEA model), by keeping unrestricted the sum of β_i's in the following equation (Douglas, 1976),

$$Y_{i,t} = Ae^{\mathrm{TFP}_i} K_{i,t}^{\beta_k} L_{i,t}^{\beta_l} M_{i,t}^{\beta_m}, \tag{1.3}$$

where $Y_{i,t}$ is the output (inpatients) generated by hospital i in year t, TFP_i is the Hicks-neutral unobserved TFP term (i.e. an increase in this term does not imply a change in the inputs composition) of hospital i, $K_{i,t}$ is the number of inpatients beds in hospital i in year t, $L_{i,t}$ is the human resources used by hospital i in year t, and $M_{i,t}$ is the expenditure on supplies, indirect services and energy by hospital i in year t.

Applying the log function to Equation (1.3) results in the linear model in (1.4) that we use for the fixed-effect panel data estimation.

$$\ln Y_{i,t} = \beta_o + \mathrm{TFP}_i + \beta_k \ln K_{i,t} + \beta_l \ln L_{i,t} + \beta_m \ln M_{i,t} + \epsilon_{i,t} \tag{1.4}$$

Notice that using a fixed-effect panel data model allows us to control for time-invariant effects, which prevents further endogeneity biases in our estimation (Del Gatto et al., 2011).

Efficiency

We use data envelopment analysis (DEA) to estimate hospital efficiency. DEA is a non-parametric technique used to evaluate the technical efficiency of decision-making units, i.e., hospitals in our case. Research assessing efficiency in healthcare using data envelopment analysis has been growing rapidly in the last decade. For example, DEA has been frequently used to assess changes in the efficiency of hospitals as a consequence of healthcare reforms (Hu et al., 2012; Ng, 2011; Sahin et al., 2011; Pilyavsky & Staat, 2008). We run a DEA output-oriented model with Variable Returns to Scale (VRS). The output-oriented model is appropriate because public rural hospitals' inputs are determined ex-ante by the Ministry of Health. As a result, hospital managers do not have direct control of inputs, but have control on the service level to target. VRS means that an increase in input does not result in a proportional increase in output. Under VRS each hospital is evaluated in relation to others that operate at that same scale (Banker, 1984). VRS is a reasonable assumption because rural hospitals may have limited competition among each other due to geographic considerations. Thus, they might not operate at the most productive scale (Banker, 1984).

An appropriate selection of inputs and outputs is critical in the assessment of the hospitals' efficiency. Following the literature, we use the three most common measures of inputs (beds, human resources and general expenses) and one output (inpatients). Problems of discrimination between efficient and inefficient hospitals might occur when the number of input and output measures is large with respect to the number of observations. To avoid discrimination problems, Cooper et al. (2007) suggest a sample size of $n \geq \max(m * s, 3(m + s))$ where m is the number of input measures and s is the number of output measures. Based on this criterion our sample size (163 hospitals) is much larger than the recommended minimum sample size (12 hospitals). The following is the output-oriented VRS DEA model, which is solved during each period $t = 2007, 2008, 2009, 2010, 2011$, for each hospital i, $i = 1, 2, ..., 163$, as will be observed in Section 5.1. For notational simplicity, we have suppressed the subscript t in the following formulation, where Y_i is the output (inpatients) generated by hospital i, K_i is the number of inpatients beds in hospital i, L_i is the human resources used by hospital i, and M_i is the expenditure on supplies, indirect services and energy by hospital i.

$$\max_{\text{Efficiency}_i, \lambda_h} \ \text{Efficiency}_i \tag{1.5}$$

$$\text{subject to:} \quad \sum_{h=1}^{163} \lambda_h Y_h \geq \text{Efficiency}_i Y_i \tag{1.6}$$

$$\sum_{h=1}^{163} \lambda_h K_h \leq K_i, \quad \sum_{h=1}^{163} \lambda_h L_h \leq L_i, \quad \sum_{h=1}^{163} \lambda_h M_h \leq M_i \tag{1.7}$$

$$\sum_{h=1}^{163} \lambda_h = 1, \quad \lambda_h \geq 0 \quad \forall h, \tag{1.8}$$

The objective function (1.5) is used to obtain the relative technical efficiency of hospital i. Restriction (1.6) guarantees that the technical efficiency of hospital i is bounded by the efficient frontier of hospitals included in the dataset. The left hand side of restriction (1.6) is a convex combination of inpatients (Y_h) for the hospitals in the efficient frontier. λ_h is the weight of each hospital in the efficient frontier in period t. The values of λ_h are positive for efficient hospitals and zero for inefficient hospitals. If restriction (1.6) is active for hospital i in period t, that hospital is part of the efficient frontier for the corresponding period. The three restrictions (1.7) ensure that the weighted sum of each of the inputs of the hospitals in the efficient frontier (K_h, L_h, M_h) is a lower bound for the inputs required by hospital i in period t. In other words, these constraints ensure that hospital i cannot use less inputs than the efficient hospitals in period t. Restriction (1.8) is the VRS constraint and it is followed by the non-negativity constraint for the weights

λ_h. To calculate efficiency, this formulation solves 815 linear programs in total. The efficiency scores obtained with the formulation above are between 1 and infinity, where efficiency scores are equal to one for efficient hospitals and efficiency scores are greater than one for inefficient hospitals. To obtain values of $\text{Efficiency}_{i,j}$ between zero and one to be used in model (1.2) we compute the inverse of the efficiency scores obtained in (1.5). From this point onward, we use $\text{Efficiency}_{i,j}$ in our analysis, which implies that an efficient hospital has efficiency equal to one while an inefficient hospital has efficiency less than one.

1.5 Case study: Colombia

We use the Colombian conflict as the setting to test our hypotheses. In the first place, the Colombian conflict is for the most part a rural and heterogeneous conflict across regions (González & Lopez, 2007). The latter creates an ideal laboratory to test our hypotheses given the existence of regions with different levels of conflict (including peaceful regions) that facilitate statistical analysis. Secondly, attacks on hospital infrastructure and staff have been a common practice by illegal guerrilla and paramilitary groups in this conflict, which enable us to test the impact these violent actions have had on hospitals' efficiency and TFP.

Colombia has a presidential constitutional republic of 48 million inhabitants and, although it has the 28th highest total Gross Domestic Product (GDP) adjusted by Purchase Power Parity, it has one of the highest inequality levels in the world. In 2013 the Gini index was 53.5 (0 represents perfect income distribution equality while 100 stands for total inequality), representing the 20th highest Gini in the world (World-Bank, 2014). Colombia declared its independence from Spain in 1810. Although it was the first constitutional government in South America, and formerly comprised of current Venezuela, Ecuador, Panama, part of Brazil and Peru, internal divisions, civil wars and political unrest between federalist and centralist parties led to the progressive disintegration of the country (Bethell, 1994).

The roots of the modern conflict in Colombia come from the country's polarization between the, so-called, liberal and conservative parties in the mid-20th century. This period began in 1946 and is commonly referred as " La Violencia Bipartidista" period. The nation faced a temporal peace process followed by the creation of the "Frente Nacional", in which both parties agreed to a 16-year coalition government. Despite that, the continuous friction between liberals and conservatives led to the formation of well-established guerrilla groups supported in part by diverse communist factions including Soviet Bloc countries. As a result, guerrilla groups such as Revolutionary Armed Forces of Colombia (FARC), Army for the National Liberation (ELN), Army for Popular Liberation (EPL) and Movement April 19 (M-19) began armed confrontations against the official government. The intensity of the conflict reached its highest point between 1980 and 1990 where not only guerrilla group actions escalated in violence, but also the country experienced the surge of several drug cartels and the creation of paramilitary groups, formed by large landowners and drug lords that fought the guerrilla groups. During the 2001-2010 decade, Colombia had two active guerrilla groups: FARC and ELN. Both of them grew in power in the 1990s and 2000s due in part to profits derived from kidnappings, illegal civilian taxation, and illegal-drug trade taxation. The conflict has resulted in thousands of casualties that include civilians, military, paramilitary and guerrilla fighters, as well as millions of internally displaced people (Restrepo et al. (2006); Bethell (1994)).

Both guerrillas and paramilitary groups have included civilian targets in their actions. Hospital infrastructure, including facilities and staff have suffered either by direct attack on the infrastructure, military use of these facilities and/or resources, and even kidnapping and killing of medical staff. According to an official report released in 2004 by the Colombian Ministry of Health, in the period running from 1999 to 2003, there were at least 538 actions against health missions and hospital infrastructure in Colombia caused by illegal groups. These include killing or threats to medical staff, murder of patients, destruction of hospitals and attacks to medical missions. Oftentimes rural hospitals send resources and medical staff to remote regions in order to provide service to people without means of transportation. Guerrilla groups recurrently kidnap medical missions' staff, rob medical supplies and destroy ambulances or other means of transportation. For instance, in 2006 government authorities confirmed the kidnapping of 13 medical staff who were on a humanitarian mission in the Teteye region of the Puerto Asis Municipality. In August 2014, the newspaper "El Colombiano" registered an attack and robbery of medical supplies carried by a local ambulance in the Municipality of Guadalupe (El-Colombiano, 2014). These are just a few examples of the different attacks and infractions illegal groups have carried out against hospital infrastructure and medical staff in Colombia.

Fortunately, in August 2014 the Government of Colombia and FARC began a peace process that may end decades of conflict. In 2015, at the time this paper was written the peace process was still ongoing and both parties seemed optimistic about reaching a final peace agreement.

1.5.1 Data

In this section we describe the data used in the empirical analysis. According to the Decree 2193 of 2004, public hospitals in Colombia are required to provide specific information regarding their finances, budget, capacity, human resources and service quality on a yearly basis. This information is used primarily by the Ministry of Health to make decisions concerning the public health policies in Colombia. Table 1.1 names the primary hospital inputs and outputs we collected from the Colombian Ministry of Health through the SIHO ("Hospitals Information System") for years 2007-2011.

Table 1.1: Hospital Variables

Category	Variable	Definition	Units
Inputs	Beds ($K_{i,t}$)	Inpatient beds	Beds
	HumanRes ($L_{i,t}$)	Wages and benefits for physicians, nurses and staff	COP* 2007
	Materials ($M_{i,t}$)	Cost of medical supplies, indirect services and energy	COP 2007
Outputs	Inpatients	Inpatients per year	Inpatients

* COP = Colombian Pesos.

The number of hospitals in our study is 163. This sample is the result of taking the universe of hospitals (934) and carrying out several cleaning processes (in the interest of comparison note that, according to the American Hospital Association, the US had 5,723 hospitals in 2014). The sample reduction is mostly explained due to missing data. For example, in variables such as number of inpatients the missing information reached almost 47% of the entries in the original dataset.

We faced difficult challenges collecting data for this study. Obtaining sound and granular conflict data at the hospital level in a developing country with an active conflict is certainly non-straightforward. The Colombian government scrutinized our research proposal and we only received access to the raw data after several field visits and interactions with staff from the Colombian Ministry of Health and the Colombian Planning Department. In his review of the evolution of data and research in conflicts, Gleditsch et al. (2014) highlight the difficulties of accessing credible, sound and disaggregated conflict data. They also mention that the Colombian geographical categorization of conflict, which we use in our study, is one of the most important and earliest initiatives in that regard. To partially overcome the data limitations, we carried out six interviews with medical staff in Colombia. First, one of the researchers traveled from the United States to Colombia to perform three face-to-face interviews at the Ministry of Health and at a hospital located in a peace region. These interviews were conducted in September

2014 and we used them to gain contextual knowledge. Second, after obtaining our results we interviewed three medical doctors located in severe-conflict regions and asked them specific questions related to our findings. These phone interviews were conducted in December 2015 and are used to substantiate the explanations of our results.

The face-to-face interviews helped to get a better idea of the type of organization we were analyzing. First, from our visit to a rural hospital in the municipality of Sopo, Cundinamarca, we learned about rural hospital's management, performance metrics and logistics. We interviewed a medical doctor who served as scientific vice-president of the Hospital and a senior ambulance driver with more than 20 years of experience at the hospital. At the time of our visit the Sopo hospital had 22 beds and 6 pediatrics beds. According to the ambulance commander, besides 13 physicians and 15 nurses, "*there are close to 80 staff working at the hospital in total (including different shifts)*". Second, we interviewed a medical doctor who reported directly to the Minister of Health and served as Director of Services and Primary Attention at the Colombian Ministry of Health. We added the perspective of the Colombian government to our contextual knowledge and gained particular insights on the service process dynamics of the public hospitals in Colombia.

The phone interviews substantiate our econometric results with qualitative data because of the data limitations we face in this research. The identities of the doctors as well as their locations are kept confidential for security reasons. Doctor 1 has 18 years of service in the same hospital located in a severe-conflict region. First she was a general physician and currently she is a pediatrician. She has also worked in another State in Colombia, where the situation is even more complicated than it is in her current location. Doctor 2 is an epidemiologist with 20 years of experience in a severe-conflict hospital. Doctor 3 was the general manager of a severe-conflict hospital for a number of years beginning in 1995. He replaced the previous general manager, who was murdered with several shots in the head while he was in a public establishment. Doctor 3 left the hospital due to death threats and currently works in a peace region hospital. The semi-structured interviews in this research were conducted in Spanish and translated to English by one of the authors following the 24 hours rule (Eisenhardt, 1989).

We capture conflict intensity by using a categorical index calculated by a Colombian Non Governmental Organization known as Conflict Analysis Resource Center (CERAC, by its acronym in Spanish). CERAC is an independent Colombian research center specialized in the measurement and analysis of the Colombian conflict. CERAC calculates the conflict index using historic information from 2000 to 2012 about the activities of illegal groups in Colombia. Further details about CERAC's methodology can be found in Restrepo et al. (2004, 2006). Conflict is a four-category variable defined as follows: 1: peace, or no evidence of conflict at all, 2: post conflict, or municipalities which after being in conflict turned to an uninterrupted peace state since 2004, 3: medium (intermittent) conflict, 4: severe conflict, or municipalities where there is evidence of conflict during the entire period. We use those conflict categories to create a geographic map of conflict in Colombia (Figure 1.1). A large number of municipalities have medium-conflict (67.8%), followed by peace (17.3%), post-conflict (11%) and severe-conflict (3.9%) regions (see Table 1.4)

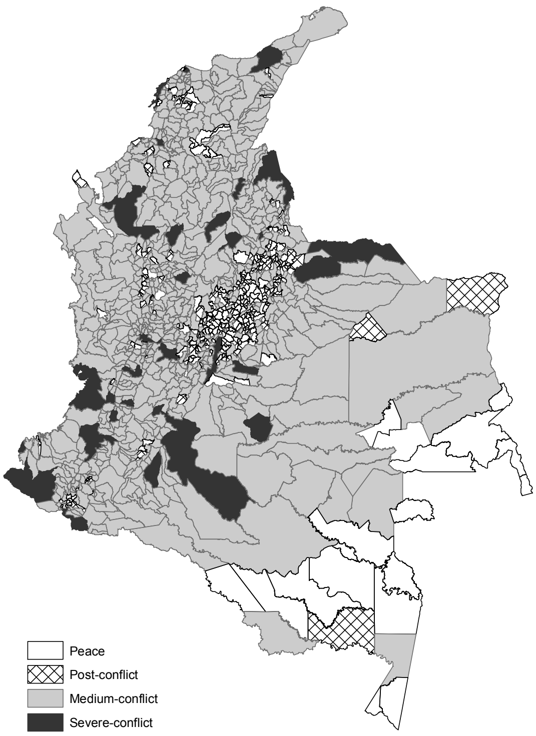


Figure 1.1: Conflict levels in Colombia, 2000 - 2012. Source: CERAC. Geo-mapping carried out by the authors.

Economic and social controls were obtained from different official and public Colombian institutions. Gross primary and secondary school enrollment, and schools were obtained from the Ministry of National Education. The unsatisfied basic needs (a measure of poverty) and the child mortality rate were obtained from the National Statistics Department (See Table 1.2).

1.5.2 Descriptive statistics

The size of the 163 hospitals as to the number of beds, is as follows: 69.9% have less than 10 beds, 27% between 10 and 50, and 3.1% more than 50 beds. The sample contains hospitals

Table 1.2: Municipality variables

Category	Variable	Definition	Units
Conflict	Conflict	Level of conflict	Categorical
Social controls	ChildMort	Deaths in under the age of 1 per 1000 births	Deaths
	PrimEdu	Gross primary school enrollment rate	Percentage
	SecondEdu	Gross secondary school enrollment rate	Percentage
Economic controls	Schools	Public schools	Schools
	UnsatNeeds	Unsatisfied basic needs index	[0-100]

from 22 of the 32 Colombian states ("departamentos"). These 22 states have 77.8% of the total population and produce 69.9% of the total national GDP. In addition, 81.6% of the total sample represents municipal hospitals. As opposed to state or national hospitals, these are hospitals intended to serve the local municipality demand. There are 161 municipalities represented in the sample, out of the 1,101 total municipalities in Colombia. Although most of our data represents rural hospitals, there are a few exceptions such as a hospital located in the city of Manizales that has 301 beds and serves rural populations that work in coffee plantations. Table 3 shows the descriptive statistics of the variables we use in the analysis.

