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## Guns and Kidneys: How Transplant Tourism Finances Global Conflict

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# Guns and Kidneys: How Transplant Tourism Finances Global Conflict\*

Alison Schultz<sup>†</sup>

February 15, 2022

## Abstract

This paper provides systematic evidence on the relationship between illegal transplanting activity and non-state violent attacks. I investigate the impact of organ trafficking on local conflict using georeferenced data on conflict events and hand-collected data on the local transplant infrastructure of eight countries. I exploit exogenous variation in kidney demand using the number of U.S. waiting list patients, their payment capacity, and their physical condition. Higher kidney demand has a positive impact on local conflict in localities in which transplanting is possible. More specifically, a one-standard deviation increase in the U.S. waiting list for kidneys is associated with a 17% increase in the probability of conflict and a 1% increase in conflict events compared to localities without access to transplant infrastructure. Consistent with the hypothesis that armed groups use organ trafficking to finance violent attacks, non-state armed groups with transplanting capacities in their home region perform more attacks when kidney demand increases, both in their home region and in other regions. Finally, higher kidney demand is associated with an increase in suspicious payments from and to countries known for illegal organ trafficking.

**Keywords:** conflict; fighting; medical tourism; organ; terrorist financing

**JEL Codes:** C23; D74; I10; K13

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# 1 Introduction

“Transplant tourists” travel from high-income countries to lower-income destinations to illegally obtain an organ for financial compensation (Flaherty et al. 2021).<sup>1</sup> The vast margins in the black market for organs make transplant tourism a lucrative business - kidney recipients report to pay between USD 100,000 and USD 200,000 while donors receive between USD 1,000 and USD 10,000 (Council of Europe 2019). International security agencies therefore worry that non-state armed groups could participate in the trade and use its proceeds to finance violent attacks (see, e.g., the House hearing on Counterterrorism and Intelligence in 2016).

However, due to the hidden nature of transplant tourism and the ensuing absence of data, we lack systematic evidence on the relationship between illegal transplanting and non-state violent activity so far (OSCE 2013; ECOSOC 2006). This paper is the first to document a systematic relationship between global organ demand, armed groups’ involvement in transplant tourism, and non-state violent attacks. I proxy a group’s potential involvement in transplant tourism by the local existence of an authorized transplant facility. As almost all reported cases of illegal transplanting happened alongside legal transplants (OSCE 2013), this strategy to proxy illegal, unobservable, activity with information on legal, observable, activity is valid for

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<sup>1</sup>Delmonico (2009) lists few cases under which transplant tourism can be legal, or even ethical after the Declaration of Istanbul. For living donation, this is the case (i) for recipients with a dual citizenship who wish to undergo transplantation from a family member in a country of citizenship that is not their residence, and (ii) for genetically related donors and recipients who wish to undergo transplantation in a country not of their residence. Deceased donation abroad can be legal and ethical under official regulated bilateral or multilateral organ sharing programs. However, the vast majority of reported cases on transplant tourism do not fulfil these conditions. Therefore, I focus on the illegal cases of transplant tourism.

transplant tourism.

Following Berman et al. (2017), I use georeferenced data on conflict events to compare the effect of increased kidney demand on local conflict in localities with a transplant center to the effect in localities without access to transplant infrastructure. I run my analyses on cells of  $0.5^\circ$  latitude  $\times$   $0.5^\circ$  longitude (about  $55\text{km} \times 55\text{km}$  at the equator) covering eight countries notorious for transplant tourism and monthly observations between 2010 and 2021. I establish causality by the use of georeferenced data and the inclusion of cell fixed effects and country  $\times$  month fixed effects. Thus, I estimate the within-transplant cell panel variation in non-state violence caused by changes in kidney demand. To rule out reverse causality concerns, I proxy exogenous variation in kidney demand with the demand for kidneys *outside* of my sample countries, namely by the number of U.S. waiting list patients, their payment capacity, and their physical condition.

I find a positive and significant impact of higher kidney demand on conflict in localities in which transplanting is possible. More specifically, in  $0.5^\circ$  latitude  $\times$   $0.5^\circ$  longitude cells with a transplant center, a one-standard deviation increase in the U.S. waiting list for kidneys is associated with a 17% increase in the probability of conflict and a 1% increase in conflict events compared to localities without a transplant center. In line with my assumption that transplant tourists need to be rich enough to afford a kidney and healthy enough to travel, this effect is stronger for waiting list patients with labor income and weaker for patients on dialysis.

After establishing a relationship between local transplant infrastructure and violence, I turn to the role of non-state armed groups. I investigate if groups perform

more attacks with increasing kidney demand when they can participate in the transplant tourism business. As this business builds on strong local connections (Krause and Milliken 2009), I assume that groups can participate in the transplant tourism business in their home region only. I therefore determine a group's potential involvement in transplant tourism by the existence of an authorized transplant center in their  $0.5^\circ$  latitude  $\times$   $0.5^\circ$  longitude cell of origin. Consistent with my hypothesis that armed groups use the proceeds from transplant tourism to finance attacks, groups with transplanting capacities perform more attacks when kidney demand increases, both in their home region and in other regions.

Transplant tourism agreements require cross-border payments. To examine if these transfers are made via the official banking system, like experts in the Homeland Security Committee (2016) suspect, I use data on payments reported as suspicious to the Financial Crime Enforcement Network (FinCEN). In a country-level analysis, I compare the effect of higher kidney demand on suspicious payments from and to countries known for transplant tourism to the effect on countries without ties to transplant tourism. I find that, indeed, higher kidney demand is associated with an increase in suspicious payments from and to countries notorious for transplant tourism.

My findings contribute to two strands of literature: First, scholars in medical anthropology, health ethics, and security studies have identified cases and discussed the dynamics of transplant tourism and illegal organ trafficking. They have analyzed the transnational space and power asymmetries in which organ transplants take place (Scheper-Hughes 2000; Scheper-Hughes 2003), have identified benefits and costs

for donors (Cohen 2003; Goyal et al. 2002) and recipients (Gill et al. 2008) and have discussed the notion of informed consent (Cohen 2003; Scheper-Hughes 2000). My paper augments their case studies, observations, and (expert) interviews with a systematic, quantitative analysis. Moreover, this study shows that also third parties suffer from the consequences of illegal organ trafficking. By demonstrating that armed groups use transplant tourism to finance their activities, I add to existing studies which suspect that criminal groups skim off huge profits from transplant agreements (e.g., Fraser 21.01.2016; Shelley 2018) but lack systematic data to prove this claim.

Hence, my paper also contributes to the literature on how terrorists and armed groups finance themselves and their attacks. Identifying donations (Limodio 2019), oil and gas business (FATF 2015) and mining activities (Berman et al. 2017) as financing sources, existing papers focus on legal sources of terrorist financing. Illegal activities like robbery, smuggling, fraud, or kidnapping (Makarenko 2004) are less researched - mainly because of the data scarcity on illegal, hidden activities (OSCE 2013; ECOSOC 2006). As illegal transplant activities mostly happen at hospitals and transplant centers alongside legal activities (OSCE 2013), my setting provides the unique opportunity to use official data to proxy the potential for illegal action.

My paper is closely related to Berman et al. (2017) who show how minerals fuel conflict in Africa. I follow Berman et al. (2017)'s identification strategy, shedding light on another financing source for violent attacks.

The remainder of this paper is structured as follows. The following section gives an overview of the existing evidence on transplant tourism and introduces my concep-

tual framework. I then describe my data in Section 3. Section 4 presents results on the impact of kidney demand on local conflict. Section 5 shows how conflict activity spreads over space by enhancing the financial capabilities of armed groups. In Section 6, I present the association between kidney demand, transplant infrastructure, and suspicious cross-border bank transfers. Section 7 concludes.

## **2 Existing Evidence and Conceptual Framework**

This chapter gives a short overview of the existing evidence on organ markets and transplant tourism. Against this background, I develop four hypotheses which I will test later in this paper.

### **2.1 The Market for Organs**

Like any market, organ markets are composed of demand and supply. On the demand side, people whose organs are failing or working poorly wish to receive a substitute organ. A transplantation can lengthen patients' life and allow those with a chronic illness to live a normal lifespan.

On the supply side, deceased or living donors offer their organs to someone in need. While some organs, such as the heart, can only be transplanted from brain dead people, others, such as the kidney or parts of the liver, can be obtained from a living donor. Conditional on professional surgery and post-transplantation care, a living donor can live a normal, healthy life after donation, relying on her remaining kidney or a regrowing liver.

Unlike for most other markets, the free exchange of organs between donors and recipients is forbidden in almost all countries of the world.<sup>2</sup> Instead, patients in need can put their names on waiting lists and receive an organ according to politically determined algorithms. These algorithms consider aspects of justice and medical utility. A patient's position on the waiting list therefore depends, for instance, on the match between recipient and donor, on the waiting time, or on the urgency of the transplantation (Health Resources and Service Administration 2021; Organ Procurement and Transplantation Network 2022).