Our dataset includes mostly public and level 1 hospitals in Colombia (98%). According to the classification of hospitals by the Colombian Ministry of Health, level 1 or low-complexity hospitals are those healthcare institutions where outpatient and inpatient services such as emergency, dental, maternity and nursing care is provided. It includes basic radiology, laboratory and pharmacy services as well. Hospitals in this category do not have the infrastructure to carry out complex surgical procedures or to provide specialized care. The Colombian law stipulates that medical staff in this category includes mainly general physicians, nurses, social workers and dentists. Therefore, hospitals in our sample can be regarded as first-layer response organizations providing urgent care services.

Table 1.3: Descriptive statistics (average per year)

Category	Variable	Max	Mean	Min	Std. Dev.	Obs
Hospital variables	HumanRes (millions)	4,600	550	38	497	815
	Materials (millions)	5,900	899	75	728	815
	Inpatients	7,593	354.46	3	568.53	815
	Beds	301	11.49	1	23.24	815
Municipality variables	Schools	65	12.88	1	14.44	610
	ChildMort	74.15	29.66	0.26	12.76	815
	PrimEdu	267.84	126.12	53.7	32.35	815
	SecondEdu	157.54	89.05	26.47	24.32	815
	UnsatNeeds	100	43.99	10.03	19.52	815

As shown in Table 1.4, the frequency of hospitals in our sample under each conflict category closely matches the frequency of municipalities in each conflict level in Colombia. Notice that in the severe-conflict stage the number of data points (20) is just enough for conducting appropriate statistical tests. We take advantage of the 5-year panel data to carry out our econometric models. However, we avoid statistical analysis on a yearly basis due to the reduced number of observations in the severe-conflict stage.

Table 1.4: Number of municipalities and hospitals by conflict stage

Level	Municipalities(%)	Hospitals 2007-2011 (%)
Peace	191 (17.3%)	23 (14.1%)
Medium conflict	746 (67.8%)	111 (68.1%)
Severe conflict	43 (3.9%)	4 (2.5%)
Post conflict	121 (11%)	25 (15.3%)

1.6 Results

A two-way fixed effect panel data model was implemented to estimate hospitals' TFP using equation (1.4). According to the Haussman test for random effects, with a Chi-square statistic of 69.46 (P-value 0), a fixed effect model is the best representation of equation (1.4). In addition to a fixed effect per hospital (TFP), we found fixed time effects significant at 1% level. The latter means the best panel data model form includes a constant effect per year (2007-2011) that explains in part output level differences observed in our data. Results indicate that the average hospital's TFP is 0.21 with a standard deviation of 1.12. The min and max values are -3.07 and 2.87.

After implementing the VRS DEA model for the period from 2007 to 2011, our results suggest the yearly average efficiency score for hospitals is always below 40% without showing a clear trend during this period of time (Table 1.5). This indicates that inefficient hospitals can increase the total number of inpatients treated per year without altering their current inputs. The number of efficient hospitals varies each year, ranging from 16 in 2007 to 10 in 2010.

Table 1.5: Efficiency estimations

Variable	Statistic	2007	2008	2009	2010	2011
$\text{Efficiency}_{i,j}$	Mean	0.38	0.34	0.37	0.30	0.30
	Max	1	1	1	1	1
	Min	0.04	0.01	0.01	0.01	0.01
	Std. Dev.	0.27	0.27	0.27	0.25	0.26

1.6.1 Hypothesis 1: Impact of conflicts on TFP

Results for Hypothesis 1 are presented in Table 1.6, column 2. We estimate the conditional marginal contribution of conflict on TFP for each conflict level as follows:

$$\delta_c = E[\text{TFP}_c] - E[\text{TFP}_{\text{peace}}], \tag{1.9}$$

where δ_c is the contribution to TFP given a conflict stage $c \neq peace$ compared to the contribution in peace, and TFP_c is the TFP contribution given a conflict stage c.

Table 1.6: Results OLS and Tobit models

Variables	H1: TFP OLS	H2: Efficiency OLS	H2: Efficiency Tobit
Post-conf	0.75*** (0.15)	0.11** (0.04)	0.12** (0.05)
Med-conf	1.25*** (0.13)	0.01 (0.03)	0.01 (0.03)
Severe-conf	1.78*** (0.19)	-0.11** (0.05)	-0.10** (0.05)
TFP		0.13*** (0.04)	0.11*** (0.04)
TFP^2		0.06*** (0.01)	0.06*** (0.01)
TFP^3		0.01* (0.00)	0.02*** (0.01)
TFP x Post-conf		0.02 (0.04)	0.03 (0.04)
TFP x Med-conf		-0.08** (0.04)	-0.07* (0.04)
TFP x Severe-conf		0.05 (0.06)	0.04 (0.06)
Schools	4.3E-07 (0.00)	-1.7E-03*** (0.00)	-1.8E-03*** (0.00)
ChildMort	-3.9E-03 (0.00)	1.1E-03 (0.00)	9.1E-04 (0.00)
PrimEdu	8.0E-03*** (0.00)	4.1E-08 (0.00)	3.5E-05 (0.00)
SecondEdu	1.1E-02*** (0.00)	3.8E-04 (0.00)	4.0E-04 (0.00)
UnsatNeeds	-8.8E-04 (0.00)	1.4E-03** (0.00)	1.5E-03** (0.00)
Intercept	-2.71*** (0.22)	0.12* (0.07)	0.11** (0.07)
R^2	0.28	0.35	
Log-Pseudolikelihood			-12.34
P-value model	0	0	0
Obs.	605	605	605

Robust errors in parenthesis. *, **, *** are 10%, 5% and 1% significance levels, respectively.

We find that in post, medium and severe conflict, $\delta_c = 0.75, 1.25$ and 1.78, respectively. These coefficients are significant at 1%. Severe conflict exhibits the highest contribution to TFP, which is followed by a contribution that decreases for medium and post conflict. These results support Hypothesis 1, which suggests that conflict has a positive impact on TFP. As discussed below, these results can be explained by the homogenization of demand, learning, and collaboration between medical staff.

It is important to provide some contextual clarification about severe conflict regions. Although we initially expected that these regions would have relatively large battles between parties in conflict with some frequency, in actuality violence is routine but it comes mostly as intimidation and violent episodes that end up in the death of two or three people and several more injured. Battles with large numbers of casualties and injured are very rare. Instead, hospitals receive a flow of conflict-related patients regularly. As a result of the demand dynamics associated to conflict, medical staff and hospital managers become skillful at procedures related to the conflict. Doctor 3 remarks: "*you learn to respond to critical emergency situations. Medical* *doctors become very skillful at treating conditions associated with violence. Administrative staff becomes fast at responding to situations related to the conflict*".

Medical staff develop informal mechanisms that consist of knowledge transfer from senior doctors with many years of experience in conflict areas (non-stress impaired physicians) to less experienced doctors. The latter are attracted to conflict areas by the high salaries but many do not endure the stressful working conditions and leave a few months after their arrival. In the words of Doctor 1: "*More experienced doctors help the less experienced ones. We receive many new doctors because there is a very high rotation. The old ones help the new ones and it becomes like an academy although there are not formalized protocols*". All three Doctors mentioned that high workloads and working hours over the regular shift are frequent, which results in challenges to formalize any new procedure or knowledge transfer.

Multi-tasking and buffering are also frequent responses to conflict demand. Doctor 1 states: "*people work on several activities at the same time and they* [hospital management] *try to involve the nursing personnel. There is always an available nurse and an available physician. That is not the case with specialists*". Doctor 2 elaborates on the same subject: "*If many people are injured and we need to treat many patients and there is not enough staff, if somebody* [a nurse] *knows how to do it, they do it*".

Furthermore, collaboration between medical doctors and nurses increases during conflict episodes. Moreover, doctors involve experienced nurses that take care of sutures and other procedures to treat wounds. In the words of Doctor 1: "*when there is increase in demand, there is more collaboration between doctors but things get done without any formal protocols. After a shift where you get patients from violent episodes you end up exhausted*". Sometimes replacement personnel might not be available immediately. Doctors are ready to assume each other's workload in contingencies derived from conflict. Doctor 2 affirms: "*there are two pediatricians and if I got kidnapped, the other would have to take on the workload of both of us because there is no one who could replace me immediately*".

The fact that most of these increases in TFP are informal is always a risk for rural hospitals. This is exacerbated by high rotation of medical staff due to death threats. Doctor 3 states: "*Some have left. My brother was a gynecologist and he was threatened with kidnapping. I was declared a military objective by the ELN and I had to leave the region. Others have stayed*". Lack of on-time payment increases rotation. This occurs despite the relatively good salaries that doctors receive in conflict regions.

1.6.2 Hypothesis 2: Impact of conflicts on efficiency

Although the estimations of efficiency and TFP use different methods, due to data limitations we obtained both variables from the same data set. This procedure could result in a problem of endogeneity that would introduce bias in the estimators of model 1.2. We include a comprehensive discussion of this issue in Appendix A.1.

The results for model 1.2 are presented in Table 1.6, columns 3-4. Examining both the OLS and Tobit models, we do not find important changes in the coefficients between the two versions of model 2. However, following the discussion from Section 4.1, we use the Tobit estimates in this analysis. Notice that the total number of observations in each model excludes missing values from control variables.

Similarly, we estimate the conditional marginal contribution of conflict on efficiency for each conflict level as follows:

$$\delta_c = E[\text{Efficiency}_c] - E[\text{Efficiency}_{\text{peace}}], \tag{1.10}$$

where δ_c is the expected contribution to efficiency given a conflict stage $c \neq peace$ compared to the contribution in peace, and Efficiency_c is the efficiency contribution given a conflict stage c.

We obtain $\delta_c = 0.12 + 0.03\text{TFP}, 0.01 - 0.07\text{TFP}, -0.10 + 0.04\text{TFP}$ for $c =$ post, medium and severe-conflict levels, respectively. The first coefficients (constant) for post and severe-conflict levels are significant at 5% while the coefficient for medium conflict is not significant at a 10% level. The interaction term with TFP is only significant for medium conflict at a 10% level. The coefficients for the severe and medium-conflict level support Hypothesis 2. Under severe conflict, the significant term corresponding to -0.10 implies a negative impact of conflict on efficiency. In medium-conflict hospitals the significant term is negative and depends on the TFP level.

Our finding is consistent with the conjecture that market and supply chain disruptions lead to distortions in the optimal allocation of resources. As discussed in Section 5, if ambulances or medical supplies availability are affected by the conflict, the hospitals will need more inputs to produce outputs, leading to higher production costs and consequently lower efficiency. The doctors we interviewed remark that in case of road blockage they usually receive supplies by plane or even by helicopter. Although these strategies mitigate disruptions, they have an impact on costs. Doctor 2 comments: "*Obviously during conflict some supplies consumption increases such as urgency supplies, canalization tubes, antibiotics. If the supplies are coming by road, it is difficult to get them. But if supplies come by plane they do not suffer*". Moreover, carriers that have the capacity to go to conflict areas charge higher prices because of the risks they face, which results in further reductions of efficiency.

Efficiency losses also relate to corruption. In the case of rural hospitals, corruption takes multiple forms. It can be through illegal taxes as the Director of Services and Primary Attention at the Colombian Ministry of Health points out, "*Vacunas (illegal taxes) are easy because there is no central procurement system. Thus, procurement may have extra costs that are used to pay vacunas.* Moreover, corruption may take the form of agreements between the parties in conflict and the hospital staff. It is not difficult to imagine that when confronted with death threats, medical staff may end up negotiating with the parties in conflict. As Doctor 1 remarks: "*They serve the paramilitaries as if they were subsidized. The paramilitaries pay to the staff. The conflict generates lots of corruption. In other hospitals it used to happen that paramilitaries got all the services but they would not be charged*".

Finally, conflict hospitals suffer losses of supplies, vehicles and kidnapping of staff. Usually, it does not happen at the hospital. Instead, these episodes occur when hospitals are visiting the community to conduct "health brigades" that consist of vaccination campaigns, pre-natal control, control of growth and development of children, and other programs of great importance for the community. According to the ministry official, "*ambulances were also military targets in the past. If a patient being transported in an ambulance was a military target, the ambulance was shot at or bombed to attack the patient*". Doctor 2 remarks: "*Some time ago I was visiting the community and we were stopped. They took all the equipment from us: medicines, first aid kits. They took the ambulance*".

In contrast, post-conflict hospitals exhibit the highest fixed contribution to efficiency compared to hospitals in peaceful regions. This result suggests that TFP gains remain in the hospital even after it reaches the post conflict stage. Therefore, hospitals accumulate TFP during the conflict stage, and later, in a post conflict scenario they use their higher TFP level to improve their operations efficiency. The latter is possible because most of the market and supply chain disruptions that had impeded optimal allocation of resources will be diminished or eliminated in a post conflict stage. It is noteworthy that, as suggested in equation (2), TFP and efficiency are closely related. In fact, given the coefficients and significance for TFP (Table 1.6), we can conclude that TFP affects efficiency positively at any conflict stage.

1.6.3 Hypothesis 3: Impact of conflicts on efficiency variability

Next, we present the summary of a battery of tests related to the variability of our DEA efficiency scores by conflict stage (see Appendix A.2 for further details on the tests performed). In Table

1.7 we observe that there exists statistical evidence to conclude that efficiency variability is the highest in peace and post-conflict hospitals. In medium-conflict hospitals the efficiency variability is larger than in severe-conflict areas, but less than in peace or post-conflict hospitals. Similar results hold when efficiency variability is compared by year (not presented here for ease of exposition). Thus, we find evidence to support Hypothesis 3.

Table 1.7: Results test $H_o = \frac{Std.Dev.Eff.(row)}{Std.Dev.Eff.(column)} = 1$

Conflict level	Medium conflict	Severe conlfict	Post conflict
Peace	1.19^{***}	1.76^{***}	1.07
Medium conflict	-	1.48^{**}	0.90^{*}
Severe conflict	-	-	0.60^{***}

*,**,*** are 10%, 5% and 1% significance levels

To explain this result, we argue that conflicts cause disruptions to the hospitals' supply chain and that risk mitigation strategies to overcome these issues, such as buffering and alternative transportation modes, are costly and may reduce hospitals' efficiency. Once hospitals implement those strategies the risk of disruption might indeed be hedged and the operational performance smoothed. Thus, if conflict hospitals implement those strategies more frequently since they face higher disruption chances, their efficiency variability should be less than in non-conflict regions.

As discussed above, conflict hospitals prepare, in most cases informally, strategies to respond to contingencies derived from conflict. For example, supply chain disruptions trigger collaboration between hospitals that borrow supplies from hospitals nearby as well as support from regional health authorities. As Doctor 2 remarks: "*If we have problems we communicate with hospitals nearby and the other institutions are also prepared. We have emergencies all the time. What do you do? You call neighbor hospitals and borrow supplies*".

Additionally, conflict hospitals try to follow standardized procedures to treat injured patients. This practice has increased over time. Some decades ago medical doctors used to practice procedures that were way beyond the official level of care of the hospital. Doctor 3 remarks: "*It was heroic. Sometimes we had to help patients that were beyond the level of service of this hospital*". However, the standardization of procedures seems to be a response to the fear hospital staff feel about the parties in conflict. Doctor 1 adds: "*If you do something that is not standard and the patient dies, you have a huge problem. If the patient lives, that is fine. It is very difficult to take heroic actions now because you may get in big trouble. The patient may be family of a paramilitary or a paramilitary. If the patient dies, you get into huge trouble*". In the case of patients that need special attention, the medical personnel at the conflict hospital follow stabilization procedures and ask the Regional Health Authorities for the air ambulance (plane or helicopter) to take the patient to a higher level hospital for specialized treatment.

Figure 1.2 summarizes the results of the three hypotheses that we tested. In line with our conjectures, conflicts have a positive effect on TFP. This may be explained by unobservable factors such as knowledge transfers, best practices, learning and speed-up effects that balance both capital and human resources disruptions in conflict hospitals. In contrast, conflicts have a negative effect on hospitals' efficiency because of the higher cost associated to disruptive supply chains. Interestingly, conflicts have a negative effect on hospitals' efficiency variability due to risk mitigation strategies and standardization of healthcare practices implemented during conflicts.

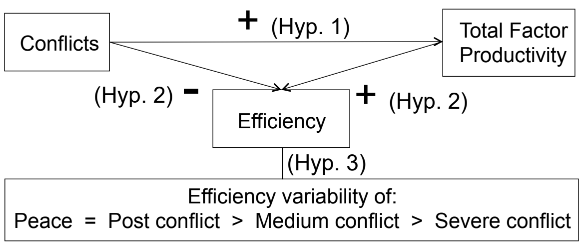


Figure 1.2: Summary of results

1.7 Conclusions

This research examines the impact of armed conflicts on the operational performance of local response organizations. In particular, we formulate three hypotheses on the impact of armed conflicts on total factor productivity and efficiency in rural hospitals. We test these hypotheses using the case of Colombia, which includes different levels of conflict ranging from peace to severe conflict. These differences in conflict intensity allow us to compare hospitals and estimate their total factor productivity and relative operational efficiency.

Our quantitative data is composed of hospital variables and municipality variables. Hospital variables include number of beds, wages and benefits for physicians, nurses and staff and expenses in materials. Municipality variables include a conflict index, social controls and economic controls. We use the quantitative data to estimate hospital total factor productivity and efficiency. We also use the data in econometric models for hypothesis testing. The data is completed with field visits and semi structured interviews with healthcare staff in Colombia.

First, we conclude that conflict has a positive effect on hospitals' total factor productivity

(TFP). Conceptually, changes in this metric are explained by unobservable elements, different from the inputs (capital, labor and materials) used in the Cobb-Douglas production function. Some of these unobservable aspects may include speed-up, managerial ability, knowledge accumulation and specialization effects. Thus, we conclude that there are a series of possible behavioral effects such as speedups and learning triggered by conflict explaining higher levels of TFP (Hypothesis 1). Second, armed conflict has a negative effect on hospitals' relative efficiency. The conflict causes supply chain disruptions and increases the relative prices of medical goods and services as well as the maintenance of medical equipment and assets like ambulances. More expensive inputs result in lower relative efficiency for hospitals that are located in municipalities that face severe conflict (Hypothesis 2). Third, the efficiency variability of (medium and severe) conflict hospitals is less than that of other (peace and post conflict) hospitals. This is explained by the risk mitigation strategies implemented by managers of conflict hospitals to avoid supply chain disruptions and standardization of healthcare delivery practices (Hypothesis 3).

In this paper we contribute to the body of knowledge on how armed conflicts impact humanitarian organizations like hospitals, and particularly, their effect on certain operations performance measures. Due to ongoing conflicts in different parts of the world, it is urgent to further understand how conflicts affect organizations involved in the response to this type of disaster. Unfortunately, as evidenced in this first attempt to study the impact of conflicts on rural hospitals, data availability is a big challenge. To overcome this issue, it is critical to work with practitioners and use field data as a mechanism to improve access to information.

Moreover, the results from this paper lead to important possibilities for future research, in particular dealing with the implications for operations management decision making. For example, when faced with armed conflict, the results raise the following questions for service organizations such as hospitals: (i) How should they develop sourcing processes capable of handling the supply disruptions that result from conflict? (ii) Should they build flexibility into their supply chain and workforce to better deal with conflict? and (iii) How should they incorporate the behavioral impacts that differing levels of armed conflict can have on their workforce in order to address any problems and take advantage of potential opportunities? In addition, the results raise questions about how humanitarian organizations outside the hospital can most effectively help the operations of hospitals both during and after periods of armed conflict.

1.8 Appendix

1.8.1 Model analysis

The results from models 1 and 2 are shown in Table 1.6. Those models use Robust Errors Ordinary Least Squares (OLS). Model 2 includes a Tobit regression following discussion from Section 4 regarding the best estimators when efficiency is the dependent variable. R^2 values for models 1 and 2 in the OLS approach are 0.28 and 0.35, respectively. Correlations among the different variables (Table 1.8) are less than the 0.7 threshold suggested for multicollinearity (Zhu & Kraemer, 2002). Furthermore, after conducting Variance Inflation Factor (VIF) tests, we did not find evidence of multicollinearity in any of these models (VIF <10) for variables different from interaction terms, square or cube transformations.

Next, we discuss the validity of model 2. First, notice the model uses TFP as an independent variable. This variable controls for hospitals idiosyncratic effects related to know-how accumulation and managerial ability as discussed in Section 3. Although both TFP and Efficiency were obtained using the same data set, these two measures convey different pieces of information about hospitals' performance. TFP is fixed for each hospital and is determined by the unobservable factors resulting from the Cobb-Douglas production function (Solow, 1957). That is, it is determined by factors not contained in capital, labor or the hospitals' budget (Hicks-neutral property). Those technological factors not included in the Cobb-Douglas function affect hospitals' efficiency (Farrell, 1957). On the contrary, efficiency is explained by capital, labor and the budget spent by each hospital. Using this reasoning, the novelty of this approach consists in using TFP as the control for factors affecting efficiency not explained by traditional inputs such as labor or capital. Second, TFP and efficiency do not convey the same piece of information if we consider their calculation methods. Both metrics were calculated under two different functions coming from the DEA model and the Cobb-Douglas production function. Efficiency scores per year are obtained as the distance between each hospital's performance and the efficient frontier, which is calculated using the input-output ratio for each hospital. We ran an optimization program for every year and hospital in order to obtain each one of the efficiency observations. TFP is captured as the residual of a Cobb-Douglas production function, which is derived from a panel data model. As we show in Table 1.8, TFP and efficiency have a relatively low correlation of 0.28. Third, some authors have used an approach similar to ours. Zheng (2015) and Duygun et al. (2013) utilize a model in which efficiency is a dependent variable and TFP, or a hicks-neutral technical progress score, is an independent variable.

Table 1.8: Correlation matrix

Variable	Effic	TFP	Peace	Post	Med	Severe	Schools	ChildM	PrimEdu	SecEdu	U.Needs
Effic	1										
TFP	0.28*	1									
Peace	-0.04	-0.27*	1								
Post	0.01	-0.10	-0.17*	1							
Med	0.034	0.25	-0.59*	-0.62*	1						
Severe	-0.04	0.08	-0.06	-0.06	-0.23*	1					
Schools	-0.02	0.16*	-0.21*	-0.16*	0.18*	0.21*	1				
ChildM	0.15*	-0.07	-0.04	-0.03	0.08	-0.07	0.02	1			
PrimEdu	0.16*	0.25*	-0.18*	-0.02	0.17*	-0.06	0.29*	0.31*	1		
SecEdu	0.04	0.26*	0.07	0.09	-0.10	-0.04	-0.08	-0.18*	0.22*	1	
U.Needs	0.12	-0.01	-0.16*	-0.03	0.13*	0.01	0.26*	0.57*	0.48*	-0.32*	1

* 5 % significance level
Bonferroni correction applied

Fourth, if TFP and Efficiency conveyed exactly the same piece of information, including TFP as an independent variable could raise doubt about TFP being correlated with the error term. One of the principal assumptions on the econometric model in Equation (2) is that the regressor TFP, although stochastic, is not correlated with the error term. We cannot reject the null hypothesis that the correlation between TFP and the error term is zero after conducting a correlation test applying the Bonferroni correction. A more robust test showing that our estimation does not present endogeneity using instrumental variables was performed. We use the variable "Number of diagnostic images by year and hospital" to undertake this procedure. This variable has not been used in any of the previous models and its correlation with TFP is 0.4759 and its correlation with efficiency is 0.08. We explore the Durbin and Wu-Haussman tests and show that with a P-value of 0.0572 and 0.0581, respectively, we do not reject the null hypothesis that TFP is exogenous. Therefore, we conclude that our model in Equation (2) has no endogeneity issues when the variable TFP is used as regressor.

Finally, it is noteworthy that including quadratic and cubic terms is supported in the concept of TFP itself. We control for what we interpret as marginal returns to knowledge and managerial ability. We expect to control for possible decreasing marginal returns to TFP. Indeed, our econometric model has the best functional form (statistically performance) when these terms are included. After conducting Ramsey's tests no evidence of omitted variables bias at a 5% significance level was found in any of the models reported (F-values for each model are 1.92 and 0.55, respectively).

1.8.2 Tests for Hypothesis 3

Table 1.9 presents the results that support our conclusion for Hypothesis 3 regarding efficiency variability at different levels of conflict. Table 1.9 shows the set of unequal variance ratio tests for each pair of conflict stages. Each test evaluates the null hypothesis of the ratio between the variance of efficiency between two conflict stages to be equal to 1.

Table 1.9: Main variance-ratio tests for Hypothesis 3

Group	Obs.	Mean	[95% C. Interval]		Std. Dev.	Ha: ratio <1 Pr$(F<f)$	Ha: ratio $\neq 1$ 2 Pr$(F>f)$	Ha: ratio>1 Pr$(F>f)$
Peace (1)	115	0.311	0.256	0.367	0.303			
Sev-conf (4)	20	0.265	0.185	0.346	0.172			
						0.9968	0.0065	0.0032
						[ratio = sd(1) / sd(4). f = 3.10. DF = (114, 19)]		
Peace (1)	115	0.311	0.256	0.367	0.303			
Med-conf (3)	555	0.345	0.324	0.366	0.254			
						0.9945	0.0111	0.0055
						[ratio = sd(1) / sd(3). f = 1.42. DF = (114, 554)]		
Peace (1)	115	0.311	0.256	0.367	0.303			
Post-conf (2)	125	0.343	0.293	0.393	0.283			
						0.7709	0.4581	0.2291
						[ratio = sd(1) / sd(2). f = 1.14. DF = (114, 124)]		
Med-conf (3)	555	0.345	0.324	0.366	0.254			
Sev-conf (4)	20	0.265	0.185	0.346	0.172			
						0.977	0.046	0.023
						[ratio = sd(3) / sd(4). f = 2.18. DF = (554, 19)]		
Post-conf (2)	125	0.343	0.293	0.393	0.283			
Med-Conf (3)	555	0.345	0.324	0.366	0.254			
						0.9452	0.1097	0.0548
						[ratio = sd(2) / sd(3). f = 1.24. DF = (124, 554)]		
Post-conf (2)	125	0.343	0.293	0.393	0.283			
Sev-Conf (4)	20	0.265	0.185	0.346	0.172			
						0.9925	0.015	0.0075
						[ratio = sd(2) / sd(4). f = 2.70. DF = (124, 19)]		

Ho: ratio = 1. DF= degrees of freedom

Chapter 2

Inventory in Times of War

In 2015, fifty armed conflicts left the highest number of fatalities in 25 years, millions displaced, and the worst humanitarian crisis since World War II (The Institute for Economics and Peace, 2016). But war is not only tragic. War is expensive and increases supply uncertainty of commodities (produced in war countries) such as oil and agricultural goods. Although inventory is a buffer against supply uncertainty, firms' inventory decision in war countries is difficult to predict. Also, there is no empirical evidence of how war affects firms' inventory.

We provide evidence of the causal effect of war on firms' inventory. But two difficulties hinder this estimation. First, collecting data from war zones is challenging. We overcome this issue by assembling a unique dataset from the Colombian civil war—one of the longest-standing civil wars in history. Two armed groups have battled this war: (i) The Armed Revolutionary Forces of Colombia (FARC), and (iii) the National Liberation Army (ELN). We collect our datasets from private and public Colombian institutions. Our data contain information of 38,916 firms, 1,122 municipalities, and 1,258 attacks. For each firm, we observe the location of its principal production facility (e.g., plantation, production plant, or factory), its inventory holdings, and other operational variables. We also observe the date, location, and the group responsible for each attack (i.e., FARC or ELN) from 2001 to 2012.

Second, establishing causality is difficult since economic variables (e.g., economy growth) affect both war intensity and firms' inventory—causing endogeneity problems. To overcome this issue, we take advantage of a natural experiment: the 2012 peace process between the Colombian government and one of the two guerrilla groups (FARC). This peace process—revealed in September 2012—led to the abrupt deescalation of all violent activities by FARC. Thus, the municipalities dominated by FARC witnessed a sudden cessation of the war, whereas those dominated by ELN remained in the war. We use this natural experiment to estimate a Difference-in-Differences model. Our "treatment" group includes firms located in municipalities under military siege by FARC, whereas our "control" group those under military control by ELN[1]. We calculate firms' inventory-to-assets ratio in the treatment and control groups, in the years preceding, and following the establishment of the peace process.

We show that across the pre-treatment period both groups had consistent inventory patterns. But after the peace process announcement, the inventory holdings in the treatment group increased sharply by 4%, whereas the inventory holdings in the control group decreased by 9%. We show that a firm's inventory-to-assets ratio can drop as much as 3.65 percent points in times of war. We also show that proximity to trade centers and distribution markets is a significant moderator of the treatment effect: firms far from trade centers increase their inventory holdings in war compared to those near trade centers. When a firm is far from a trade center, its inventory travels longer distances. Thus, the firm's inventory shipping costs will be higher compared to the shipping costs of a firm close to a trade center. When inventory has to travel less, war primarily affects the firm's holding cost (and not the shipping cost[2]). We find that the treatment effect is four times larger across firms in municipalities where the intensity of war is in the top decile of the distribution, compared with those at the bottom decile of the distribution.

Our results have implications for global supply chain management. When a firm can transport its inventory easily (i.e., the firm is near a principal trade center), its inventory holdings will decrease following a civil war. But when a firm has difficulties transporting its cargo, its inventory holdings will increase. Thus, when evaluating entry or selecting suppliers from war zones, global companies can use firms' location to improve their decision making. Firms can adjust their safety stocks or implement alternative mitigation strategies (e.g., multisourcing, demand management, production flexibility, etc.) to cope with lower product availability. Our results are relevant in current times where strategic zones are increasingly imperiled by conflicts and global supply chains increasingly depend on the commodities produced in war countries.

2.1 Literature Review

This paper spans literature in man-made disasters and inventory management. In man-made disasters management, Pinker (2007) models government warnings and physical deployments to combat terrorism. The author shows that warnings can deter attacks, but as attacks' time

[1]The two armed groups have traditionally operated in different geographic clusters, and often respect their territorial boundaries (similar to gang groups in urban areas). There is little military overlap between these two groups.

[2]During a civil war, insurgent groups derive profits in two ways. First, these groups typically attack farms, plantations, and production facilities to steal inventory (increasing holding costs). Second, armed groups strategically position their troops across roads to steal shipments and cargo (increasing shipping costs).

and location become certain, deployments are preferred to neutralize attacks. Zhuang & Bier (2007) construct a theoretical-game model to evaluate defense systems to terrorism. The authors conclude that better defense systems can be ineffective because terrorists might attempt to compensate these investments with more effort. Pedraza-Martinez & Van Wassenhove (2013) study vehicle replacement in conflict zones. By using field data, the authors find that conflict intensity does not affect the salvage value of vehicles used for humanitarian operations. Jola-Sanchez et al. (2016) use the Colombian civil war to study the operational performance of rural hospitals in war zones. By using a panel from 163 hospitals (from 2007 to 2011), the authors conclude that conflict hospitals have higher total factor productivity, but are 11% less cost efficient than peace hospitals.

We contribute to the literature in man-made disaster management by providing evidence of how firms use inventory to respond to war. This knowledge is useful for decreasing supply uncertainty across supply chains.

In inventory management, Chen et al. (2005) study 7,433 U.S. manufacturers from 1981 to 2000, and show that these firms have reduced their inventory holdings at a yearly rate of 2%. Xiaodan (2017) studies 149 U.S. manufacturers and reports that these firms have decreased their inventory-to-assets ratio from 27.2% to 12.7% from 1970 to 2009. Rumyantsev & Netessine (2007) use 177 firms from the retail and wholesale industry to show that a 1% increase in supplier lead time increases inventory by 0.02%, and a 1% increase in sales uncertainty decreases inventory by 0.02%. Olivares & Cachon (2009) use data from 200 auto dealerships to show that increasing the number of dealerships one standard deviation above the mean increases dealerships' inventory by 12.5%. Cachon & Olivares (2010) conclude that, in the U.S. automakers industry, increasing production flexibility one standard deviation increases inventory by 8%. Jain et al. (2013) study how global sourcing affects firms' inventory investment. Using sea shipments data from global suppliers (approximately half a million custom forms), the authors find that a 10% shift in sourcing from domestic to global suppliers increases inventory by 8.8%. By using 482 manufacturing firms, Han et al. (2013) conclude that firms decrease their inventory when they enter emerging markets. Finally, Steven & Britto (2016) use 327 manufacturing firms to find that a 10% increase in the proportion sourced from emerging markets increases 0.52 days the manufacturers' inventory days.

We contribute to this literature by providing evidence on how a firm's location relative to the principal trade centers and battle zones affects its inventory holdings. This knowledge improves inventory and sourcing decisions of firms entering or sourcing from suppliers in war zones.

2.2 The Colombian Civil War

The Colombian conflict is the world's longest-running civil war. This conflict began in 1964 with the establishment of two Marxist, anti-government guerrilla groups: the Revolutionary Armed Forces of Colombia (FARC) and the National Liberation Army (ELN).

The Colombian Government estimates that the civil war has left approximately one million deaths and eight million internal displacements. From 1988 to 2012, FARC and ELN have carried out 5,138 attacks against private property and transport infrastructure; FARC has committed 55% of these attacks. These attacks include the bombing of firm infrastructure, plantations, machinery and oil fields, stealing of merchandise, cattle, oil and raw material (Figure 2.1), destruction of roads and bridges, and burning of vehicles and cargo (Figure 2.2). Both groups fund their operations by stealing firms' inventory, charging ransoms, and imposing illegal "taxes" on firms (Rettberg, 2002).

Figure 2.1: Private-property attacks. Left: ELN bombs the Cano Limon-Covenas oil pipeline. Photo by Omar Ahumada Rojas (El Tiempo, 2014). Right: FARC attacks the Bojaya Municipality with cylinder bombs. Photo by Jesus Abad Colorado, 2002.