A closer look into the global statistics on waiting lists and performed transplants reveals the core problem of existing organ markets: Demand highly exceeds supply (The Economist 2008; Health Resources and Service Administration 2021).

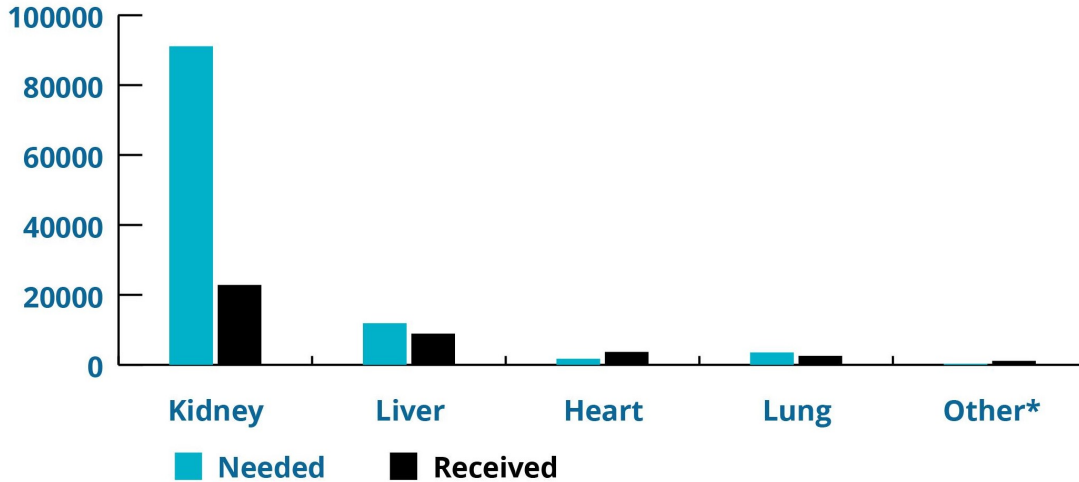
For example, as shown in Figure 1, only about 20,000 of the 90,000 patients registered for a kidney on the U.S. waiting list received one in 2020 (Health Resources and Service Administration 2021). These numbers are not directly comparable; patients on the list are a stock, received kidneys a flow variable. Nevertheless, more than half of all U.S. patients die on the waiting list before having received an organ (Astier 18.02.2020). Worldwide, the WHO assumes that only one in ten patients in need receives a kidney by legal means (The Economist 2008).

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<sup>2</sup>Iran is the only country which offers people a legal way to sell organs. However, the organ market in Iran is still strictly regulated: A government foundation registers buyers and sellers, matches them up and sets a fixed price of USD 4,600 per organ (Bengali 15.10.2017).



Figure 1: Patients on U.S. waiting lists and transplants performed  
By organ in 2020



\*Other includes allograft transplants like face, hands, and abdominal wall.

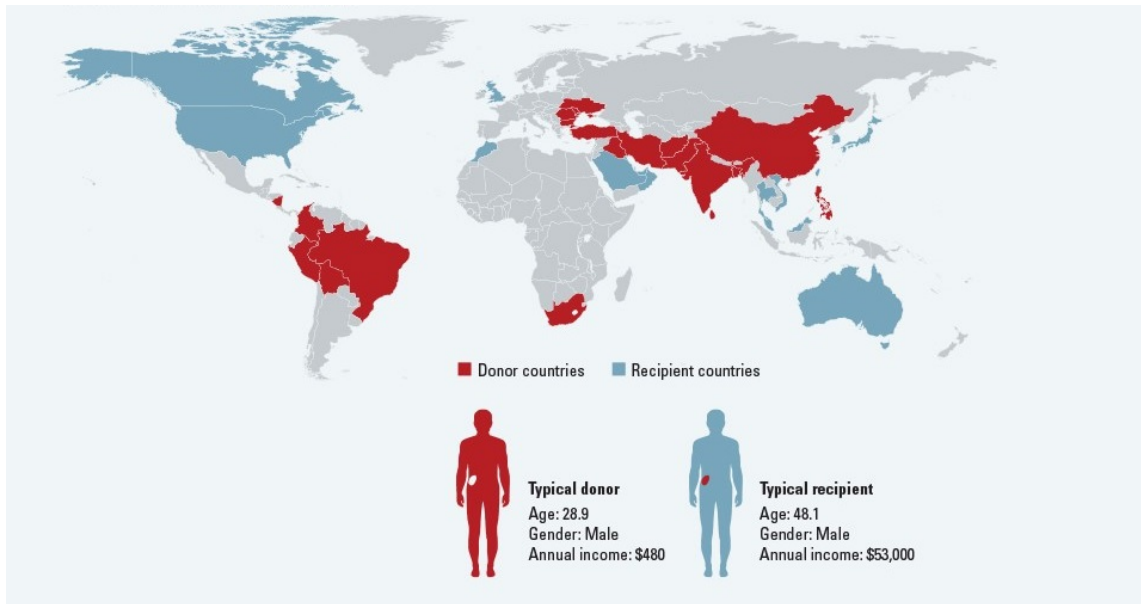
Source: Health Resources & Services Administration

## 2.2 Organ Black Markets and Transplant Tourism

As a consequence of the shortage in legal organs, illegal trade flourishes. Researchers expect that 5% to 10% of all transplants happen in black markets. The black market is expected to be specifically vivid for living donations, given the willingness of people in need to make quick money by selling their "spare" organs or organ parts. As 75% of the illegal trade is over kidneys (Hazell 28.05.2012), this paper focuses on transplant tourism for kidneys.

The black market for kidneys is global. Combining anecdotal information from newspaper articles, security agency reports and case studies, Figure 2 provides a stylized picture of the structure of transplant-tourism agreements: The mostly male donors are typically from low-income countries. They are, on average, younger than

Figure 2: The Global Market for Kidneys



Source: Der Spiegel, Coalition for Organ Failure Solutions, Organ Watch, ESOT

30 and have an annual income of less than USD 500. Recipients are also predominantly male. They come from high-income countries, are, on average, 48 years old and have an annual income of about USD 53,000.

Research on illegal organ donors shows that most of them see compensated kidney donation as an opportunity to pay off debt. A minority also sells their kidneys to raise money for a dowry, to buy a house, or to start a business (Cohen 2003; Goyal et al. 2002; Scheper-Hughes 2000). However, Goyal et al. (2002) find for a sample of 305 individuals who sold their kidney in Chennai, India, in the 1990s and 2000s that expected economic benefits did not materialize. Some years after the donation, three quarters of participants were still (or, again) indebted. Average donor family income decreased by one third after the donation and the number of participants living in

poverty increased.

These negative economic consequences were mostly due to deteriorated employment opportunities caused by health problems in consequence of unprofessional surgeries or a lack of post-transplant care: About 86% of participants reported a deterioration in their health status after nephrectomy. As a result, 79% of participants would not recommend others to sell a kidney (Goyal et al. 2002).

In addition to voluntary donations, there are incidences of forced transplants, e.g., of doctors who took out kidneys without the patient's knowledge during another surgery (Scheper-Hughes 2000), or of criminals who killed for organs (Expansión 2014). However, forced transplants are a minority of reported cases. For my analysis, I remain ignorant about the question if donation was forced out of circumstances or organs were taken without consent. My setting does not allow me to distinguish between the two cases and both entail the opportunity for non-state armed groups to make profits and finance attacks.

Moreover, there are several reported cases of forced organ removal from prisoners after their execution. This practice mainly happens in China (Allison et al. 2015). As possible revenues from these organ removals accrue to the government, rather than to non-state groups, I do not include China in my analysis.

Although most existing studies focus on the weak position of illegal kidney donors, kidney recipients might also suffer unfavourable consequences. Gill et al. (2008) investigate post-transplantation outcomes of 33 transplant tourists from the U.S. and compare them with patients who underwent transplantation at UCLA. Most of the surveyed patients traveled to their region of ethnicity. The majority underwent

living unrelated transplantation in China (44%), Iran (16%), and the Philippines (13%). Of Gill et al. (2008)'s sample, four patients needed urgent hospitalization, three of those lost their graft. Seventeen (52%) patients got infections, nine of them requiring hospitalization. One patient died from complications related to donor-contracted hepatitis B. Tourist's one-year graft survival was 89%, compared to 98% for the matched UCLA cohort. The rate of acute rejection at one year was 30% in tourists and 12% in the matched cohort.