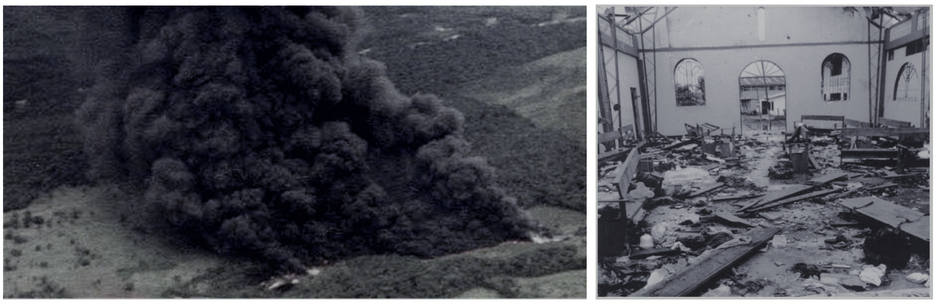


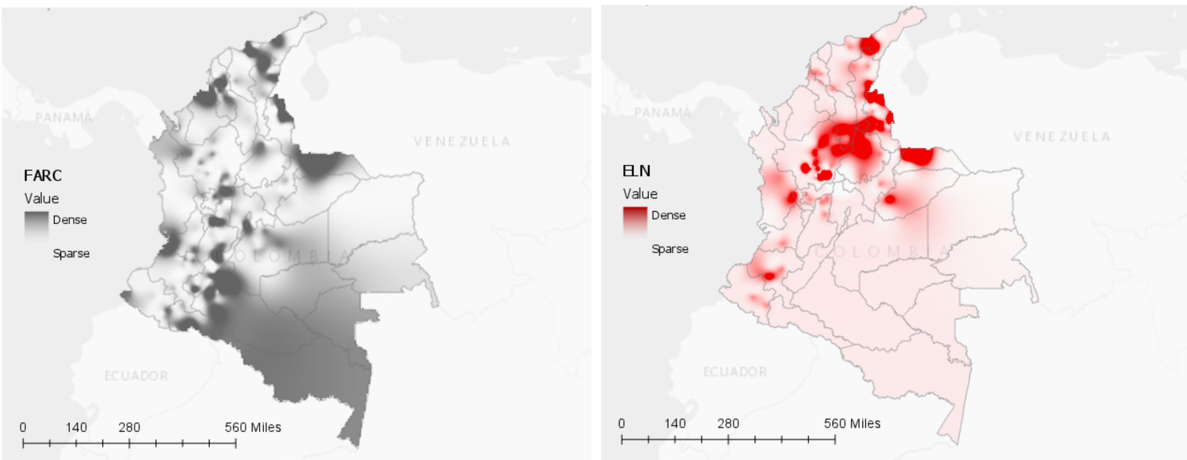
Figure 2.2: Transport attacks. Left: ELN blocks a road and burns trucks. Photo by Jesus Abad Colorado, 2000. Right: FARC bombs a bridge. Photo by Javier Agudelo, (El Tiempo 2002).

In September 2012, after seven months of secret negotiations, the Colombian government announced the beginning of a peace process with FARC. Political reasons motivated FARC to participate in the peace process[3]. After the announcement, the conflict with FARC rapidly deescalated to the point where attacks virtually disappeared; by 2015, compared to the historical mean, attacks and casualties by FARC had decreased by 98%, and military confrontations with the government had fallen by 91% (CERAC, 2016).

In the meantime, the war persisted between the government and ELN. This guerrilla group did not participate in the peace negotiations and continued attacking transport and private-property infrastructure (El-Espectador, 2014; RCN-News, 2016, 2015). After the announcement, ELN became the principal armed actor in the country. For example, this group became responsible for the 96.5% of the attacks against the oil industry in Colombia (FIP, 2015).

Figure 2.3 depicts the geographic boundaries of the two guerrillas groups. Whereas firms in the Northeastern and Inner States of the country remained under military siege by ELN, firms in the Southern and Western States remained under control by FARC. The geographic boundaries were held constant throughout the peace process since FARC did not abandon its territories during the peace process. FARC and the government reached a final peace agreement in 2017.

Figure 2.3: Geographic distribution of attacks. Geo-maping carried out by the authors using the spline with barriers tools from ArcGis. Note: zones with extreme war conditions can be identified as the darker spots. Left: FARC. Right: ELN.



[3]Before the peace process started, FARC and the Government signed an agreement where FARC expressed their interest in obtaining political participation as a result of the peace process.

2.3 Data

By gleaning five independent data sources, we obtain three types of data: municipality-, war-, and firm-level data.

1. **Municipality-level data.** For each of the 1,123 Colombian municipalities, we obtain information on their population, longitude, latitude, altitude, and surface area. We collect these data from the Colombian administrative and political registry from the Colombian Statistics Department. Table 2.1 provides sample entries.

Table 2.1: Data sample municipality level

Code	Municipality	Population	Longitude	Latitude	Altitude	Surface
05002	Abejorral	19,853	-75.438	5.804	2,125	497
05004	Abriaqui	2,458	-76.085	6.625	1,920	293
27006	Acandi	10,103	-77.283	8.433	5	869
50006	Acacías	59,817	-73.723	4.010	522	1149
54003	Abrego	35,862	-73.158	8.019	1,398	917

Altitude is measured in meters above sea level.
Surface area is measured in km^2.

2. **War-level data.** For each municipality-year data point, we obtain the number of battle-related deaths and attacks. We also observe—for each of the 1,258 attacks—the type and date of each attack, and also the group at fault (FARC, ELN). The time span of this panel ranges between 2001 and 2012. We obtain these data from the Colombian Department for Social Prosperity.

   In our sample, 91% of municipalities witnessed attacks by only one armed group—as shown in Figure 2.3, the two guerrillas maintained military monopolies across different local regions (violating these boundaries typically result in cross-fire attacks). Table 2.2 provides sample entries.

Table 2.2: Data sample war level

				Sample attacks		
State	Municipality	Deaths	Attacks	Date	Group	Type of attack
				March 8, 2002	FARC	Vehicle burning
Bolivar	El Carmen	189	15	May 25, 2002	FARC	Private property
	de Bolivar			June 29, 2002	FARC	Transport infrastructure
				January 1, 2002	ELN	Vehicle burning
Antioquia	San Luis	319	9	May 26, 2002	ELN	Public infrastructure
				December 31, 2002	ELN	Transport infrastructure

Data sample correspond to 2002.

3. **Firm-level data.** We collect a panel of all 38,916 legally established Colombian businesses, such as coffee plantations, livestock breeders, lumber and raw material producers.

For each firm-year observation, we obtain its legal identifier and the location of its production facilities. We also gather a panel of operational data that comprises dozens of variables (akin to Compustat's Dataset). For instance, we observe the firms' total and current assets, equity, cash holdings, revenue, and net income after taxes. We also have information on the different types of inventory held by the firms, including raw-material, work-in-process, finished-goods, and total inventory. We obtain these data from the Colombian Ministry of Trade, Tourism and Industry. Table 2.3 provides a data sample of a coffee plantation.

Table 2.3: Data sample firm level

ID	Mun-icipio	Name	Year	Assets Total	Assets Current	Equity	Cash	Revenue	Net Income	Raw Material	WIP	Finished Product	Total Inventory
		Sociedad	2010	13,063	604	12,588	106	(671)	(192)	2	239	116	402
		Promotora	2011	15,158	1,416	14,613	68	(104)	130	4	263	103	369
8919-	Caice-	Agro-	2012	15,230	1,507	14,763	61	(151)	260	6	324	84	423
02949	donia	industrial	2013	15,566	2,144	14,632	246	8	864	9	330	40	385
		Cafetera	2014	15,954	2,179	15,129	102	91	423	11	253	73	342
		Ltda	2015	17,150	2,079	16,306	107	183	810	15	285	28	332

WIP: Work-in-Process
All numeric variables are expressed in millions of Colombian pesos (local currency).

Sample selection

After merging these three types of data, we obtain a panel of 38,916 firms (157,865 firm-year observations). For each firm-year observation, we observe the characteristics of the municipality— where the firm is located, and the war-level metrics for the corresponding municipality-year observation. For example, we observe that *Agricola el Chaco S.A.*, a rice producer, has its plantations located in the Region of Chaco, Tolima (i.e., Latitude 4.28, Longitude -75.58). In 2010, the total assets of this firm were valued at \$2,423 million COP (approximately \$800,000 USD), and its total inventory amounted to \$608 million COP (\$200,000 USD). In the municipality where the firm operates FARC performed ten attacks, including a vehicle-burning event (with no reported casualties), an attack to military infrastructure (with eight reported casualties), and an ambush (with one reported casualty). ELN performed no attacks.

The majority of firms in our sample were operating throughout the entire span of our sample. While some firms may enter (after the beginning of our sample period) or exit the market (before the end of our sample period), there is no missing data due to misreporting.

2.4 Model

As discussed in Section 2.2; in 2012, the Colombian Government and the insurgent group FARC unexpectedly announced the beginning of a peace-process (after months of secret pre-negotiations). Shortly after the announcement, FARC agreed to a temporary cessation of all attacks; in contrast, ELN kept the same level of war activities (as verified by our data). This allows us to identify (i) a treatment group (i.e., firms in municipalities controlled by FARC) and (ii) a control group (i.e., firms in municipalities controlled by ELN). Thus, we can identify the causal effect of war on inventory by comparing the inventory of the treatment group, prior and after the 2012 peace process announcement, with the inventory of the control group, pre- and post-announcement. We use three years of data to investigate the pre-announcement phase (i.e., 2010 through 2012), and three years to study the post-announcement stage (2013 through 2015).

2.4.1 Identifying the Treatment and control group

To identify observations in the treatment and control groups, we follow a two-step procedure. First, we identify municipalities afflicted by war and municipalities in peaceful regions. We eliminate from our sample municipalities that have experienced no war-related attacks in the decade preceding our sample. We also removed municipalities with less than five battle-related deaths per 100,000 inhabitants, to exclude cities that have suffered isolated attacks or minor situations of belligerence (i.e., this criterion only ended up affecting twenty-three municipalities). At the end of this step, we kept 308 municipalities, comprising 67,989 firm-year observations.

Second, we create a dummy variable: $FARC_m$, which takes the value of 1 if the majority of the attacks performed at the municipality m in the past decade were carried out by FARC; or 0 if the majority of attacks were carried out by ELN. We remove from our sample municipalities where ties occur.

2.4.2 Difference-in-Difference Equation

We take advantage of the natural experiment— and our unique data—to estimate a Difference-in-Differences model, which provides causal estimates of the effect of war on inventory. Heretofore, we refer to this effect as the Average Treatment Effect on the Treated (ATET). If we used a proxy of war (e.g., deaths or attacks) to explain firms' inventory, confounding variables would create endogeneity issues[4].

Thus, we identify ATET (β_3) using the following regression model:

$$INV_{i,t} = \alpha + \beta_1 FARC_i + \beta_2 AFTER_t + \beta_3 (FARC_i \cdot AFTER_t) + \beta_4 (X_i) + \varepsilon_{i,t}, \qquad (2.1)$$

where $INV_{i,t}$ is the inventory-to-assets of firm i in year t, $FARC_i$ is a dummy equal to 1 if the firm i is dominated by FARC (treatment group), $AFTER_t$ is a time-dummy equal to 1 if year

[4]War and economy have a reinforcing feedback relationship known as the "poverty-conflict trap" (Blomberg & Hess, 2002).

t belongs to the treatment period (2013, 2014, 2015), X_i are the covariates of firm i, and $\varepsilon_{i,t}$ is the error term.

2.4.3 Variables definition

Our variable of interest is $FARC_i \cdot AFTER_t$. This variable is a dummy equal to 1 if firm i is in a FARC territory and the firm's inventory in the year t belongs to the treatment period. (We define the rest of our variables in Table 2.4.)

Table 2.4: Variable Definitions

Variable name	Definition
$INV_{i,t}$	$\frac{\text{Inventory}_{i,t}}{\text{Assets}_{i,t}}$ of firm i in year t.
$FARC_i$	Dummy equal to 1 if firms i belongs to the treatment group (FARC).
$AFTER_t$	Dummy equal to 1 if an observation occurs during the treatment period (2013, 2014, 2015).
$\log(DIST_i)$	Log of the linear distance from firm's i location to Bogota, which is the capital of Colombia.
$\log(ALTITUDE_i)$	Log of the municipality's altitude where firm i is located. Colombian municipalities can be at 3,000 MASL or more. This can affect firms' access to markets.
$\log(SIZEM_i)$	Log of the municipality's surface area where firm i is located.
$ROE_{i,t}$	$\frac{\text{Net Income After Taxes}}{Equity}$ of firm i in year t.
$CASH_{i,t}$	$\frac{\text{Available Assets}}{\text{Current Assets}}$ of firm i in year t.
$\log(SIZEF_{i,t})$	Log of firms' i assets in year t.

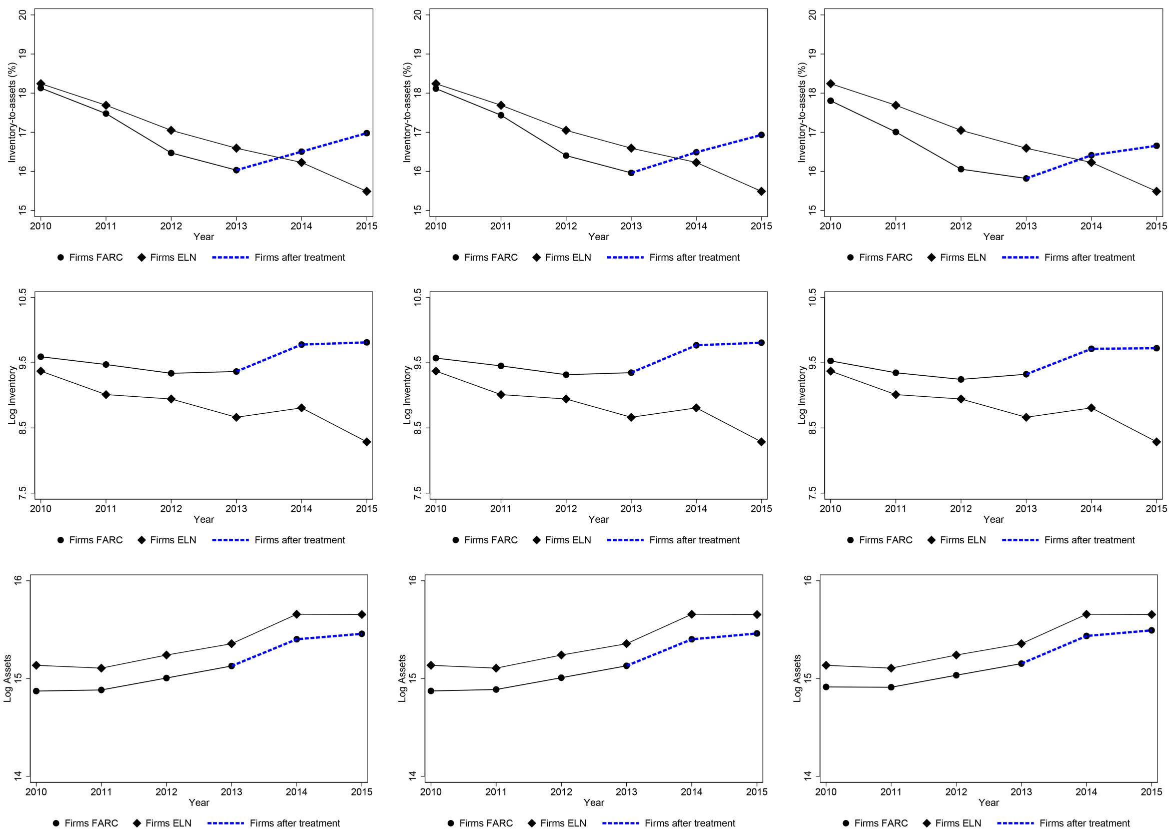
Our identifying assumption is that firms' inventory-to-assets in the treatment and control groups would have had parallel trends if no peace process had occurred (common trend assumption). Thus, our specification is fully nonparametric since no further assumptions are needed for identification purposes (Lechner et al., 2011). Despite this, our results hold for alternative models that include municipality-level controls. In those specifications, we use fixed-effects rather than time-varying controls to satisfy the strict exogeneity assumption (the treatment can not influence covariates). We present descriptive statistics in Table 2.5.

Attack-level control

When a guerrilla attacks a municipality, its effect ripples across municipalities nearby. To incorporate this, we formulate models where an attack affects firms in the nearest and second nearest municipality from the attack epicenter. By using Vincenty's equations (Vincenty, 1975)[5], we find that, on average, the linear distance from a municipality to the nearest and second nearest municipality is 36.58kms and 50.37kms. Figure 2.5 shows time plots for these two geographical

[5]This implementation uses the coordinates (longitude, latitude) of two municipalities under the WGS 1984 reference ellipsoid (standard for cartography and GPS navigation). It uses the Stata module of Picard et al. (2012)).

Figure 2.4: Outcome Variable: INV (first row), log(INVENTORY) (second row) and log(ASSETS) (third row). War intensity: Low (first column), Medium (second column), High (third column).



Low: includes municipalities with an average battle-related deaths greater than 30. **Medium**: includes municipalities with an average battle-related death greater than 39—which corresponds to the 2009-Colombia rate. **High**: includes municipalities with an average battle-related deaths greater than 50.

controls (37kms and 50kms).

2.5 Main model results

The Average Treatment Effect on the Treated (Difference-in-Differences coefficient–DiD) ranges from 0.92 to 1.22 percent points. This result is consistent and statistically significant in each case (37kms, 50kms), war threshold (low, medium, high), and specification (with and without covariates). The DiD coefficients for the 37kms case (columns 3, 5, 7, Table 2.6) vary from 0.98 to 1.22 percent points. The estimates for the 50kms case vary from 0.92 to 1.14 percent points (Table 2.7). The covariate coefficients are not consistently significant except for log(ALTITUDE), which is positive and significant in the medium and high war threshold. The DiD coefficients of the 37kms and 50kms cases are not significantly different[6]. Thus, for ease of exposition, we

[6] We take the difference between the maximum (1.22) and minimum (0.92) coefficients and conduct a (two-tail) T-test on the difference. The mean difference is 0.3, and its standard error is 0.64. This generates a t-statistic of

Table 2.5: Descriptive Statistics.