Regardless of the economic and health consequences for donors and recipients, illegal transplants are lucrative for other parties involved: The price paid by a kidney recipient is typically about ten times as high as the compensation received by the donor. The Council of Europe (2019) reports that recipients typically pay between USD 10,000 and USD 100,000 for a kidney while donors receive between USD 1,000 and USD 10,000.

Existing literature is ambiguous on who absorbs most of this profit: While newspaper articles have identified doctors and hospital as beneficiaries, middlemen or brokers probably capture most of the profit (Council of Europe 2019).

In line with Fraser (21.01.2016) and Shelley's statement in the Homeland Security Committee (2016), I suspect that local, non-state armed groups act as a broker or collaborate with brokers by protecting their transplant tourism business. Organ brokers need to be well-connected with the local population, but also with doctors and authorities, as they need to find trusting donors and organize the surgery, but also plan the international travel and solve legal issues. Most non-state armed groups do, indeed, have these local connections, with some important ties to administrative

bodies and the local population, including professionals like doctors (Krause and Milliken 2009). In this context, it is worth mentioning that most non-state violent attacks are performed by relatively small, local groups, rather than by large, transnational groups like Al-Qaeda or Al-Nusra. For my sample, this is visible from the list of sample non-state armed groups provided in Appendix A.

### 2.3 Hypotheses

I start from the assumption that non-state armed groups are financially constrained (c.f. Berman et al. 2017). To finance their next attack, groups therefore need a money inflow, for example the proceeds from an illegal transplant. As payments for organs are mostly made prior to the transplantation, timewise, violent attacks should and illegal transplants should happen at close dates. Consequently, the more organs can be sold in a given time period and the higher the price of these organs, the higher the probability of an attack and more attacks should happen.

As supply of organs is unobservable in my setting, I assume it to be constant, on average. The probability and number of attacks should thus be positively influenced by organ demand, which, in turn, depends on three facets: first, on how many patients need an organ, second, on the payment capacities of these patients, and third, on patients' ability to travel. Therefore, I test the following hypotheses:

**Hypothesis 1:** The larger the number of patients on a waiting list, the higher the probability of an attack and the more attacks are performed in locations with transplant infrastructure.

**Hypothesis 2:** This effect is stronger for waiting list patients with a higher income

and weaker for patients whose physical condition is worse.

Armed groups will mainly participate in transplant tourism in their home region. However, they might use the proceeds from transplant tourism to perform violent attacks all over the country, or even cross-border. I therefore test if the total number of a group's attacks, both in its homeland and in other regions, increases with higher kidney demand:

**Hypothesis 3:** The larger the number of patients on a waiting list, the higher the probability and number of attacks by groups whose home region has a transplanting infrastructure.

Payments between broker and donor mainly occur from hand-to-hand and in local currency. Transfers between recipient and broker are, however, cross-border payments and require currency clearing. It is unclear how exactly these payments are made. Security experts, e.g., in the Homeland Security Committee (2016), suspect that most of the payments are done via official bank transfers. Bain and Mari (31.07.2018) also assume that surgeons, anaesthetists and nurses, laboratories or medical facilities, but also individual brokers receive payments for illegal transplants on their normal bank accounts.

In my analysis, I assume that at least some of the payments for illegal kidneys pass the official payment system and that international banks identify at least a subset of them as suspicious (c.f. Bain and Mari 31.07.2018). Moreover, I assume that one illegal transplantation can induce several payments within a criminal network,

both between different members of the network and between third parties, e.g., payments for weapons financed with the proceeds of transplant tourism. I therefore test the following, fourth hypothesis:

**Hypothesis 4:** The larger the number of people on the waiting list, the more suspicious payments are made to and from localities with a transplanting infrastructure.

Before I test these hypotheses in Section 4 to Section 6, the following section provides details on the data used.

### 3 Data

I base my analyses on a sample of localities in 8 countries which are known for transplant tourism activities (Cohen 2003; Council of Europe 2019; Goyal et al. 2002; Scheper-Hughes 2000; Scheper-Hughes 2003; ECOSOC 2006; OSCE 2013).<sup>3</sup> Following Berman et al. (2017), I define a locality as a subnational unit of  $0.5^\circ$  latitude  $\times$   $0.5^\circ$  longitude. The structure of my dataset is hence a full grid of the sample countries divided into subnational units of  $55 \times 55$  kilometers size (at the equator) or a little more (elsewhere). I prefer this level of aggregation over using administrative boundaries to avoid that my unit of observation is endogenous to conflict events.

My unit of observation in the baseline analysis in Section 3 is cell-month. I use the months between January 2010 and March 2021, as conflict data is available in adequate detail for my sample from 2010 on only. In the following, I describe the

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<sup>3</sup>These are Argentina, Armenia, Bulgaria, Hungary, India, Pakistan, Russia, and South Africa.

data used and show descriptive statistics on my sample.

## 3.1 Data Description

### 3.1.1 Conflict events

The publicly available Armed Conflict Location and Event Data Project (ACLED) provides real-time data on locations, dates, actors, fatalities and types of all reported political violence and protest events across the world (Raleigh et al. 2010).<sup>4</sup> ACLED obtains events from various sources, including press accounts from regional and local news, humanitarian agencies, or research publications. The database serves my purpose well because it contains detailed information on conflict events, most importantly on the exact day and location of a conflict, but also on the type of events and on names and characteristics of all involved actors. Moreover, it records political violence without a battle-related deaths threshold, which is important in my setting in which local, small groups matter.

I assign each conflict event to a cell and a month using the information on latitude and longitude and the day associated with each event. I only include conflict events of non-state actors and exclude events of "protest" and "looting" as I do not consider them violent attacks.

I construct two variables measuring different dimensions of conflict. First, I capture the extensive margin of conflict with a *Conflict dummy* indicating if at least one event happened in a cell in a given month. Second, I measure the intensive margin of conflict by the number of *Conflict events* in a cell in a given month. As

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<sup>4</sup>Armed Conflict Location & Event Data Project (ACLED); [acleddata.com](http://acleddata.com)



this number is skewed to the right, I use its logarithm.

Figure 3 shows in a heat map how conflict events are distributed over my sample countries. Figure 4 reports how the average probability of conflict, the number of conflict events and the number of fatalities vary over time. The data exhibits considerable variation in both the local and the temporal dimension.

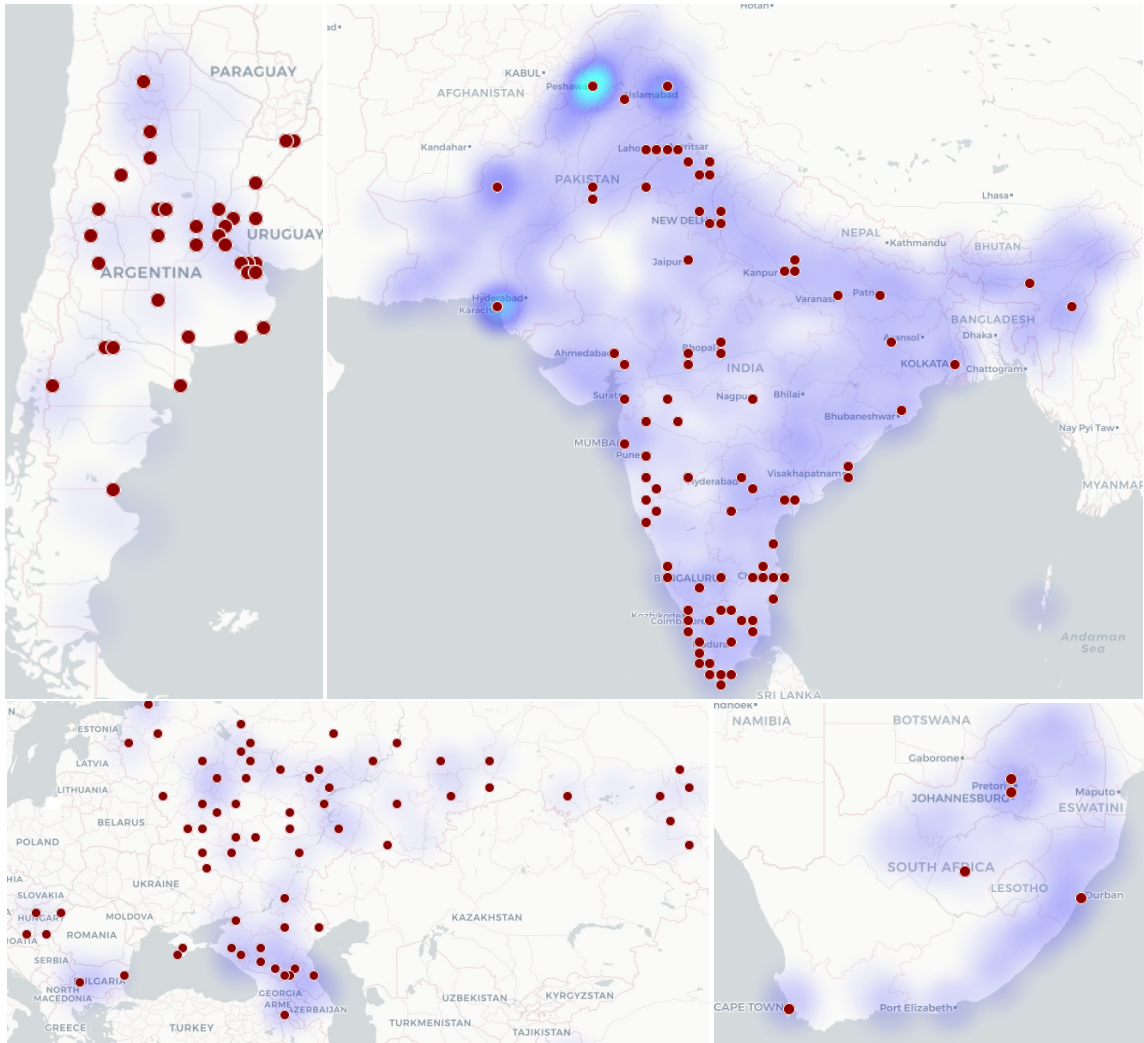
For my second analysis, investigating if armed groups increase their overall number of attacks with higher kidney demand if their home region has transplant infrastructure, I bring the dataset on an armed group-month level. Here, I define the *Conflict dummy* to be one if the group is involved in at least one event in a given month. I aggregate *Conflict events* on the group level and, again, use logged values.