Type	Variable	Low Mean	Low Std.Dev.	Medium Mean	Medium Std.Dev.	High Mean	High Std.Dev.
Outcome	INV (%) FARC	16.80	20.76	16.89	20.83	16.71	20.81
	INV (%) ELN	17.23	21.01	17.08	21.18	17.08	21.18
Controls	log(DIST) FARC	5.57	0.66	5.56	0.68	5.59	0.69
	log(DIST) ELN	5.60	0.16	5.61	0.16	5.61	0.16
	log(ALTITUDE) FARC	6.14	1.46	6.14	1.37	6.15	1.43
	log(ALTITUDE) ELN	7.21	0.45	7.19	0.47	7.19	0.47
	log(SIZEM) FARC	6.54	1.06	6.69	0.96	6.65	0.98
	log(SIZEM) ELN	5.31	1.29	5.54	1.14	5.54	1.14
	ROE FARC	0.25	1.66	0.29	1.79	0.23	1.13
	ROE ELN	0.22	0.32	0.27	0.31	0.27	0.31
	CASH FARC	0.14	0.05	0.14	0.05	0.14	0.06
	CASH ELN	0.12	0.02	0.12	0.02	0.12	0.02
	log(SIZEF) FARC	16.36	0.84	16.26	0.79	16.30	0.81
	log(SIZEF) ELN	16.78	0.40	16.78	0.42	16.78	0.42
War data	Homicides rate FARC	104.08	81.18	115.37	82.28	122.17	82.83
	Homicides rate ELN	106.24	38.89	114.31	32.31	114.31	32.31
Obs.	FARC	14,116	-	12,124	-	11,087	-
	ELN	22,776	-	20,455	-	20,455	-

Case 50Kms. Obs.: observations

display results for the 50kms case heretofore.

Table 2.6: Results main moder 37kms case.

Variable	Low		Medium		High	
DiD (%)	1.14^{***}	1.15^{***}	0.98^{**}	0.98^{**}	1.22^{***}	1.20^{**}
	(0.40)	(0.40)	(0.46)	(0.46)	(0.46)	(0.46)
FARC (%)	−0.74	1.52	−0.39	1.68	−0.65	1.51
	(1.33)	(1.21)	(1.38)	(1.27)	(1.45)	(1.28)
AFTER (%)	-1.39^{***}	-1.39^{***}	-1.32^{***}	-1.31^{***}	-1.32^{***}	-1.31^{***}
	(0.22)	(0.22)	(0.27)	(0.27)	(0.27)	(0.27)
log(DIST)		0.00		0.00		0.00
		(0.01)		(0.01)		(0.01)
log (ALTITUDE)		0.01		0.01^{**}		0.01^{**}
		(0.01)		(0.01)		(0.01)
log (SIZEM)		−0.01		−0.01		−0.01
		(0.00)		(0.00)		(0.00)
ROE		0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)
CASH		-0.24^{***}		−0.25		−0.24
		(0.08)		(0.09)		(0.09)
log (SIZEF)		-0.04^{***}		-0.04^{***}		-0.04^{***}
		(0.01)		(0.01)		(0.01)
Observations	36,909	36,909	32,633	32,633	31,616	31,616
Clusters	251	251	231	231	219	219

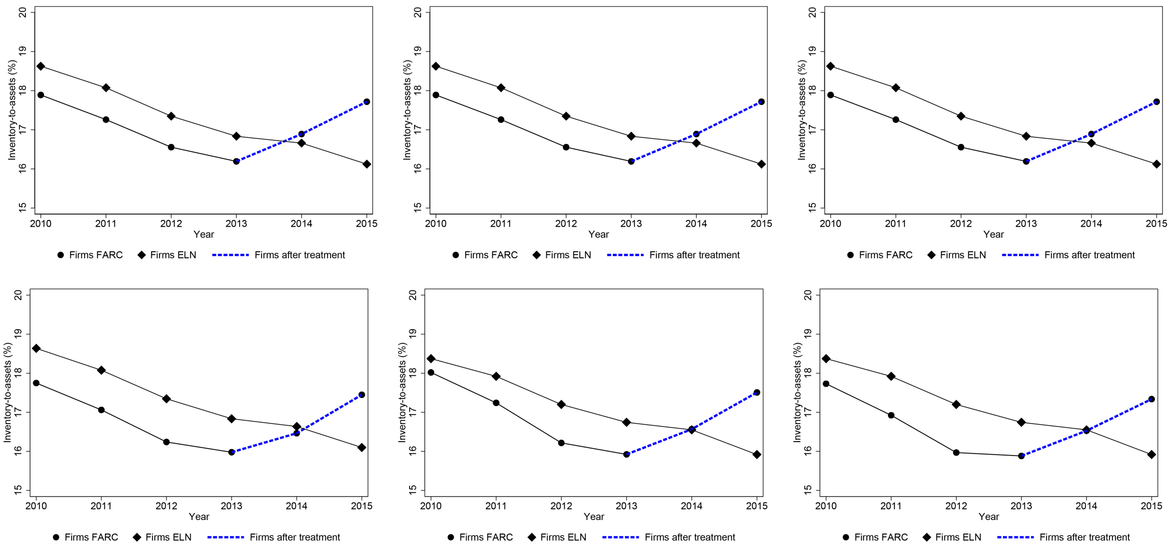
Robust errors clustered by Municipality in parenthesis. Observations winsorized at 5%. DiD: FARC x AFTER. Significance levels: 1%***, 5%**, 10%*.

In Sections 2.8.1 and 2.8.2, we show that changes in inventory-to-assets are explained by changes in inventory (and not by changes in assets). Then, when a firm increases 1 percent point its inventory-to-assets, keeping its assets value constant, its inventory goes up by 6%[7]. Also, our results suggest there is a negative relationship between war intensity and firms' inventory. In

0.46 (n = 458). Thus, we reject the hypothesis that the coefficients are significant different.

[7] On average, firms in the treatment group have an inventory-to-assets ratio of 16.8%.

Figure 2.5: Cases: 37kms (first row), 50kms (second row). War intensity: Low (first column), Medium (second column), High (third column)



other words, inventory increases when firms experience transitions from war to peace, whereas inventory decreases when firms undergo transitions from peace to war. In Section 2.8.3, we provide evidence that firms in the vicinity of an attack, one year later, decrease their inventory 1.09 percent points.

2.5.1 Inventory under extreme war conditions

Colombia has zones where war is extremely intense, and others where war is mild. We obtain DiD estimates using war thresholds that incorporate extreme war conditions. Table 2.8 shows that, by setting the war threshold to 5, the DiD coefficient becomes 0.89 (with a significance level of 1%). The 5 war threshold is comparable to the battle-related deaths per 100,000 in Ukraine (Pettersson & Wallensteen, 2015). In contrast, by setting the war threshold to 185, the DiD coefficient increases to 3.65 (at a 5% significance level). The latter threshold is comparable to the battle-related deaths per 100,000 in Syria (Pettersson & Wallensteen, 2015)[8] The DiD coefficient for the 185-threshold model is significantly higher than the 5-threshold model at a 1% level[9].

Thus, from a geographical perspective, there is a negative relationship between war intensity

[8]The war threshold of 25 is comparable to the battle deaths in Yemen, and 105 is (approximately) the 75th percentile of the battle deaths distribution in Colombia.

[9]We perform a (two tail) T-test. The mean difference between the two parameters is 2.76, and its standard error is 1.14. This generates a T-value of 2.41 (n= 406), which rejects the null hypothesis that the mean difference is equal to zero. We confirm the alternative hypothesis that the difference is positive at a 1% level

Table 2.7: Results main model 50kms case.

Variable	Low		Medium		High	
DiD (%)	1.08***	1.10***	0.92**	0.92**	1.14**	1.14**
	(0.40)	(0.40)	(0.46)	(0.45)	(0.46)	(0.46)
FARC (%)	−0.97	0.92	−0.61	1.00	−0.89	0.76
	(1.35)	(1.44)	(1.41)	(1.52)	(1.48)	(1.55)
AFTER (%)	−1.41***	−1.41***	−1.34***	−1.34***	−1.34***	−1.33***
	(0.21)	(0.21)	(0.26)	(0.26)	(0.26)	(0.26)
log(DIST)		0.00		0.00		0.00
		(0.01)		(0.01)		(0.01)
log(ALTITUDE)		0.01		0.01*		0.01*
		(0.01)		(0.01)		(0.01)
log(SIZEM)		−0.01**		−0.01		−0.01
		(0)		(0.01)		(0.01)
ROE		0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)
CASH		−0.11		−0.11		−0.08
		(0.12)		(0.13)		(0.14)
log(SIZEF)		−0.02		−0.03		−0.02
		(0.01)		(0.02)		(0.02)
Observations	36,892	36,892	32,579	32,579	31,542	31,542
Clusters	262	262	241	241	228	228

Robust errors clustered by Municipality in parenthesis. Observations winsorized at 5%. DiD: FARC x AFTER. Significance levels: 1%***, 5%**, 10%*.

and firms' inventory. That is, a firm holds less inventory when the firm is in a municipality with a higher war intensity level.

2.5.2 Firm location and inventory

We further investigate the geographical dimension by exploring how a firm's location in a war zone affects its inventory. We study firms' location relative to battle zones and trade centers.

Effect of proximity to battle zones

To investigate how proximity to a battle zone affects firms' inventory, we identify the top 10 municipalities in Colombia by the number of attacks and calculate firms' distance to these municipalities. To consider battle zones in constant war conditions, we use information before the 2012 peace announcement. We identify the effect of proximity on firms' inventory with β_1.

$$INV_{i,t} = \alpha + \beta_1 \log(DIST_i) + \beta_2 FARC_i + \beta_3 X_i + \beta_4 2011 + \beta_5 2012 + \varepsilon_{i,t}, \tag{2.2}$$

where $INV_{i,t}$ is the inventory-to-assets of firm i in year t, $\log(DIST_i)$ is the log of the distance between the firm's i location and the nearest battle zone, $FARC_i$ is a dummy equal to 1 if the firm i is dominated by FARC (treatment group), X_i is the set of covariates, 2011 is a dummy for year 2011, 2012 is a dummy for year 2012, and $\varepsilon_{i,t}$ is the error term.

In Table 2.9, the coefficient of regression for $\log(DIST)$ shows that a firm closer to a battle

Table 2.8: Results with extreme war thresholds.

Variable	5	25	105	185
DiD (%)	0.89^{***}	0.93^{***}	1.53^{***}	3.65^{**}
	(0.33)	(0.32)	(0.48)	(1.73)
FARC (%)	-0.43	0.21	-3.14^{**}	-0.85
	(0.91)	(1.16)	(1.29)	(2.71)
AFTER (%)	-1.40^{***}	-1.41^{***}	-1.46^{***}	-3.58^{**}
	(0.21)	(0.21)	(0.22)	(1.68)
log(DIST)	-0.76	-0.12	5.31^{***}	4.09^{**}
	(0.63)	(1.24)	(1.96)	(2.02)
log(ALTITUDE)	0.13	0.39	1.41^{**}	1.42^{**}
	(0.26)	(0.46)	(0.58)	(0.65)
log(SIZEM)	-0.81^{***}	-0.75^{**}	1.25	0.99
	(0.28)	(0.34)	(0.92)	(1.05)
ROE	0.02	-0.03	-0.13	-0.29
	(0.18)	(0.20)	(0.24)	(0.28)
CASH	-21.9^{*}	-14.57	-3.30	-22.36^{*}
	(11.83)	(12.12)	(10.84)	(12.16)
log(SIZEF)	-2.31^{**}	-2.14^{*}	-0.80	-1.8^{*}
	(1.11)	(1.26)	(1.2)	(0.96)
Observations	67,982	49,191	21,187	2,812
Clusters	308	269	170	100

Robust errors clustered by Municipality in parenthesis.
Observations winsorized at 5%. Case 50kms.
DiD: FARC x AFTER. Significance levels: 1%***, 5%**, 10%*.

zone hold less inventory compared to a firm far from a battle zone. Thus, the negative relationship between war intensity and firms' inventory is stronger as firms locate closer to battle zones.

Effect of distance to trade centers

A firm far from the main trade centers might incur in more shipping costs (to obtain its supplies) compared to a firm near a trade center. We study the effect of distance to trade centers by implementing a triple Difference-in-Differences model. Our model uses differences before and after the 2012 announcement, across the treatment and control groups, and across firms at different distances from the main trade centers. The main trade centers in Colombia are the cities of Bogota, Medellin, and Cali. In 2009, these cities produced (approximately) 70% of the goods and services across the 50 largest cities in Colombia.

We conduct the following model:

$$\begin{aligned} INV_{i,t} = \alpha + \beta_1 FARC_i + \beta_2 AFTER_t + \beta_3 \log(DIST_i) + \beta_4 (FARC_i \cdot AFTER_t) + \beta_5 [\log(DIST_i) \cdot FARC_i] \\ + \beta_6 [\log(DIST_i) \cdot AFTER_t] + \beta_7 [AFTER_t \cdot FARC_i \cdot \log(DIST_i)] + B_8 X_i + \varepsilon_{i,t}, \end{aligned} \tag{2.3}$$

where $INV_{i,t}$ is the inventory-to-assets of firm i in year t, $\log(DIST_i)$ is the log of the distance between the firm's i location and the nearest trade center, $FARC_i$ is a dummy equal to 1 if the firm i is dominated by FARC (treatment group), $AFTER_t$ is a time-dummy equal to 1 if year t corresponds to the treatment period, X_i is the set of covariates, and $\varepsilon_{i,t}$ is the error term.

Table 2.9: Results distance to battle zones

Variable	Coefficient
log(DIST) (%)	1.05^{***} (0.40)
FARC (%)	-3.23^{**} (1.42)
log(ALTITUDE)	0.00 (0.00)
log(SIZEM)	-0.01^{***} (0.00)
ROE	0.00 (0.00)
CASH	-0.16^{*} (0.09)
log(SIZEF)	-0.02^{*} (0.01)
2011	-0.01^{***} (0.00)
2012	-0.02^{***} (0.00)
Clusters	303
Observations	69,748

Robust errors clustered by Municipality in parenthesis.
Significance levels: 1%***, 5%**, 10%*.
Observations winsorized at 5%.

Table 2.10 shows that the DiD coefficient is negative and significant at a 5% level. Thus, the treatment led firms far from the principal trade centers to reduce their inventory-to-assets compared to firms near to these centers. This result is consistent with the regression coefficient of log(DIST), which is positive and significant at a 5%. It suggests that, in times of war, firms hold more inventory when they are located far from the principal trade centers compared to firms near these centers. Firms far from the trade centers incur more shipping costs as cargo travels longer distances. In war, attacks increase shipping costs—leading firms to hold more inventory. In peace, shipping costs decrease—leading firms to reduce their inventory.

The regression coefficient of $FARC \cdot AFTER$ is positive and significant at a 1%, and it provides further support to our main model. That is, after controlling for firms' distance to the principal trade centers, this coefficient shows inventory increases as war intensity decreases.

2.6 Discussion: The holding and ordering cost effect

In war zones, higher shipping costs lead to higher ordering costs (inventory increases), while higher security and insurance premiums lead to higher holding costs (inventory decreases). Our results suggest the holding cost effect dominates the ordering cost effect.

Table 2.10: Results distance to principal trade centers.

Variable	Coefficient
DiD (%)	-0.47^{**}
	(0.24)
FARC x AFTER (%)	3.17^{***}
	(1.17)
LDIST x FARC (%)	-0.64
	(0.72)
LDIST x AFTER (%)	0.03
	(0.48)
AFTER (%)	-1.11
	(0.72)
FARC (%)	0.50
	(3.45)
log(DIST) (%)	1.07^{**}
	(0.48)
log(ALTITUDE)	0.01^{**}
	(0.00)
log(SIZEM)	-0.01
	(0.00)
ROE	0.00
	(0.00)
CASH	-0.20^{**}
	(0.10)
log(SIZEF)	-0.01
	(0.01)
Clusters	333
Observations	47,193

Robust errors clustered by Municipality in parenthesis.
Significance levels: 1%***, 5%**, 10%*.
Case 50kms. DiD: FARC x AFTER x LDIST.
Observations winsorized at 5%.

2.6.1 The holding cost effect

Economic losses due to terrorist attacks reached 113.5 billion in 2015 (IEP, 2016). When an armed group bombs a firm's warehouse, or steal its inventory, inventory can get damaged or destroyed. In Colombia, these events (private-property attacks) have affected from commercial to non-profit organizations[10].

Consequently, firms invest in security and insurance as a response to these attacks. A survey to 1,113 Colombian firms reveals that firm security costs increase in war: 54% of firms spend 1% to 2% of their sales in security, while the rest spend 3% or more (similar with insurance expenses) (Rettberg, 2008). The Institute for Economics and Peace (2016) calculates the world private security expenses in US $672.8 billion. Also, Abkowitz (2014) estimates that insurance policies are three times more expensive than insurance policies in peace zones —especially after terrorist attacks[11].

2.6.2 The ordering cost effect

When an armed group bombs transport infrastructure (e.g., roads, bridges, or pipelines), firms are subject to transport disruptions and higher shipping costs. In Colombia, transport attacks lead to *"disruptions of the distribution and transport networks"* (Rettberg, 2008), which increase transport costs.

Transport disruptions increase shipping costs. In Afghanistan, the military uses helicopters to supply fuel to their ground units, taking the cost of providing oil to $400 USD per gallon (WSJ, 2011). In Colombia, firm switch to safer but more expensive transport means such as air transport. In other cases, firm transport large amounts of cargo using military or private convoys (RCN-News, 2014). In Iraq, the oil transport depends on truck convoys to ship oil and refined oil out of the country (Robson, 2004).

In summary, higher security expenses and costly insurance premiums in war zones lead to higher holding costs and less inventory. However, expedited transport and (private or military) convoys lead to higher ordering costs and more inventory. Our results suggest the holding cost effect dominates the ordering cost. Moreover, when a firm is close to a battle zone, that firm is likely to be more affected by property attacks that increase holding costs (inventory decreases). But when a firm is far from a trade center, the firm is likely to be more affected by transport

[10]Between 1999 and 2003; the guerrilla groups carried 500 assaults against health care organizations (Ministry of Health, 2013).

[11]For instance, premiums in the Yemen area increased 300% right after two terrorist attacks had affected the warship USS Cole and the Limburg tanker in 2000 and 2002 (Enders & Sandler, 2011).

attacks that increase the firm's ordering costs (inventory increases).

2.7 Conclusions

This paper investigates how war affects firms' inventory. Using the 2012-peace process announcement with one of the two guerrillas in Colombia, and unique panel data, we implement a Difference-in-Differences model that shows that firms' inventory-to-assets decrease in times of war. Further, we show that war intensity and firms' inventory have a negative relationship. This relationship holds from transitions to peace to war, or war to peace, as well as across zones with different war intensities. The firms' location (relative to the principal trade centers and battle zones) moderate our results. Transport attacks increase ordering costs and lead firms far from their main trade centers to hold more inventory. However, attacks increase holding costs too and firms near battle zones hold less inventory compared to firms far from these zones. We conduct additional robustness checks to verify the validity of our claims (Sections 2.8.4, 2.8.5, and 2.8.6).

Our findings have two set of implications for global supply chain management. First, they predict that following a transition from peace to war, firms' inventory would decrease in war zones. Then, firms sourcing from these zones should adjust their safety stocks, or use alternative strategies to mitigate the lower product availability. We show that lower inventory holdings in war zones exacerbate the effect of war on global supply chains. Second, our results show that firm location affects inventory holdings. Firms' location relative to battle zones and trade centers can increase or moderate the effect of war on inventory. Then, when global firms evaluate entry or selecting suppliers from war zones, they should consider suppliers' location as an input for improving forecasts and decision making.

2.8 Appendix 1: Robustness checks

2.8.1 Effect of war on firms' assets

To show that changes in firms' assets do not drive our estimates, we investigate firms' asset value during our period of study and conduct a Difference-in-Differences model to explore firm's assets after the 2012 announcement.

Figure 2.6 presents the log of firms' assets value before and after the 2012 announcement. It shows that firms' asset value did not react to the treatment. Firms' assets value shows a consistent (increasing) pattern before and after the 2012 announcement in the treatment and control groups.

To confirm this observation, we conduct a Difference-in-Differences model using the log of firms' assets as our dependent variable. Table 2.11 shows that the DiD coefficient is not significant at a 10% level in neither specification. Thus, we conclude that changes in inventory explain our main results, and not by changes in firms' asset value.

Figure 2.6: Case 50kms. Log of firms' assets by war threshold. Low (left), Medium (center), High (right).

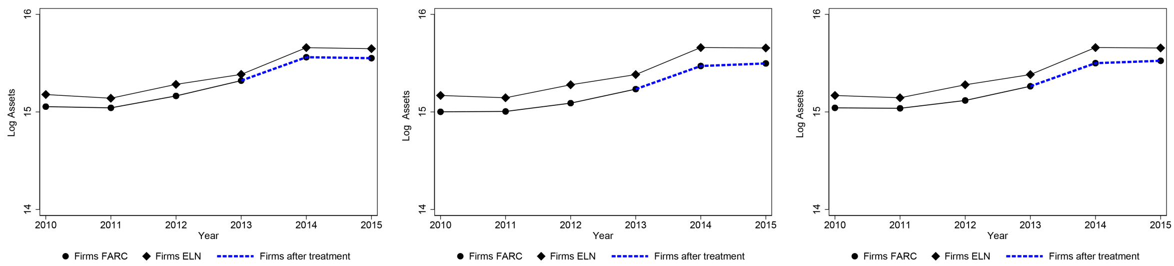


Table 2.11: Results with Log Assets.

Variable	Low		Medium		High	
DiD (%)	0.03	0.03	0.00	0.01	0.00	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
FARC (%)	−0.10	0.01	−0.15	0.02	−0.12	0.02
	(0.10)	(0.03)	(0.11)	(0.03)	(0.12)	(0.03)
AFTER (%)	0.34^{***}	0.34^{***}	0.35^{***}	0.34^{***}	0.35^{***}	0.34^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
log(DIST)		0.01		0.01		0.01
		(0.01)		(0.01)		(0.01)
log(ALTITUDE)		0.00		0.00		0.00
		(0.00)		(0.01)		(0.01)
log(SIZEM)		0.00		0.00		0.00
		(0.00)		(0.01)		(0.01)
ROE		0.00		0.00		0.01
		(0.00)		(0.00)		(0.00)
CASH		−0.44		−0.50		−0.52
		(0.30)		(0.33)		(0.35)
log(SIZEF)		0.86^{***}		0.85^{***}		0.85^{***}
		(0.03)		(0.04)		(0.04)
Observations	36,892	36,892	32,579	32,579	31,542	31,542

Robust errors clustered by Municipality in parenthesis. Observations winsorized at 5%.
DiD: FARC x AFTER. Case 50kms. Significance levels: $1\%^{***}$, $5\%^{**}$, $10\%^{*}$.

2.8.2 Effect of war on inventory value

To illustrate the impact of war on firms' inventory value (in contrast to inventory-to-assets), we replicate the main model (for the 50kms case) using the log of firms' inventory value as our dependent variable. Inventory value is in thousands of Colombian pesos. Table 2.12 shows that inventory value increased as a result of the 2012 announcement. All specifications are positive and significant at a 1% level, supporting our previous findings. The average DiD coefficient by war threshold is 0.68.

Table 2.12: Results using Log Inventory Value.

Variable	Low		Medium		High	
DiD (%)	0.70^{***}	0.71^{***}	0.66^{***}	0.66^{***}	0.67^{***}	0.69^{***}
	(0.20)	(0.19)	(0.21)	(0.2)	(0.22)	(0.21)
FARC (%)	-0.01	1.21^{**}	0.11	1.26^{**}	0.07	1.16^{**}
	(0.60)	(0.48)	(0.59)	(0.50)	(0.61)	(0.50)
AFTER (%)	-0.49^{***}	-0.50^{***}	-0.49^{***}	-0.50^{***}	-0.49^{***}	-0.50^{***}
	(0.15)	(0.14)	(0.17)	(0.16)	(0.17)	(0.16)
log(DIST)		0.27		0.28		0.35
		(0.44)		(0.47)		(0.52)
log(ALTITUDE)		0.28		0.16		0.16
		(0.19)		(0.24)		(0.24)
log(SIZEM)		-0.57^{***}		-0.63^{***}		-0.66^{***}
		(0.16)		(0.20)		(0.19)
ROE		-0.01		-0.01		-0.14^{*}
		(0.05)		(0.06)		(0.08)
CASH		-5.36		-3.36		-2.09
		(4.39)		(4.82)		(4.9)
log(SIZEF)		0.76		0.97^{*}		1.06^{*}
		(0.52)		(0.57)		(0.58)
Observations	36,892	36,892	32,579	32,579	31,542	31,542

Robust errors clustered by Municipality in parenthesis. Observations winsorized at 5%. Case 50kms. DiD: FARC x AFTER. Significance levels: 1%***, 5%**, 10%*.

2.8.3 Inventory one year after attacks

We collect information of all attacks from 2010 to 2012. Then, we select municipalities with attacks in 2011 only. We study firms' inventory-to-assets in those municipalities before and after 2011. Table 2.13 shows a description of the events studied.

Table 2.13: Resulting attacks for the event study

Municipality	Date	Group	Type of attack
Medellin	27-Jun-11	ELN	Private property-electric infrastructure
	22-Jul-11	-	Private property-firm infrastructure
Neiva	28-Jan-11	FARC	Private property-firm infrastructure
	3-Feb-11	FARC	Private property-retailer infrastructure
	14-Apr-11	FARC	Private property-retailer infrastructure
	10-May-11	FARC	Private property-firm infrastructure
	3-Dec-11	FARC	Private property-transport means
Palermo	18-May-11	FARC	Transport attack-vehicle burning
Popayan	5-Jun-11	ELN	Transport attack-sabotage
Villavicencio	3-Oct-11	FARC	Transport attack-vehicle burning

Table 2.14 shows the average inventory-to-assets in each of the municipalities of study. The average change in percentage points from 2010 to 2011 was 0.43, whereas the average change from 2011 to 2012 was -1.09—one year after the attacks.

Table 2.14: Inventory-to-assets in selected municipalities

Municipality	2010		2011			2011-2010	2012		2012-2011
	INV (%)	Obs.	INV (%)	Attacks	Obs.		INV (%)	Obs.	
Medellin	17.43	2,100	16.67	2	2,269	-0.76	16.06	2,353	-0.61
Neiva	20.49	158	20.92	5	162	0.43	19.03	177	-1.90
Palermo	0.23	2	0.13	1	3	-0.10	0.52	2	0.38
Popayan	25.29	62	28.23	1	67	2.94	26.46	64	-1.77
Villavicencio	22.33	156	21.93	1	179	-0.39	20.38	169	-1.55
Mean	17.15		17.58			0.43	16.49		-1.09

2.8.4 Economic changes throughout the period of study

To evaluate if the treatment correlates with economic changes in the treated or control groups, we estimate the effect of the 2012-peace process on the total production of goods and services. We use Added Value production to measure the net value of all products generated in a municipality. This variable represents the gross value of the local production minus the cost of the intermediate consumption.

We obtain yearly data from the Colombian Department of Statistics of the Added Value Production in each municipality from 2011-2015. We use this variable as the dependent variable in the main model. Table 2.15 shows that DiD coefficient is negligible. This result has two implications. First, the 2012-peace process announcement is not associated with changes in economic factors taking place in 2012. Second, this result suggests the local demand was kept constant after the peace process announcement compared to the pre-treatment period.

Table 2.15: Results using the Added Value Production.

Variable	Low		Medium		High	
DiD (%)	-0.02	0.00	0.00	0.02	0.01	0.02
	(3.77)	(3.51)	(4.37)	(4.33)	(4.39)	(4.47)
FARC (%)	-1.61^{**}	-2.24^{***}	-1.76^{***}	-2.25^{***}	-1.79^{***}	-2.25^{***}
	(66.72)	(44.92)	(62.02)	(44.33)	(62.46)	(44.23)
AFTER (%)	0.18^{***}	0.18^{***}	0.17^{***}	0.16^{***}	0.17^{***}	0.16^{***}
	(2.73)	(2.53)	(3.43)	(3.26)	(3.43)	(3.26)
log(DIST)		-0.39^{**}		-0.4^{**}		-0.41^{**}
		(0.16)		(0.16)		(0.17)
log(ALTITUDE)		0.21^{*}		0.3^{**}		0.3^{**}
		(0.12)		(0.14)		(0.14)
log(SIZEM)		0.69^{***}		0.73^{***}		0.72^{***}
		(0.14)		(0.19)		(0.19)
ROE		0.00		0.02		0.02
		(0.08)		(0.09)		(0.09)
CASH		3.42^{*}		2.53		2.64
		(1.81)		(1.77)		(1.8)
log(SIZEF)		0.82^{***}		0.70^{**}		0.71^{**}
		(0.3)		(0.3)		(0.31)
Observations	31,268	31,268	27,604	27,604	26,743	26,743
Clusters	251	251	231	231	219	219

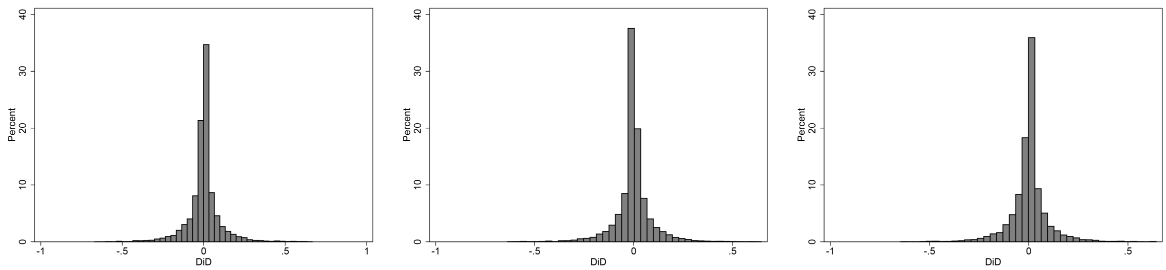
Robust errors clustered by Municipality in parenthesis. Observations winsorized at 5%. Case 50kms. DiD: FARC x AFTER. Significance levels: 1%***, 5%**, 10%*.

2.8.5 Placebo test

To show that spurious correlation does not drive our estimates, we conduct a placebo test. We run 10,000 Difference-in-Difference models using the war thresholds from our main model (low, medium, high). We obtain the sample municipalities from each war threshold specification, and then we assign the treatment randomly (FARC or ELN). If correlation drives our results, then the random assignment would lead to significant treatment results.

Figure 2.7 shows histograms for each of our war levels after 10,000 regressions. These estimates are distributed around zero, showing that the random treatment distribution does not generate consistently better estimates than those in our main model. The DiD coefficient in the low threshold model is on average $-4.5x10^{-4}$, $4.8x10^{-5}$ in the medium, and $-5x10^{-5}$ in the high threshold model. For these models, across the 10,000 estimations, the average DiD coefficient is not different from zero at a 1% significance level. Therefore, we conclude that spurious correlation does not drive our results and that our estimates explain the effect of war on firms' inventory.

Figure 2.7: Placebo test by war threshold. Low (left), Medium (center), High (right). DiD = FARC x AFTER



2.8.6 Main model with fixed effects

To show how sensitive is our model to the specification from Equation 2.1, we formulate a Difference-in-Differences model using an alternative specification with fixed effects in cross sections and units of time (Generalized Difference-in-Differences). We formulate the following model:

$$INV_{i,t} = \alpha + \rho_m + \gamma_t + \beta(FARC_i \cdot AFTER_t) + \varepsilon_{i,t}, \tag{2.4}$$

where $INV_{i,t}$ is the inventory-to-assets of firm i in year t, ρ_m are municipality fixed effects, γ_t are year fixed effects, $FARC_i$ is a dummy equal to 1 if the firm i is dominated by FARC (treatment group), $AFTER_t$ is a time-dummy equal to 1 if year t corresponds to the treatment period, and $\varepsilon_{i,t}$ is the error term.

Table 2.16 shows the results for specifications with the three war thresholds (low, medium, high) and the two cases (37kms, 50kms). We find that the DiD coefficients are significant and consistent with our main results.

Table 2.16: Results with fixed-effects specification.

	Low		Medium		High	
Case	37kms	50kms	37kms	50kms	37kms	50kms
DiD (%)	1.00^{**}	1.02^{**}	0.81^{*}	0.81^{*}	0.99^{**}	0.98^{**}
	(0.4)	(0.4)	(0.48)	(0.47)	(0.48)	(0.47)
Municipality Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,909	36,892	32,633	32,579	31,616	31,542

Robust errors clustered by Municipality in parenthesis. DiD: FARC x AFTER
Observations winsorized at 5%. Significance levels: $1\%^{***}$, $5\%^{**}$, $10\%^{*}$.

Chapter 3

Communities in the Crossfire: How Companies Can Do Well by Doing Good

3.1 Introduction

Nigeria, 2003. Two age-long ethnic rivals are fighting in the "delta oil region" where Chevron operates. Several villages are destroyed, dozens are killed, and thousands flee their homes. In dealing with the crisis—which has disrupted one-third of the firm's oil production, Chevron bets on developing social investments to help decrease the violence intensity. Eighteen months later, these social efforts paid off[1]:

> Among the tangible outcomes of the company's efforts is a measurable improvement in the security of the operating environment, a substantial improvement in the health, education and economic well-being of local communities and most of all, a remarkable improvement in the cordial relationship between the local communities and the company.

Firms' social investments can improve the well-being of communities afflicted by war. But how viable are those investments? Do firms benefit from them? In this paper, we provide evidence that firms in conflict zones do well by doing good. We find that by influencing core operational processes of workforce, sourcing, and logistics management, social investments improve firm operational performance.

However, showing that social investments in war zones improve firm operational performance is difficult. First, data from war zones is sensitive and difficult to get. Second, measuring and collecting social investment data at the firm level is challenging. Because there is no one category of social investment in the financial statements, these expenses are difficult to identify[2]. Third, establishing causality is an issue. Even if we had firms' social investment expenses to explain firm performance, reverse causality and omitted variable issues would lead to endogeneity issues. For

[1]Further reference at `www3.weforum.org/docs/WEF_Chevron_in_Nigeria.pdf`
[2]Following the International Financial Reporting Standards (IFRS).

instance, firms with the highest margins, or the most productive, might be the same executing these social investments.