I define a group's home region as the cell in which (i) the group has its headquarter, or (ii) the group was founded, or (iii) the ethnic affiliation of the group is based, or (iv) the community mentioned in the group's name is based. I use Wikipedia and other sources suggested by a Google search to determine these locations. I provide a list of all groups of the analysis and their determined home region in Appendix A.

### **3.1.2 Transplant Infrastructure**

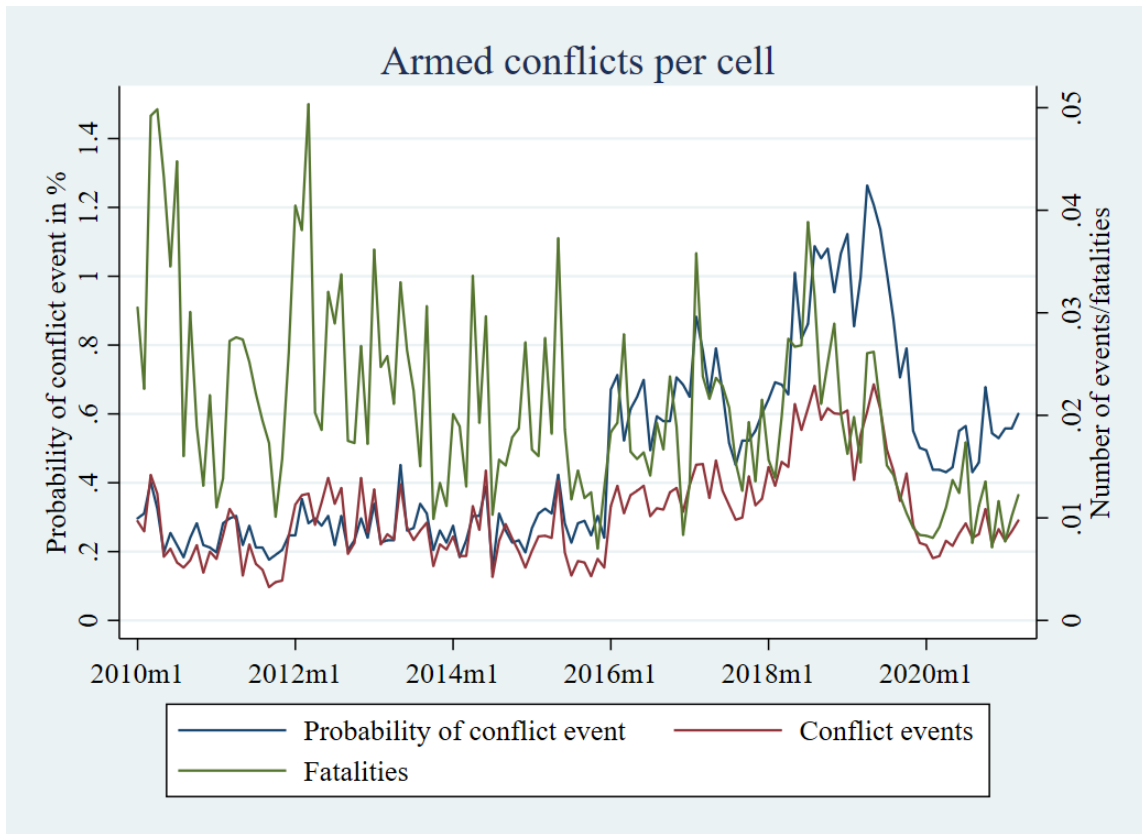
In almost all reported cases, illegal transplanting happened alongside legal transplants (OSCE 2013). I therefore proxy the local potential for transplant tourism by the existence of a legal transplant infrastructure in a given cell. I use official government lists of authorized transplant centers to determine their location. For some of the countries, these lists are publicly available via the health ministry's websites. For others countries, I contacted the health ministries or the agency responsible for

Figure 3: Transplant Centers and Conflict Events



This figure shows a heatmap of non-state violent conflicts from ACLED which happened in my sample countries between 2010 and March 2021. It further shows hand-collected transplant centers as red dots.

Figure 4: Probability of Conflict, Conflict Events and Fatalities



Source: ACLED

transplantation via email. For some countries that I would have liked to included in my analysis, especially Libya, Lebanon, and Egypt, I was unable to obtain a list with official transplant centers as the relevant institution did not reply to my email. Appendix B gives an overview of the data sources for authorized transplant centers in my sample.

I manually searched for the coordinates of all transplant centers via Google Maps and assigned them to a  $0.5^\circ$  latitude  $\times$  0.5 longitude cell. The variable *Transplant center* assumes the value of one if at least one authorized transplant center is located in a cell. For most countries, no information is available about when a transplant center first received or when it lost its authorization. Therefore, I assume that transplant infrastructure is constant over my sample period. Figure 3 shows the distribution of transplant centers in my sample countries as red dots.

Using authorized transplant centers to proxy the potential for illegal transplant activities ignores possible illegal transplant centers which have no local association with a legal center. This will affect my results only if illegal transplant centers are dis-proportionally placed in the absence of legal centers. In this case, my estimates would set a lower bound of the actual effect.

To test if armed groups increase their attacks with higher kidney demand if their home region has transplant infrastructure, I define a group to have a *Transplant center at home region* if there is at least one transplant center in its home region.

For my country-level analyses on the relationship between suspicious payments and transplant infrastructure, I create two variables identifying countries as possible candidates for transplant tourism. I define a country to be a *Transplant country* if

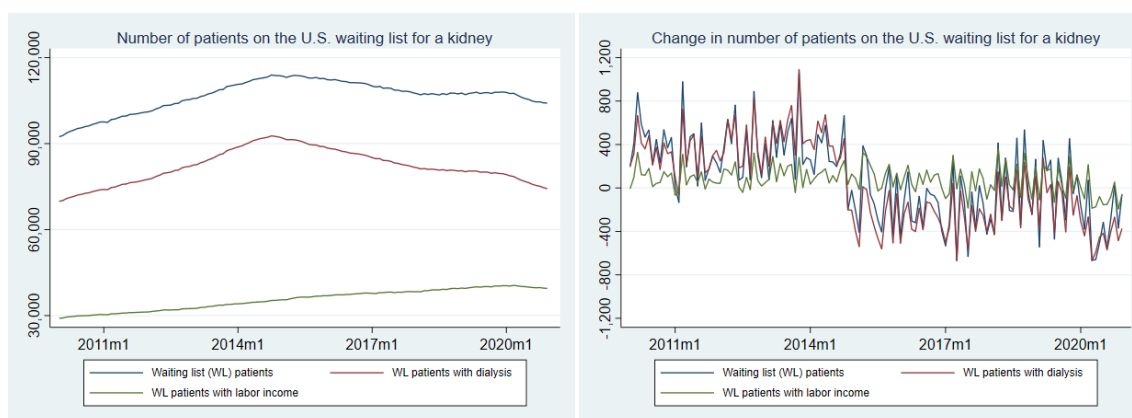
it performed an above-median number of official kidney transplants in a given year. This variable is time-varying. For robustness, I define a country to be a *Trafficking country* if it is involved in organ trafficking, according to a list compiled in Wikipedia (2021) based on different sources.

### 3.1.3 Kidney Demand

I use information on all waiting list registrations and transplants that have been listed or performed in the U.S. since October 1, 1987 from the United Network of Organ Sharing (UNOS) Standard Transplant Analysis and Research File (National UNOS STAR file). This datafile includes detailed medical information on each patient registered on the waiting list. For my analysis, I use the exact day of entering and leaving the waiting list, the start and the end of a possible dialysis and the information if a patient has a labor income when entering the list.

I first construct the variable *Waiting list patients*, counting the total number of patients on the U.S. waiting list for a kidney in a given month. Second, to capture the payment capacity of people on the waiting list, I generate the variable *Waiting list patients with labor income* counting all people on the U.S. waiting list for a kidney who had a labor income when entering the waiting list. Third, the variable *Waiting list patients on dialysis* proxies for patients' ability to travel. Here, I assume that a patient who is already on dialysis is in a condition which hampers international travel, in particular to a lower-income country and a lower-quality hospital. To calculate this variable, I use the number of people on the U.S. waiting list for a kidney that need dialysis in a given month. Figure 5 shows the number of waiting list patients,

Figure 5: Demand for Kidneys on the U.S. Waiting List



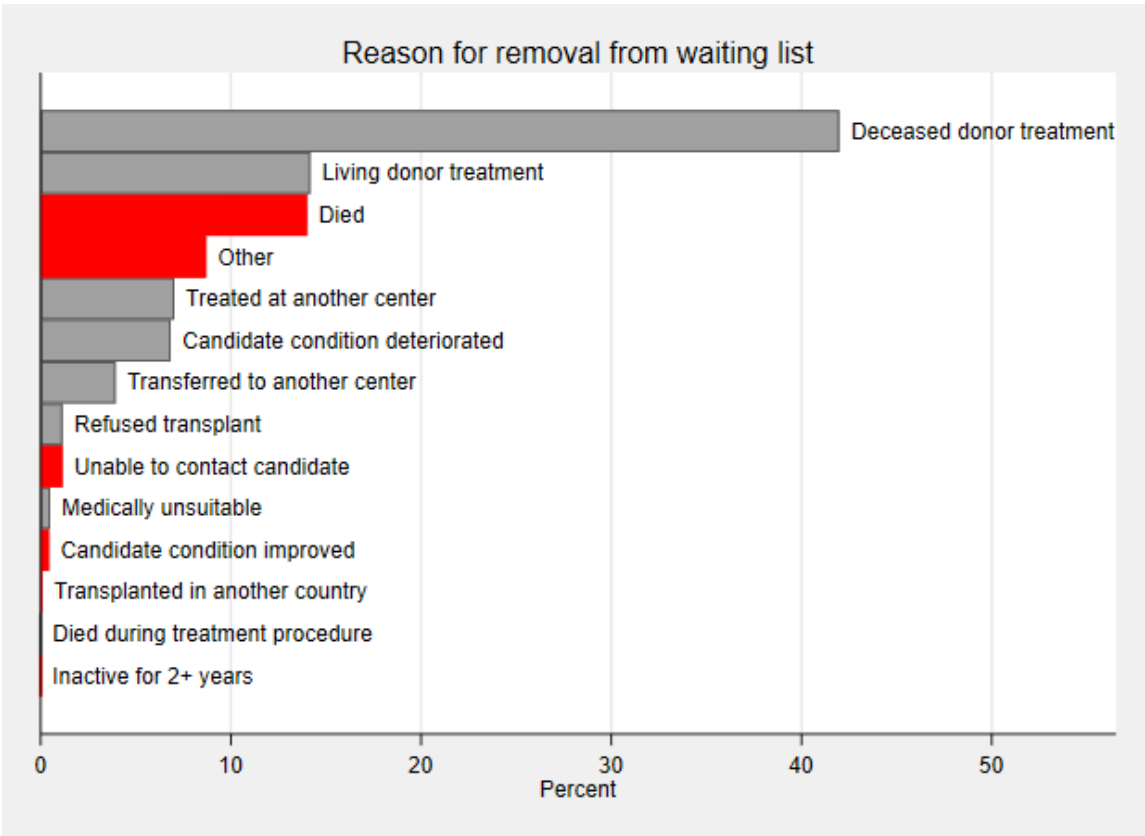
Source: UNOS STAR files

those with labor income and those under dialysis over our sample period.

As can be seen from the graph on the left of Figure 4, in the long run, the number of waiting list patients seems relatively stable. However, as the right graph of Figure 4 shows, the number varies considerably on a monthly basis. As all my analyses include cell or group fixed-effects, what matters here is the change over time. My decision to use monthly data was also based on the concern that the waiting list data could be leveled out too much in yearly data.

What happens to patients registered on the U.S. waiting list after having obtained an organ via a transplant tourism agreement? Given the illegality of the transaction, patients might not drop out of the waiting lists, or, if they do, under a pretext. Given the relatively small chance of receiving an organ via the list, most transplant tourists might simply stay registered until they die and are correctly classified as dead. Figure 6 shows different reasons under which patients exit the list. Stated reasons which could include successful transplant tourists are marked in red.

Figure 6: Reasons for Being Removed from the U.S. Waiting List for Kidneys



Source: UNOS STAR files

## 3.2 Suspicious Payments

To measure *Suspicious payments* from and to countries potentially involved in transplant tourism, I draw on available data on the so-called *FinCen files*. These files report international payments which global correspondent banks have flagged as suspicious with the U.S. financial crime enforcement network (FinCen). In fall 2020, the International Consortium on Investigative Journalists (ICIJ) leaked and published parts of this data.

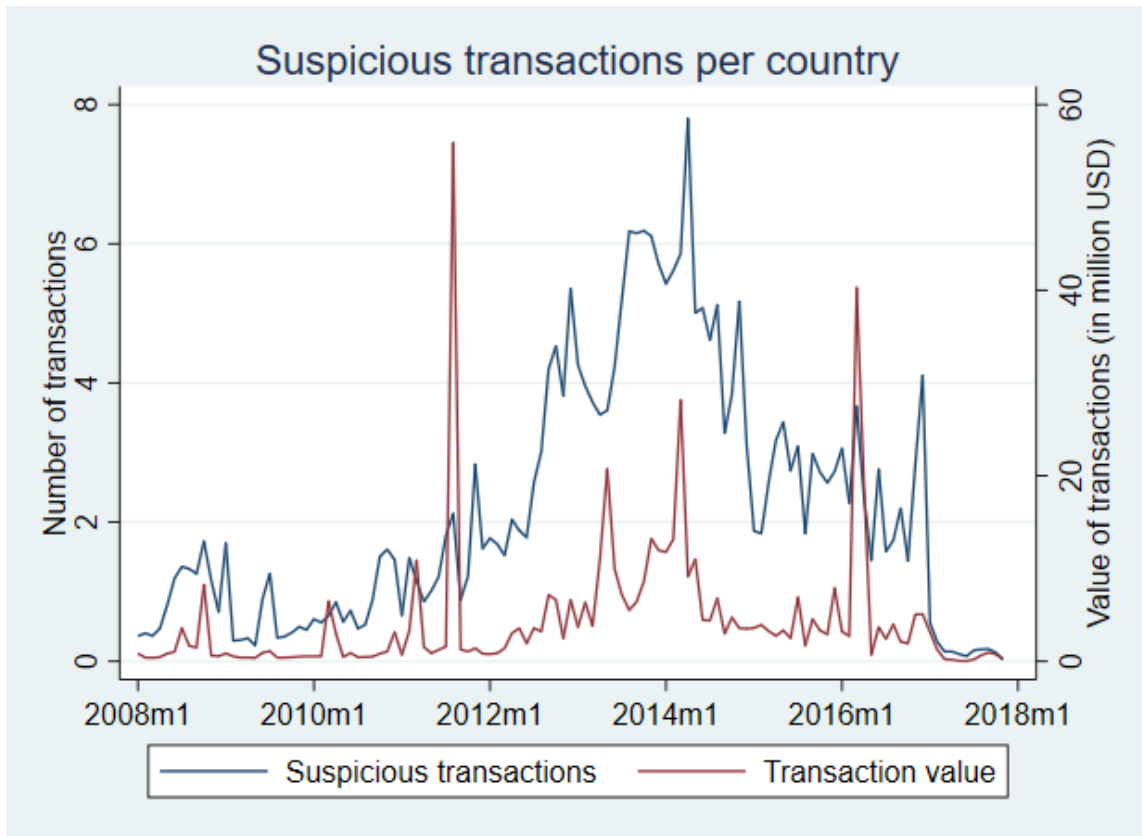
I include all countries, except for the USA, in the analysis on suspicious payments. I aggregate payments on a country and month level for all available years, that is, from 2008 to 2018. I sum up incoming and outgoing payments from countries as the business of transplant tourism may involve several partners, some of them receiving money within the country of the business, some of them receiving money outside of the transplanting country, e.g., as a compensation for arms delivery. As the number of suspicious payments is skewed to the right, I take the log of absolute payments. The average number of suspicious payments from and to a country from 2008 to 2018 is shown in Figure 7.