We address these difficulties by using a natural experiment from the Colombian oil industry, an industry that suffers from the civil war and comprises two types of firm: exploration and production firms and oil service firms. In 2003, the industry witnessed a major shift in its social investments policies. The Colombian government approved a law obliging all oil exploration and production firms to invest 1% of their exploration and production budget in social affairs. While firms in the exploration and production sector were subject to the law, firms in the oil service sector were not—even when both share the same industry characteristics. We study the 2003 law by collecting a panel with all 252 firms in the Colombian oil industry: 114 firms from the oil exploration and production sector and 138 from the oil service sector.

We implement a Difference-in-Difference model to obtain causal estimates of the effect of social investments on firm performance. Whereas oil exploration and production firms (those spending 1% of their budget in social investments) constitute our treatment group, oil service firms (those the 2003 law did not affect) constitute our control group. As a response to the law, we find that firms in the treatment group increased their operating margin 23 cents for every dollar in sales. We also show that larger firms earn higher yields from social investments. To understand why social investments improve firm performance, we collected qualitative evidence from the Colombian oil industry. After two field visits and thirteen semi-structured interviews, we find evidence that firms benefit from social investments via fewer war-related disruptions. We find these benefits translate into higher revenue and lower costs.

Our work provides evidence that social investments improve firm operational performance. However, some questions remain unanswered, for example, What type of social investment suits the needs of communities and firms best: employment, education, or health projects? Also, How should social investments projects be managed to maximize both the communities' and firms' goals?

3.2 Literature

According to the European Commission, social investment is about investing in people.

> It means policies designed to strengthen people's skills and capacities and support them to participate fully in employment and social life[3].

[3] http://ec.europa.eu/social/main.jsp?catId=1044

Armed conflicts pose unique challenges for communities and humanitarian organizations. Table 3.1 presents the main differences between natural disasters and armed conflicts. Armed conflicts lead to displacement, migration, and destruction of capital and labor force (Collier, 1999; Gustavsson, 2003; Wieloch, 2003; Harvey, 2013). Also, the humanitarian response should be sustained for longer periods, and this response faces security issues including transport attacks, land piracy, and terrorist attacks (Camacho & Rodriguez, 2013; Restrepo et al., 2006; Rettberg, 2002).

Table 3.1: Parallel between natural disasters and armed conflicts

Dimension	Natural disasters	Armed conflicts
Interaction (actors)	Actors are mostly neutral	Actors are strategic
Duration	Typically short, lasts days or months	Short or long (years)
Migration	Limited to a specific group (for evacuation)	Massive forced migration
Security	Mild insecurity during early response	Security issues during long periods
Humanitarian response	Sequential response	Continuous response

The effect of social investments on firm performance has been a neglected topic of study in the man-made disaster management literature. In this literature, authors have studied the impact of conflicts on humanitarian organizations. Pedraza-Martinez & Van Wassenhove (2013) study vehicle replacement in conflict zones. By using field data, the authors find that conflict intensity does not affect the salvage value of vehicles used for humanitarian operations. Jola-Sanchez et al. (2016) study the operational performance of rural hospitals in war zones in Colombia. By using a panel from 163 hospitals (from 2007 to 2011), the authors conclude that conflict hospitals have higher total factor productivity but are 11% less cost efficient than peace hospitals.

Through social investments firms can provide humanitarian aid to communities suffering civil wars. However, the impact of social investments on war-reduction efforts is not clear. Crost et al. (2014) estimate the causal effect of development programs on the conflict in the Philippines. The authors find that municipalities eligible for these programs experience increases in conflict compared to ineligible municipalities in the early stages of the program. The authors argue insurgents try to sabotage these programs because the programs' success would weaken their support in the community. Nunn & Qian (2014) study the US Food Aid program. By using information from the UCDP[4] dataset, the authors show that an increase in US food aid increases the number of incidences and duration of civil conflicts. On the other hand, Berman et al.

[4]Uppsala Conflict Data Program

(2013) use attack and aid data from Iraq to explore the effect of development programs on rebel violence. The authors show that aid spending reduces violence when these programs are small and community members value them. Beath et al. (2016) use data from a development program in Afghanistan. The authors conclude that the program reduce violence, improve economic outcomes, and increase support for the government.

3.3 Background

Over five decades, the Colombian civil war has afflicted the oil industry, whose operations—mostly in rural zones, have overlapped the most heated war zones in the country (Mantilla Valbuena, 2012). With oil exports equal to 50% of merchandise exports[5]—the six highest in the world, Colombia's economy heavily depends on the oil industry.

According to the International Standard Industrial Classification[6], the Colombian oil industry comprises two types of firms. The first type corresponds to "extraction of crude petroleum and natural gas" firms (code C1110) and the second to "services related to the extraction of petroleum and natural gas" firms (code C1120). In 2003, to aid communities affected by the oil exploitation—and the civil war, the government approved a law compelling exploration and production firms (C1110) to invest 1% of their budgets in programs benefiting communities (Law 1760 of 2003, Article 5). Since the government (National Hydrocarbons Agency) signs a contract with all the exploration and production firms, all contracts starting 2004 included this new social component. Before 2004, these social investments did not exist[7].

To understand what social investment means, we asked managers in the largest oil companies in Colombia[8] about their social investments. We conducted two field visits and thirteen interviews; we obtained 8.7 hours of audio and 102 pages of transcripts. We found these investments aim to improve human development and quality of life within communities—which is not surprising. But what is surprising is that these programs influence core operational processes of workforce, supply chain, and logistics management.

1. **Workforce:** To provide economic participation, firms train community members and make them part of their workforce. Community members not only gain skills but also obtain well-paid jobs. These jobs provide up to four times more income to local households than

[5]World Bank Development Indicators.

[6]United Nations classification, version 3.1, adapted for Colombia.

[7]We corroborated this information with the National Hydrocarbons Agency. Further details provided in Appendix 2.

[8]We interviewed the operations vice president, corporate social responsibility manager and other professionals of five oil firms.

other local jobs. Firms aim for all the non-qualified labor force and at least 70% of the qualified force to employ community members.

2. **Supply chain:** Local suppliers have priority. Further, firms ensure local providers are able to offer competitive goods and services by developing capacity and promoting local institutional development. For example, community programs include the provision of work tools and technology to boost the production of local agricultural goods. Other initiatives include institutional developments to boost entrepreneurship and local production capacity.

3. **Logistics:** Some projects improve communities access to healthcare, education, and social services; others improve local infrastructure. Firms invest in projects such as road maintenance and municipality infrastructure renovation (e.g., libraries, schools, and cultural centers).

3.4 Data

We collect a panel of all 252 legally-established firms in the Colombian oil industry: 114 firms in the exploration and production subsector (C1110) and 138 classified in the oil service sector (C1120). The time span of this panel ranges between 2001 and 2006: three years before and after the law passed. Our panel contains 804 firm-year observations. For each firm-year observation, we obtain operational data, including firms' total and current assets, inventory, equity, revenue, costs of goods sold, operating income, and net income after taxes (akin to the Compustat's Dataset). We obtain these data from the Colombian Ministry of Trade, Tourism and Industry. Table 3.2 provides a data sample of a C1110 and a C1120 firm. The majority of firms in our sample were operating throughout the entire span of our sample. While some firms may enter (after the beginning of our sample period) or exit the market (before the end of our sample period), there is no missing data due to misreporting.

3.5 Model

Firms in the Colombian oil industry (C1110 and C1120) have similar business models, uncertainties (e.g., oil prices), and operational schemes. In 2003, the Colombian government approved a law obliging all firms in the oil exploration and production sector (C1110) to invest 1% of their annual exploration and production budget in social investments. The law did not affect oil service companies (C1120)—which do not sign contracts with the Colombian government. Thus,

Table 3.2: Data sample of firms in the C1110 and C1120 sector

ID	Sector	Name	Year	Assets			Equity	Income			
				Total	Current	Inventory		Revenue	COGS	Operating	Net
8000-00750	C1110	Petro-Santander Inc	2001	39,246	11,323	73	(1,998)	62,600	11,100	43,348	25,628
			2002	43,007	16,145	103	10,219	60,600	12,900	37,754	33,142
			2003	56,475	18,716	146	2,779	76,500	15,500	48,477	38,595
			2004	67,651	4,947	113	11,505	95,100	28,700	46,581	32,560
			2005	78,023	3,844	50	5,664	114,000	23,100	76,940	42,239
			2006	114,200	17,252	171	35,580	138,000	18,600	90,937	51,123
8605-16178	C1120	Tucker Energy Services S.A.	2001	2,710	1,404	116	1,886	4,357	1,133	409	(122)
			2002	2,076	645	159	1,481	2,310	717	(977)	(1,257)
			2003	3,427	1,659	108	1,864	6,159	1,989	1,538	601
			2004	3,589	1,634	231	2,297	3,675	1,193	(450)	(739)
			2005	5,062	2,751	342	3,502	8,464	2,004	2,095	558
			2006	7,593	4,525	515	4,866	12,700	2,505	4,130	1,934

All numeric variables are in millions of Colombian pesos.
COGS: Costs of Goods Solds.

our treatment group consists of firms in the C1110 sector, and our control group of firms in the C1120 sector. We use three years of data to investigate the pre-law phase (i.e., 2001 through 2003) and three years to study the post-law phase (i.e., 2004 through 2006).

Difference-in-Differences Equation

We use a Difference-in-Differences model to estimate the effect of social investments on firms' operational performance. Heretofore, we refer to this effect as the Average Treatment Effect on the Treated (ATET). We identify ATET (β) using a generalized Difference-in-Differences model (fixed effects):

$$PERFORMANCE_{i,t} = \alpha + \rho_i + \gamma_t + \beta(C1110_{i,t} \cdot AFTER_{i,t}) + \varepsilon_{i,t}, \qquad (3.1)$$

where $PERFORMANCE_{i,t}$ is the operational performance of firm i in year t, ρ_i are firm fixed effects, γ_t are year fixed effects, $C1110_{i,t}$ is a dummy equal to 1 if the firm i in year t is in the C1110 sector (treatment group), $AFTER_{i,t}$ is a dummy equal to 1 if year t belongs to the treatment period (2004, 2005, 2006), and $\varepsilon_{i,t}$ is the error term.

Performance variable: Operating Margin ($OPMARGIN$)

We use firms' operating margin to study operational performance. A firm's operating margin measures the firm's ability to transform revenue (sales) into profits. For example, if a firm has an operating margin of 10%, this firm earns $0.10 for every dollar of sales—after discounting fixed and variable operational expenses. We define this metric as: $OPMARGIN_{i,t} = \frac{\text{Operating Income}_{i,t}}{\text{Revenue}_{i,t}}$, where Operating Income$_{i,t}$ is the firm's i earnings in year t after discounting operational expenses such as wages and fixed costs. Revenue$_{i,t}$ includes the total sales of firm i in year t. Figure 3.1 shows that, before the 2003 law, firms' operating margin in the treatment and control groups had a consistent trend. But after the announcement, firms' operating margin in the treated group increased to 18.9%, while the operating margin in the control group decreased to -2.8%.

Figure 3.1: Operating Margin in the Treatment and Control groups

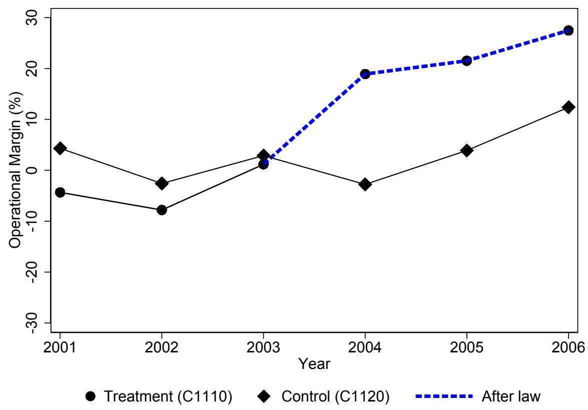


Table 3.3 shows descriptive statistics of our sample using other operational variables. We observe that, on average, firms in the treatment group have a higher Operating Margin, Cash Ratio, ROA, and Size. Firms in the control group have a higher Leverage ratio and Inventory level. We calculate these variables as follows:

1. Leverage Ratio ($LEVERAGE$): This ratio shows the ability of a firm to meet its financial obligations. We define $LEVERAGE = \frac{\text{Total Debt}}{\text{Total Assets}}$, where Total Debt includes short- and long-term debt.

2. Cash Ratio ($CASH$): This metric assesses a firm's ability to meet its short-term liabilities. We define $CASH = \frac{\text{Available Assets}}{\text{Current Assets}}$.

3. Inventory-to-assets(INV): This ratio shows how much inventory a firm uses as a proportion of total assets. We define $INV = \frac{\text{Inventory}}{\text{Total Assets}}$.

4. Return on Assets (ROA): This metric shows how profitable a firm is relative to its total assets. We define $ROA = \frac{\text{Net Income After Taxes}}{\text{Total Assets}}$.

5. Size ($\log ASSETS$): It is defined as the log of firms' total assets.

3.6 Results

Our results suggest the effect of social investments on firms' operating margin is positive. Compared to the control group, firms in the treatment group observed higher operating earnings

Table 3.3: Descriptive statistics

Variable	C1110 (Treatment Group)			C1120 (Control Group)		
	Mean (%)	Std. Dev.	Obs.	Mean (%)	Std. Dev.	Obs.
OPMARGIN	9.1%	0.59	229	3.8%	0.35	366
LEVERAGE	33.8%	0.27	364	41.2%	0.28	440
CASH	22.4%	0.27	360	14.2%	0.20	438
INV	0.9%	0.02	364	6.5%	0.10	440
ROA	1.1%	0.27	364	-1.3%	0.25	440
log (ASSETS)	15.9	2.99	364	15.3	2.09	440
Firms		114			138	

Observations winsorized at 5%.
Std. Dev.: Standard Deviation. Obs.: Observations.

after the 2003 law. Table 3.4 shows the ATET (Average Treatment Effect on the Treated) for five models. The first uses firm- and year-fixed effects, and its ATET is 0.23 (Row DIFF-DIFF); the second uses firm-fixed effects only, and its ATET is also 0.23. The third and fourth models employ random effects; their ATET is 0.17 and 0.16, respectively. The fifth model uses the variables provided in Table 3.3 as covariates instead of firm and year effects; its ATET is 0.13. Whereas higher firm ROA and log $ASSETS$ increase firm operating margin, higher $LEVERAGE$ decreases it. INV and $CASH$ do not explain firms' operating margin significantly. We draw our conclusions using the firm- and year-fixed effects model (column I). After running a Hausman test, we conclude that a fixed-effects model is a better fit for our data than a random-effects model[9]. Also, the fifth model does not control for idiosyncratic variables explaining firm performance—unobserved in our data—such as productivity and managerial ability.

Size of the social investments

We find firms' operating margin increases as firms take on larger social investments. We show this effect by adding firm size (log of $ASSETS$) as an explanatory variable and including the proper interaction terms in a triple difference-in-difference equation. Since the 2003 law set social investments at 1% of firms' annual budget on exploration and production, the larger the firm, the higher the social investments[10]. Table 3.5 shows that, after the law passed in 2003, the larger the firm, the larger the effect on its operating margin. In the year- and firm-fixed effects model (column III), this effect increases with the log of $ASSETS$ by 0.08 percent points (row DIFF-DIFF).

[9]With a Chi^2 of 7.33 and a P-value of 0.291, we cannot reject the null hypothesis that the average difference between the two models is not systematic. The average difference between the two models (columns I and III) is 0.061.

[10]We assume larger oil firms have larger exploration and production budgets.

Table 3.4: Results main model

Variable	(I)	(II)	(III)	(IV)	(V)
DIFF-DIFF	0.23***	0.23***	0.17**	0.16**	0.13**
	(0.09)	(0.09)	(0.08)	(0.07)	(0.06)
AFTER		-0.01		0.04	-0.03
		(0.04)		(0.03)	(0.03)
C1110					-0.09**
					(0.04)
LEVERAGE					-0.12**
					(0.05)
CASH					-0.02
					(0.06)
INV					-0.11
					(0.11)
ROA					1.51***
					(0.1)
log (ASSETS)					0.01*
					(0.01)
Firm effects	Yes	Yes	Yes	Yes	No
Year effects	Yes	No	Yes	No	No
Observations	595	595	595	595	595
R^2	0.60	0.59	0.04	0.03	0.57

Robust errors in parenthesis. Observations winsorized at 5%
DIFF-DIFF: C1110 x AFTER. Significance: 1%***, 5%**, 10%*.
Model I and II: Fixed effects, Model III and IV: Random Effects
Model V: Covariates

Social investments in war zones

To understand why social investments improve firms' operational performance in war zones, we interviewed thirteen subjects from five oil firms in Colombia[11]. We find that social investments affect workforce, sourcing, and logistics processes. By employing community members, sourcing from local suppliers, and developing local infrastructure projects, a firm not only provides solutions to its operational needs, but also improves its response to the operational challenges in war zones.

With social investments, communities become a stakeholder in the company. And this relationship is mutually beneficial because communities have privileged information about the modus operandi of armed actors in their regions. By realizing that war-related events affect the communities interests too, sharing their privileged information becomes beneficial. Some community members will inform about terrorist attacks, blockages, or other war-related disruptions; others will protect the firm from these violent actions themselves.

> They [community] have privileged information; they get around in the zone, and at some point, they know the difficulties that we might have in the transport. They contribute important information concerning the activities of armed groups against

[11] Appendix 3 provides information about the qualitative data collected.