## 3.3 Descriptive Statistics

Table 1 reports descriptive statistics for my sample. I use the data of Panel A, B and C in the locality-level analysis in Section 4. I use the data of Panel B, D and E in the armed group level analysis in Section 5. I use the data of Panel F and B in the analysis on suspicious payments in Section 6.



Figure 7: Suspicious Payments



Source: ICIJ

Table 1: Descriptive Statistics

This table shows descriptive statistics for all variables used in the following regression models. Data in Panel A, B and C are used in the locality-level analysis in Section 4. Data in Panel B, D and E are used in the armed group level analysis in Section 5. Data in Panel F and B are used in the analysis on suspicious payments in Section 6.

	N	Mean	SD	Median	Min	Max
<b>Panel A: Cell-month level</b>						
<b>Conflict</b> in 15,876 cells over 135 months						
Probability of conflict in %	2,143,260	.448	6.67	0	0	100
Number of events	2,143,260	.0096	.272	0	0	62
Events > 0	9,592	2.17	3.45	1	1	62
<b>Panel B: Month level</b>						
<b>Kidney demand</b> over 135 months						
Waiting list patients	2,143,260	106,554	5,347	107,526	92,409	113,951
on dialysis	2,143,260	81,857	6,025	81,015	69,849	92,709
with labor income	2,143,260	33,409	4,290	34,506	24,538	38,952
<b>Panel C: Cell level</b>						
<b>Transplant infrastructure</b> in 15,876 cells						
N transplant centers	2,143,260	.03937	.632	0	0	31
At least one center in %	2,143,260	1.37	12	0	0	100
<b>Panel D: Group-month level</b>						
<b>Conflict</b> of 723 groups over 135 months						
Probability of conflict in %	97,605	1.67	13	0	0	100
Number of events	97,605	.0315	.35	0	0	20
Events > 0	1,633	1.88	1.95	1	1	20
<b>Panel E: Group level</b>						
<b>Transplant infrastructure at home region</b> of 723 groups						
N transplant centers	97,605	2.88	6.63	0	0	31
At least one center in %	97,605	31	46	0	0	100
<b>Panel F: Country-month level</b>						
<b>Financial transactions</b> from and to 105 countries over 291 months						
Suspicious payments	17,850	1.46	7.15	0	0	162

## 4 The Impact of Organ Demand on Local Conflict

I now turn to the empirical analysis of the impact of organ demand on local conflict. First, I discuss my identification strategy. Second, I report results of different specifications.

### 4.1 Methodological Issues

Establishing a causal relationship between global organ demand on local conflict comes with some methodological challenges. The first and most important one is a concern about reverse causality: War zones are a major target for organ recruitment and create organ demand at the same time. Consequently, the more conflicts happen, the more organs can be acquired and the more organs are needed, implying a positive correlation, just as my proposed hypothesis. To address this concern, I exploit variation in U.S. organ demand, which is highly unlikely to be affected by local conflict in my sample countries.

The second concern refers to a spurious correlations between conflict and organ demand over time. As visible from Figure 4 and Figure 5, both the number of reported conflicts and the number of waiting list patients have increased in my sample over time. A positive correlation between both variables could therefore be an artefact of their common trend. To solve this problem, I estimate my coefficients in a difference-in-difference manner: I compare the effect of a change in kidney demand on local conflict in those cells in which transplant tourism could take place, i.e., cells with a transplant infrastructure, to the effect in cells in which this is not possible. In particular, I estimate the following regression for each locality  $i$  in country  $c$  and

month  $t$ :

$$\begin{aligned} Conflict_{it} = & \beta_0 + \beta_1 Transplant\ center_i \times Kidney\ demand_t + \\ & FE_i + FE_{ct} + \epsilon_{it} \end{aligned} \tag{1}$$

$Conflict_{it}$  is one out of the two variables  $Conflict\ dummy_{it}$  and  $Conflict\ events_{it}$ .  $Transplant\ center_i$  is a binary variable assuming the value of 1 for cells with a transplant center and 0 for all other cells.  $Kidney\ demand_t$  is the number of patients on a waiting list, the number of waiting list patients on dialysis, or the number of those patients who have entered the waiting list with a labor income, respectively.  $FE_i$  are cell fixed effects,  $FE_{ct}$  is an additional battery of fixed effects that can vary at different levels (e.g., month, country  $\times$  month).

$\beta_1$  is the coefficient of interest. It can be interpreted as the difference between the impact of a one unit-increase in kidney demand on conflict in cells with and without a transplant center.

This effect is, by design, stronger for any subset of waiting list patients which proxy their total number. Therefore, I standardize the three waiting list variables in all my analyses. Standard errors are clustered two-way by cell and month.

## 4.2 Results

Table 2 reports the results for the linear probability model in which I regress the *Conflict Dummy* on the independent variables. Coefficients are reported in basis points.

The regressions reveal a significant and sizable effect of increased kidney demand

on violent conflict in cells with a transplant center. Compared to cells without a transplant center, a one standard-deviation increase in the number of patients on the waiting list increases the cell's probability of conflict by 93.27 basis points in the model with month fixed effects, and by 77.19 basis points in the model with month  $\times$  country fixed-effects, respectively. Compared to a base probability of conflict of 5.57% in transplant cells, this is an increase of 17% or 14%, respectively. This effect is economically significant, considering that a one standard deviation increase in the waiting list for kidneys is equivalent to 5,347 new registrations on a list which has, on average, 106,554 patients.

In line with Hypothesis 2, the effect is non-existent for waiting list patients on dialysis and stronger for waiting list patients who have entered the list with a labor income. A one standard deviation increase in the number of patients with income even leads to an increase of conflict of 2.62 or 2.05 percentage points, on average, which is an increase of 47% or 37%, compared to non-transplant cells. Again, this effect is sizable considering that a one standard deviation increase in patients with income is equivalent to 4,290 new registrations to the average 33,409 patients with income.

Table 3 reports the results of regressing the log number of conflict events on the independent variables. The coefficients show that an increase in kidney demand does not only increase the extensive, but also the intensive margin of conflict. A one standard deviation increase in the waiting list for kidneys increases the number of conflict events in transplant cells by an average of 0.9% or 0.8%, respectively, as compared to non-transplant cells. Like for the extensive margin, the effect is

Table 2: The impact of organ demand on conflict probability

This table reports OLS coefficients of a linear probability model regressing a binary conflict variable on the interaction between transplant infrastructure and kidney demand (see equation (1)). The sample consists of monthly observations of 15,876 cells of  $0.5^\circ$  latitude  $\times$   $0.5^\circ$  longitude, covering 8 countries between 2010 and 2021. The dependent variable is a binary variable indicating if a conflict took place in a given month. Independent variables are the binary variable *Transplant center*, indicating the existence of an authorized transplant center in an  $0.5^\circ$  latitude  $\times$   $0.5^\circ$  longitude cell, and the standardized number of (i) patients on the U.S. waiting list for a kidney, (ii) patients on the U.S. waiting list for a kidney on dialysis, and (iii) patients on the U.S. waiting list for a kidney who had a labor income when entering the waiting list. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country  $\times$  month fixed effects. Standard errors are two-way clustered by group and month and shown in parentheses.

	Dependent variable: Probability of conflict (in basis points)					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center						
$\times$ waiting list (WL) patients	93.27*** (24.20)	77.19*** (20.88)				
$\times$ WL patients on dialysis			-4.96 (25.49)	2.02 (21.44)		
$\times$ WL patients with income					262.29*** (42.76)	205.48*** (39.77)
Observations	2,143K	2,142K	2,143K	2,142K	2,143K	2,142K
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country $\times$ month FEs	No	Yes	No	Yes	No	Yes
Base prob. transplant cells	557.09	569.56	557.09	569.56	557.09	569.56
R-squared	0.28	0.29	0.28	0.29	0.28	0.29

Standard errors (two-way clustered by cell and month) in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

insignificant for waiting list patients on dialysis and stronger for waiting list patients with income: On average, the number of events in a cell with transplant infrastructure increases by 2% or 1.5% with a one standard-deviation increase in waiting list patients with income.

Overall, these results support Hypothesis 1 and 2 from Section 2: Conflicts increase with a rising kidney demand in cells with a transplant infrastructure, both in the extensive and the extensive margin. This effect is stronger for waiting list patients with income and absent for waiting list patients on dialysis.

## **5 How Transplant Tourism Increases Fighting Capabilities of Armed Groups**

The findings of the previous section show that higher kidney demand induces local non-state violence in regions with a transplant center. In this section, I show that increased financial capabilities of local armed groups are responsible for these attacks. In particular, I show that armed groups whose home region has a transplant center increase their attacks with increasing kidney demand, both in and outside their home region.

### **5.1 Methodological Issues**

I estimate the following regressions on the level of a non-state armed group and month. Like explained in Section 3, I now focus on the number of attacks performed by a certain group, rather than within a certain cell, as well as on groups'

Table 3: The impact of organ demand on the number of conflict events

This table reports OLS coefficients of a regression of the number of local conflict events on the interaction between transplant infrastructure and kidney demand (see equation (1)). The sample consists of monthly observations of 15,876 cells of  $0.5^\circ$  latitude  $\times$   $0.5^\circ$  longitude, covering 8 countries between 2010 and 2021. The dependent variable is the log number of conflict events in cell in a given month. Independent variables are the binary variable *Transplant center*, indicating the existence of an authorized transplant center in an  $0.5^\circ$  latitude  $\times$   $0.5^\circ$  longitude cell, and the standardized number of (i) patients on the U.S. waiting list for a kidney, (ii) patients on the U.S. waiting list for a kidney on dialysis, and (iii) patients on the U.S. waiting list for a kidney who had a labor income when entering the waiting list. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country  $\times$  month fixed effects. Standard errors are two-way clustered by group and month and shown in parentheses.

	Dependent variable: Log conflict events					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center						
$\times$ waiting list (WL) patients	0.009*** (0.00)	0.008*** (0.00)				
$\times$ WL patients on dialysis			0.002 (0.00)	0.003 (0.00)		
$\times$ WL patients with income					0.020** (0.01)	0.015* (0.01)
Observations	2,143K	2,142K	2,143K	2,142K	2,143K	2,142K
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country $\times$ month FEs	No	Yes	No	Yes	No	Yes
Mean events transplant cells	0.07	0.07	0.07	0.07	0.07	0.07
R-squared	0.42	0.43	0.42	0.43	0.42	0.43

Standard errors (two-way clustered by cell and month) in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$



transplanting infrastructure. Consequently, I attempt to compare the effect of an increase in kidney demand on violent attacks of groups with a transplant center in their homeland to the effect on violent attacks of groups without such transplantation infrastructure. In particular, I run the following specification for armed groups  $j$  in country  $c$  and month  $t$ :

$$\begin{aligned} Conflict_{jt} = & \beta_0 + \beta_1 Transplant\ center\ at\ home\ region_j \times Kidney\ demand_t \\ & + FE_j + FE_{tc} + \epsilon_{jt} \end{aligned} \quad (2)$$

$Conflict_{jt}$  captures the two dimensions of conflict,  $Conflict\ Dummy_{jt}$  is a dummy indicating if a group has performed an attack and  $Conflict\ Events_{jt}$  is the logged number of attacks performed in a given month.  $Transplant\ center\ at\ home\ region_j$  assumes the value of one if the group's home region has a transplant center and zero otherwise.  $Kidney\ demand_t$  is defined like in the previous section.  $FE_j$  are group fixed effects,  $FE_{ct}$  is an additional battery of fixed effects that can vary at different levels (e.g., month, country  $\times$  month).

$\beta_1$  is the coefficient of interest. It can be interpreted as the difference between the impact of a one unit-increase in kidney demand on attacks by groups with and without a transplant center.

Similar to the previous section, I standardize the waiting list variables and cluster standard errors by group and month, using two-way clustering.

## 5.2 Results

Table 4 reports the results of the analysis. A one standard deviation increase in the number of waiting list patients increases a group's probability of conflict in a given month by 26.61 basis points or 25.71 basis points, respectively. Compared to the base probability of conflict of 2.2%, this is an increase of 12%. Although the effect is only significant on the 10% level, it is economically large.

As hypothesized, coefficients are larger for an increase in the number of waiting list patients who have entered the list with a labor income: A one standard-deviation increase in the number of these patients is associated with an increase in conflict probability of 51.59 or 57.05 basis points, respectively, compared to groups without a transplant center at home. This is a 23% or 26% increase compared to the base probability.

An increase in the number of waiting list patients on dialysis, however, has no disproportionate impact on violence of groups with and without a transplant infrastructure at home.

These results are in line with the first part of Hypothesis 3 that groups with the potential to involve in transplant tourism increase their overall number of attacks with an increase in the number of waiting list patients. To investigate the second part of the hypothesis, i.e., that armed groups use the transplant infrastructure at home to finance attacks in other cells, results in Table 5 only consider a group's attacks outside its home region.

Conflicts outside the group's home region are a subset of all conflicts. Coefficients in Table 5 should therefore, by design, be smaller than in Table 4, given that the

Table 4: The impact of organ demand on a group’s conflict probability

This table reports OLS coefficients of a linear probability model regressing a binary conflict variable on the interaction between transplant infrastructure and kidney demand (see equation (2)). The sample consists of monthly observations of 723 non-state armed groups between 2010 and 2021. The dependent variable is a binary variable indicating if the group was involved in a conflict in a given month. Independent variables are the binary variable *Transplant center*, indicating the existence of an authorized transplant center in the group’s home region, and the standardized number of (i) patients on the U.S. waiting list for a kidney, (ii) patients on the U.S. waiting list for a kidney on dialysis, and (iii) patients on the U.S. waiting list for a kidney who had a labor income when entering the waiting list. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country  $\times$  month fixed effects. Standard errors are two-way clustered by group and month and shown in parentheses.

	Dependent variable: Group’s probability of conflict (in basis points)					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center at home region						
$\times$ waiting list (WL) patients	26.61*	25.71*				
	(13.67)	(13.32)				
$\times$ WL patients on dialysis			8.34	4.79		
			(13.31)	(12.43)		
$\times$ WL patients with income					51.59*	57.05*
					(30.23)	(30.52)
Observations	97,605	97,470	97,605	97,470	97,605	97,470
Actor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country $\times$ month FEs	No	Yes	No	Yes	No	Yes
Base prob. transplant actors	219.93	220.91	219.93	220.91	219.93	220.91
R-squared	0.13	0.13	0.13	0.13	0.13	0.13

Standard errors (two-way clustered by actor and month) in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

hypothesized mechanism is at work. This is the case in my analyses.

The base probability of a conflict outside a group's home region of 1.6% increases significantly by 23.36 or 22.51 basis points with a one standard deviation increase in patients on the waiting list, an increase of 14%. The effect is larger, but insignificant, for patients who entered the waiting list with income. A one standard-deviation increase in these patients increases the base probability by 43.46 or 48.15 basis points, an increase of 27% or 29%, respectively. For waiting list patients on dialysis, there is no effect.

Results for a group's log number of total conflict events or a group's log number of events outside their home region point in the same direction but are insignificant on a 10% level. They are reported in Appendix C.

Overall, my results lend support to Hypothesis 3: An increase in kidney demand increases the probability of conflict more for those groups with a transplant center at home as for groups without such center in their home region.

## **6 Organ Demand, Transplant Infrastructure, and Suspicious Payments**

In this section, I provide correlations consistent with Hypothesis 4 claiming that a higher kidney demand induces more suspicious payments to and from transplant localities.

Table 5: The impact of organ demand on a group’s conflict probability outside its home region

This table reports OLS coefficients of a linear probability model regressing a binary conflict variable on the interaction between transplant infrastructure and kidney demand (see equation (2)). The sample consists of monthly observations of 723 non-state armed groups between 2010 and 2021. The dependent variable is a binary variable indicating if the group was involved in a conflict outside its home region in a given month. Independent variables are the binary variable *Transplant center*, indicating the existence of an authorized transplant center in the group’s home region, and the standardized number of (i) patients on the U.S. waiting list for a kidney, (ii) patients on the U.S. waiting list for a kidney on dialysis, and (iii) patients on the U.S. waiting list for a kidney who had a labor income when entering the waiting list. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country  $\times$  month fixed effects. Standard errors are two-way clustered by group and month and shown in parentheses.

	Dependent variable: Group’s probability of conflict outside home region (in bp)					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center at home region						
$\times$ waiting list (WL) patients	23.36*	22.51*				
	(12.63)	(12.19)				
$\times$ WL patients on dialysis			7.48	4.34		
			(12.07)	(11.20)		
$\times$ WL patients with income					43.36	48.15
					(29.69)	(30.06)
Observations	97,488	97,353	97,488	97,353	97,488	97,353
Actor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country $\times$ month FEs	No	Yes	No	Yes	No	Yes
Base prob. transplant actors	163.42	164.15	163.42	164.15	163.42	164.15
R-squared	0.16	0.16	0.16	0.16	0.16	0.16

Standard errors (two-way clustered by actor and month) in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## 6.1 Methodological Issues

Ideally, I would also like to investigate payments on a granular local level. However, due to the lack of granular data on suspicious payments, I use aggregated data on the country-month level. My results should consequently be interpreted with caution as those countries with transplant facilities or notorious for organ trafficking might share other developments, which are spuriously related to U.S. kidney demand.