Table 3.5: Effect of firms size

Variable	(I)	(II)	(III)
DIFF-DIFF	0.09**	0.09**	0.08**
	(0.04)	(0.04)	(0.04)
AFTER x C1110	-1.32*	-1.28*	-1.11*
	(0.77)	(0.77)	(0.66)
log(ASSETS) x AFTER	-0.06**	-0.06**	-0.01
	(0.03)	(0.03)	(0.03)
log(ASSETS) x C1110	-0.03	-0.03	0.11*
	(0.04)	(0.04)	(0.09)
AFTER	0.95**	0.97**	0.09
	(0.45)	(0.45)	(0.49)
C1110	0.34	0.33	-2.46
	(0.65)	(0.66)	(1.59)
log (ASSETS)	0.07***	0.07***	0.1**
	(0.02)	(0.02)	(0.05)
Firm effects	No	Yes	Yes
Year effects	No	No	Yes
Observations	595	595	595
R^2	0.08	0.09	0.64

Robust errors in parenthesis. Observations winsorized at 5%
DIFF-DIFF: C1110 x AFTER x log(ASSETS).
Model II and III: Fixed effects
Significance: 1%***, 5%**, 10%*.

infrastructure, roads, and bridges (Company 2, Subject 2).

> Sometimes they are [community members] who inform us of possible events—There is going to be a blockage! There is going to be an armed action! A terrorist attack affects not only the firm but also a lot of people. This is not a formal agreement but something spontaneous. (Company 2, Subject 1).

> Inasmuch as the community and the company work together, and the community sees the company as an ally, I believe the community starts protecting the company; the trust between the firm and the community is what shields us from these public-order issues (Company 1, Subject 1).

As a result, by investing in communities and improving their relationship with the locals, firms mitigate war-related disruptions. The firm-community alliance leads to higher revenue and lower operational costs for firms. When a war-related event takes places, oil production can be interrupted, and revenue decreases. The opportunity cost of production shutdowns is high. Companies 1 and 2 have suffered more than 1,500 attacks and have had 3 million barrels of oil spilled—the BP oil spill in the Gulf of Mexico in 2010 was 4.9 million barrels.

> We have had interruptions of 20 days, almost a month. Although the production

is automated, the last incident caused more than 10 million dollars in production losses (Company 2, Subject 1).

A metric [of the benefit of social investments] is the frequency of social events, which has been reduced, year after year. Before, we could have disruptions of 10 or 15 days. Today, we might have 3-day disruptions, and we can solve them fast (Company 1, Subject 1).

The work with communities reduces the number of social events and costs decrease. Without doubts [costs decrease] because [without working with communities] we have to increase security investments if we want to get equipment to our areas. Often, we need support from the military, and that involves additional costs. There would be higher security and logistic costs. Usually, we would have to pay standby costs [costs of holding inventory on the road] for our cargo; ultimately, we would need to use air transport (Company 1, Subject 1).

Validity and robustness checks

To validate the natural experiment, we conducted two interviews with the Colombian Petroleum Association. We also performed robustness checks that included a balanced panel model (22 treatment and 28 control firms), a model with firms' Gross Margin Ratio as the independent variable, a model using the U.S. oil industry as the control group, and the analysis of firms' revenue and costs trends. Our results are consistent. Appendices 1 and 2 provide further details.

3.7 Conclusions

The objective of social investments is to improve people's wellbeing. Through social investments firms can provide humanitarian aid and economic opportunities to local communities afflicted by war. In this paper, we provide evidence from the Colombian oil industry that, from every dollar in sales, social investments of 1% of the firms' annual budget, lead to an increase of 23 cents in the firms' operating margin. Also, by collecting qualitative data, we find that firms observe higher operating margins—due to social investments—because they suffer fewer war-related disruptions, which increases revenue and decreases costs. We also provide evidence that social investments influence core operational processes of workforce, sourcing, and logistics management. Future research should study how other industries—operating in war zones—

would benefit from making social investments. Also, further research opportunities include studying what type of social investment (e.g., poverty reduction, employment, education, etc.) suits the needs of communities and firms best, and how these projects can be managed to become more efficient and effective.

3.8 Appendix 1: Robustness checks

3.8.1 Balanced Panel

We study a balanced panel of 22 treatment and 28 control firms. By using a firm and year fixed-effects model, we show the Difference-in-Differences estimator is 0.17 (DIFF DIFF row, Table 3.6). Also, we calculate firms' gross margin, $GMARGIN_{i,t} = \frac{\text{Revenue}_{i,t} - \text{COGS}_{i,t}}{\text{Revenue}_{i,t}}$, where $\text{COGS}_{i,t}$ is the Cost of Goods Sold by firm i in year t, and find the Difference-in-Differences estimator is 0.07 in that case. Thus, our results are robust to different specifications and operational performance variables.

Table 3.6: Balanced panel

Variable	$OPMARGIN$	$GMARGIN$
DIFF-DIFF	0.17^{**}	0.07^{**}
	(0.07)	(0.04)
Firm effects	Yes	Yes
Year effects	Yes	Yes
Observations	300	300
R^2	0.51	0.82

Robust errors in parenthesis.
DIFF-DIFF: C1110 x AFTER.
Observations winsorized at 5%
Significance levels: $1\%^{***}$, $5\%^{**}$, $10\%^{*}$.

3.8.2 Control group: U.S. Oil industry

As an alternative model, we use the U.S. exploration and production industry as the control group. We use the Damodaran Online dataset[12] to obtain firm Operating Margins before taxes[13] for the U.S. "petroleum (producing)" industry. Table 3.7 shows the Difference-in-Differences estimator, which is consistent to our estimates and equal to 0.16.

Table 3.7: Difference-in-Differences

	Before Law	After Law	DIFF
C1110	-0.04	0.23	0.26
U.S.	0.33	0.44	0.10
DIFF	-0.37	-0.21	0.16

Treatment (C1110): 44 firms.
Control (U.S. firms): 178 firms.

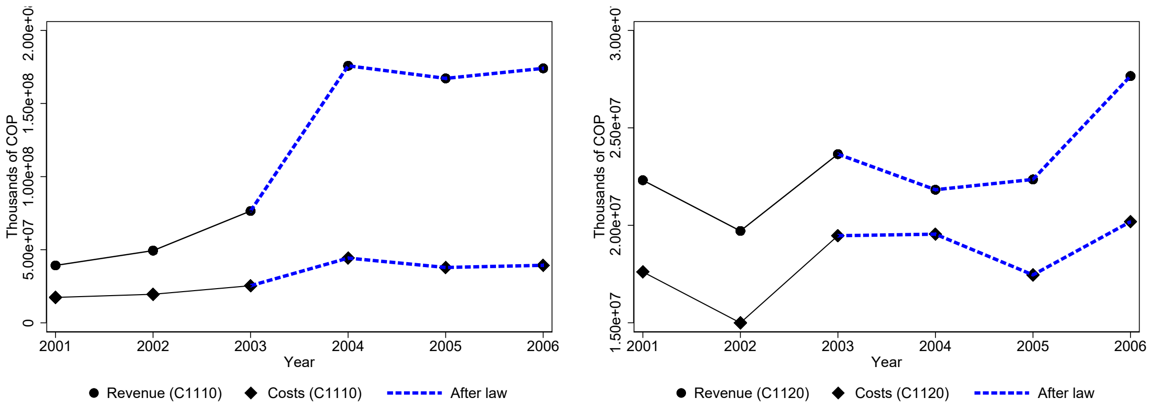
3.8.3 Revenue and costs

Figure 3.2 shows the firms' revenue and total costs[14] over the period of study. On the left, the treatment group observes a major change in their revenue-cost gap after the law was approved.

[12] Available at `http://people.stern.nyu.edu/adamodar/New_Home_Page/dataarchived.html`
[13] Earning Before Interest and Taxes over Sales
[14] It includes the Cost of Goods Sold, Administration Costs and Operational Costs.

Costs did not grow at the same pace than revenue did. Instead, on the right, the control group shows a revenue-costs gap that does not seem affected by the 2003 event.

Figure 3.2: Revenue and costs in the treatment and control groups



Includes all 252 firms in the Colombian oil industry.

3.9 Appendix 2: Validity check

3.9.1 National Hydrocarbons Agency and Colombian Petroleum Association

We raised a formal petition to the National Hydrocarbons Agency (ANH) to provide information about the 2003 (law) Program in Benefit of Communities. The National Hydrocarbons Agency is the official government entity that supervises and evaluates the execution of these investments. Their response on March 26, 2018 validates our experimental setting:

> The ANH started subscribing hydrocarbons contracts from the second semester of 2004. Since then, it has been included the Programs in Benefit of Communities as part of the contractor's duties (National Hydrocarbons Agency, 2018).

Also, we conducted two interviews with an expert of the Social Management division in the Colombian Petroleum Association. This association is the union that represents the private firms dedicated to the exploration, production, transport and distribution of oil and gas in Colombia. According to our interviewee, 2004 saw the beginning of the mandatory social investments in the Exploration and Production sector in Colombia. These social investments follow the guidelines of the ANH and the PNUD (United Nations Office for the Development).

3.10 Appendix 3: Summary of interviews

We study five oil companies affected by the Colombian civil war. We contacted the supply chain department of oil firms operating in conflict zones. We conducted two field visits to Colombia and thirteen interviews with current or former employees (in the supply chain department) of the oil firms studied. Table 3.8 lists the interviews conducted.

Table 3.8: Summary of interviews

Sector	**Company**	**Subject**	**Position**	**Experience (years)**	**Date**	**Duration (mins)**
C1110	1	1	Supply Chain Manager	15	7-Mar-18	31
		2	Inventory Manager	17	1-Jun-17	22
	2	1	Corporate Social Responsibility Manager	13	18-Mar-18	83
		2	Logistics and trade supervisor	34	12-Mar-18 1-Jun-17	23 79
	3	1	Corporate Social Responsibility Manager	12	12-Mar-18	41
	4	1	Logistics Manager	20	29-May-17	33
C1120	5	1	Vice president operations	15	11-Mar-18 18-May-17	23 27
	6	1	Adviser operations	20	24-May-17	52
		2	Vice president operations	35	27-Mar-18	48
n.a.	ACP	1	Professional Social Management	5	5-Mar-18 25-May-17	61 44

Conclusions

This dissertation opens a new stream of research in operations management: the study of armed conflicts in humanitarian and commercial operations. My work examines three research questions:

1. *How do armed conflicts affect the productivity and efficiency of healthcare response organizations?*
2. *How do armed conflicts affect firms' inventory?*
3. *How do social investments in conflict zones affect the firms' operational performance?*

I contribute to the operations management literature by using unique qualitative and quantitative data from the longest-standing civil war on the Americas. In the first chapter, by exploiting the multiple levels of conflict in Colombia, I compare hospital total factor productivity and relative operational efficiency in municipalities with different conflict intensities. My quantitative data contains hospital and municipality-level variables. My qualitative information consists of semi-structured interviews with healthcare staff in Colombia. I conclude that conflict has a positive effect on hospitals' total factor productivity. Changes in this metric are explained by unobservable elements of the hospitals' production function such as speed-up, managerial ability, knowledge accumulation and specialization effects. Second, armed conflict has a negative effect on hospitals' relative efficiency. The conflict causes disruptions and increases medical inputs prices, which result in lower relative efficiency for hospitals in severe-conflict municipalities. Third, the efficiency variability of (medium and severe) conflict hospitals is less than that of other (peace and post conflict) hospitals. This is explained by the risk mitigation strategies managers of conflict hospitals implement to avoid disruptions and aim for the standardization of healthcare practices.

In the second chapter, by using the 2012 peace process announcement with one of the two guerrillas in Colombia, I implement a Difference-in-Differences model to study firms' inventory. Unique firm-, municipality-, and attack-level data let me show that firms' inventory-to-assets increase in times of peace. Indeed, war intensity and firms' inventory have a negative relationship. This relationship holds from transitions to peace to war or war to peace as well as across zones with different war intensities. My results indicate firms' location relative to the principal trade centers and battle zones affect firms' inventory holdings. In times of war, transport attacks increase ordering costs and lead firms far from their main trade center to hold more inventory compared to firms near these centers. However, property attacks increase holding costs and lead firms near battle zones to carry less inventory compared to firms far from these zones. Following a transition from peace to war, firms' inventory would decrease in war zones. Then, firms sourcing from these zones should adjust their safety stocks or use alternative strategies to mitigate the lower product availability. Thus, lower inventory holdings in war zones exacerbate the effect of war on global supply chains.

In the third chapter, by using qualitative and quantitative data from the Colombian oil industry, I obtain causal estimates of the effect of social investments on the firms' operational performance. I study a regulatory event that obliged some firms in the Colombian oil industry to invest 1% of their budget in social investments. By using a Difference-in-Difference model, I present evidence that social investments are beneficial for firms. I show that, from every dollar in sales, social investments lead to an increase of 23 cents in the firms' operating margin. Also, by using qualitative data, I find that firms observe higher operating margins—due to social investments—because they suffer fewer war-related disruptions.

More research is needed to advance our knowledge of operations management in times of war. Other research questions regarding healthcare operations include: (i) How should hospitals develop sourcing processes capable of handling the supply disruptions that result from conflict? (ii) Should these organizations build flexibility into their supply chain and workforce to deal with conflict better? and (iii) How should they incorporate the behavioral impacts that differing levels of armed conflict can have on their workforce? Regarding commercial operations: (iv) What is the effect of war on supply chain efficiency? (v) Does war lead global firms to increase their inventory? (vi) Does war lead to bullwhip effect? And regarding social investments: (vii) What type of social investment (e.g., poverty reduction, employment, education, etc.) best suits the needs of communities and firms? and (viii) How can social investments be managed to become more efficient and effective?

My dissertation opens a new stream of research in operations management and contributes to the body of knowledge of man-made disaster management. Moving forward, data availability seems to be the most critical obstacle to enhance our understanding of armed conflicts in operations management. My work suggests it is essential to work with practitioners and use field data to substantiate these data limitations. In the future, I plan to formulate other case studies to gain more contextual knowledge, obtain data, and advance my understanding of humanitarian and commercial operations in times of war.

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Curriculum Vitae

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Education

Kelley School of Business, Indiana University, USA	
Ph.D. Operations Management and Decision Sciences	2018
MBus. Operations Management	2016
Universidad de los Andes, Colombia	
MSc. Industrial Engineering	2010
BSc. Economics	2010
BSc. Industrial Engineering	2008

Ph.D. Dissertation

Operations Management in Times of War
Committee: A.J. Pedraza-Martinez (Chair), K. Bretthauer, R. Beer, G. Ball, J.C. Serpa

Research Interests

Humanitarian and Commercial Operations in War and Urban Crisis, Public Service Operations in Emerging Markets

Refereed Publications

[1] **Jola-Sanchez, A. F.**, Pedraza-Martinez, A. J., Bretthauer, K. M., and Britto, R. A. (2016), Effect of Armed Conflicts on Humanitarian Operations: Total Factor Productivity and Efficiency of Rural Hospitals, *Journal of Operations Management*, 45, 73-85

[2] Mills A. F., Helm J. E., **Jola-Sanchez A. F.**, Tatikonda M. V., and Courtney B. A. (2018), Coordination of Autonomous Healthcare Entities: Emergency Response to Multiple Casualty Incidents, *Production and Operations Management*, 27, 184-205

Academic Awards and Honors

⋆ Ranked 8th (out of 4,039 examinees) in the National Graduate Examinations, Industrial Engineering, Colombia, 2007

⋆ Academic Excellence Graduate Scholarship, Universidad de los Andes, Colombia, 2008

⋆ Doctoral Fellowship, Kelley School of Business, 2013

⋆ Dean's Fellowship, Kelley School of Business, 2013

⋆ Doctoral Student Research Productivity Award, Kelley School of Business, 2016

⋆ Doctoral Student Research Productivity Award, Kelley School of Business, 2017

⋆ Outstanding Doctoral Student Award, Kelley School of Business, 2018

Academic Positions

Kelley School of Business, Indiana University, Bloomington, USA *Associate Instructor* (2013 - 2018)
School of Engineering, Sergio Arboleda University, Colombia *Assistant Professor* (2011-2012)

Government Positions

National Planning Department (Leading think tank) and Ministry of Finance, Colombia, *Researcher, public service operations* (2010-2012)
Statistical Analysis and Methodology, National Statistics Department, Colombia, *Researcher, service sector statistics* (2009-2010)

Conference Presentations

◦ **Inventory in Times of War**, INFORMS, Houston, Texas, October 2017

◦ **Operations Management in Times of War**, EURO HoPE (Humanitarian Operations), Vienna, Austria, June 2017

◦ **Effect of Armed Conflicts on Humanitarian Operations: Efficiency, Total Factor Productivity, and Patient Satisfaction of Rural Hospitals**, POMS, Washington D.C., USA, May 2015

◦ **Healthcare Response to Urban Disasters: Empirical and Mathematical Investigation of Healthcare Infrastructure Readiness, Vulnerability, and Improvement**
Kelley School of Business, Bloomington, USA, April 2015
POMS, Washington D.C., USA, May 2015

Managerial Publications

- Columnist of Portafolio (top business newspaper in Colombia) since 2014 (10 articles) online version: http://www.portafolio.co/columnista/andres-jola-sanchez

Citizenship and Languages

- Colombian Citizen. Spanish (native), English (fluent), French (beginner), and Polish (beginner)