For each country  $c$  in month  $t$ , I estimate the following model:

$$\begin{aligned} \text{Payments}_{ct} = & \beta_0 + \beta_1 \text{Transplant Infrastructure}_{ct} \times \text{Kidney Demand}_t \\ & + \beta_2 \text{Transplant Infrastructure}_{ct} + FE_c + FE_t + \epsilon_{ct} \end{aligned} \quad (3)$$

$\text{Payments}_{ct}$  is the log number of suspicious payments from and to country  $c$  in a given month.  $\text{Transplant Infrastructure}_{ct}$  is either the time-varying variable  $\text{Transplant country}_{ct}$ , i.e., a dummy if the country has performed an above-average number of kidney transplant in a given year, or the variable  $\text{Traficking country}_c$ , i.e., a non-varying dummy if the country is known for organ trafficking, according to a Wikipedia list compiled by different sources. I include country and month fixed effects in all regressions.

$\beta_1$  is the coefficient of interest. It can be interpreted as the difference between the impact of a one unit-increase in kidney demand on payments to and from countries with a transplant infrastructure and the impact on countries without infrastructure. Like in the previous section, I standardize the waiting list variables.

## 6.2 Results

Table 6 reports the results of the analyses. The negative coefficient on the base effect of the variable *Transplant country* shows that countries with an above average number of kidney transplants generally have fewer suspicious payments. This is not surprising, as high-income countries typically perform more transplants and are associated with fewer suspicious payments at the same time. Coefficients of the interaction between *Kidney demand* and *Transplant country*, however, show that payments from and to countries with an above-average transplanting activity, indeed, increase more with an increase in U.S. kidney demand.

In particular, a one standard deviation increase in the number of waiting list patients is associated with 25.9% more suspicious payments from and to transplant countries. For waiting list patients on dialysis, this effect is weaker, but still significant: A one standard deviation increase in waiting list patients on dialysis is associated with 19.2% more suspicious payments from and to countries that transplant. The effect is of similar size, 18%, for waiting list patients who have entered the waiting list with a labor income.

Results are similar for the alternative definition of transplant infrastructure: A one standard deviation increase in waiting list patients is associated with 19% more suspicious payments to and from *Trafficking countries*. Coefficients are a little smaller for an increase in the number of patients on dialysis or with labor income.

Note that suspicious payments of my sample are a small subsample of all detected payments, as the ICIJ only published parts of the FinCEN data. Therefore, the mean number of payments from and to transplant or trafficking countries reported in Table

Table 6: Organ Demand, Transplant Infrastructure, and Suspicious Payments

This table reports OLS coefficients of the regression of suspicious payments on the interaction between transplant infrastructure and kidney demand (see equation (3)). The sample consists of monthly observations of 105 countries between 2008 and 2018. The dependent variable is the log number of payments that have been reported as suspicious to the FinCEN by a global correspondent bank from and to a country. Independent variables are the binary variables *Transplant country*, indicating if a country has an above-average number of kidney transplants in a given year, and *Trafficking country*, indicating if a country is notorious for organ trafficking based on a Wikipedia list compiled by different sources, the standardized number of (i) patients on the U.S. waiting list for a kidney, (ii) patients on the U.S. waiting list for a kidney on dialysis, and (iii) patients on the U.S. waiting list for a kidney who had a labor income when entering the waiting list. All models include country and month fixed effects. Standard errors are shown in parentheses.

	Dependent variable: Log suspicious payments					
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Transplant country</b>						
Transplant country	-0.171***	-0.068**	-0.000			
	(0.03)	(0.03)	(0.04)			
× waiting list (WL) patients	0.259***					
	(0.02)					
× WL patients on dialysis		0.192***				
		(0.02)				
× WL patients with income			0.180***			
			(0.02)			
<b>Trafficking country</b>						
× waiting list (WL) patients				0.190***		
				(0.02)		
× WL patients on dialysis					0.157***	
					(0.01)	
× WL patients with income						0.134***
						(0.02)
Observations	9,357	9,246	8,836	17,850	17,325	16,275
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean payments transp. countr.	0.50	0.51	0.54	0.42	0.43	0.45
R-squared	0.57	0.58	0.59	0.48	0.49	0.51

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$



6 cannot be interpreted.

These results are in line with Hypothesis 4 that higher kidney demand induces more suspicious payments from and to transplant countries. This, in turn, means that transplant tourism is, at least partly, processed via the official banking system. However, due to the high aggregation level, my results do not allow for a causal statement here.

## 7 Conclusion

This paper provides systematic evidence on the impact of transplant tourism on non-state violent conflict. I use monthly panel data with a spatial resolution of  $0.5^\circ$  latitude  $\times$   $0.5^\circ$  longitude covering eight countries from 2010 to 2021. Combining geo-referenced data on non-state conflict, hand-collected data on local transplant infrastructure, and data on exogenous kidney demand on U.S. waiting lists, I find a significant and sizable effect of higher kidney demand on the extensive and intensive margin of local conflict for localities with a transplant infrastructure. Moreover, I show that groups with a transplant infrastructure at their home region increase their violent attacks if kidney demand is higher.

My findings indicate that armed groups participate in the lucrative business of transplant tourism and use the proceeds of this business to finance violent attacks. This reinforces concerns of security agencies that the pressing organ scarcity provides new financing sources for violent groups and terrorists.

# A Sample of Non-State Armed Groups and their Home Region

Actor	Home Region	
	Latitude (rounded to closest half degree)	Longitude (rounded to closest half degree)
AAP: Aam Aadmi Party	29	77
Ababaki Communal Militia (Pakistan)	30	67
Ababeel Group	33	76
Abbas Nagar Communal Militia (Pakistan)	32	73
Abbottabad Communal Militia (Pakistan)	34	73
Abdul Ghafoor Communal Militia (Pakistan)	25	67
ABMSM: Abahlali Basemjondolo Shack Dwellers Movement	-34	19
Abran Communal Militia (Pakistan)	34	77
ABVP: Akhil Bharatiya Vidyarthi Parishad	19	73
Adamzai Communal Militia (Pakistan)	33	71
Adezai Communal Militia (Pakistan)	34	72
Agang South Africa Party	-26	28
Agwanpur Communal Militia (India)	29	78
Ahmedabad Communal Militia (India)	23	73
AIADMK: All India Anna Dravida Munnetra Kazhagam	13	81
Ajnala Communal Militia (India)	33	74
Akbarpura Communal Militia (Pakistan)	32	75
Akhnoor Communal Militia (India)	33	75
Akhorwal Tribal Militia (Pakistan)	34	72
Al-Badr	35	73
Aligarh Communal Militia (India)	28	78
All Jammu and Kashmir Muslim Conference	35	74
Alupur Communal Militia (India)	28	77
Aman Kot Communal Militia (Pakistan)	34	72
Aman Lashkar	32	75
Aman Nagar Communal Militia (India)	24	70
Amarkot Communal Militia (India)	31	75
Ambernath Communal Militia (India)	19	73
AMMK: Amma Makkal Munnetra Kazhagam	13	81
Anandapur Communal Militia (India)	22	86
Anantapur Communal Militia (India)	15	78
ANC: African National Congress	-29	26
ANC-Motlanthe: African National Congress (Motlanthe Faction)	-29	26
ANCYL: African National Congress Youth League	-29	26
ANC-Zuma: African National Congress (Zuma Faction)	-26	28
Angul Communal Militia (India)	21	85
ANLA: Achik National Liberation Army	26	92
Anoop Nagar Communal Militia (India)	29	77
ANP: Awami National Party	34	73
Antah Communal Militia (India)	25	77
Arain Communal Militia (Pakistan)	31	76
Areraj Communal Militia (India)	27	85
Arifwala Communal Militia (Pakistan)	31	73
Arnia Communal Militia (India)	33	75
ASS: Anjuman-e-Sipah-i-Sahaba	34	73
Atalgarh Communal Militia (Pakistan)	31	77
Athal Communal Militia (Pakistan)	31	79
Athwal Communal Militia (India)	32	76
Aurangzeb Butt Communal Militia (Pakistan)	32	75
Azadpur Mandi Communal Militia (India)	32	77
Baba Goth Communal Militia (Pakistan)	25	67
Babarian Communal Militia (India)	33	74
Badaber Communal Militia (Pakistan)	34	72
Badbher Communal Militia (Pakistan)	34	72
Baddi Communal Militia (India)	31	77
Badli Communal Militia (India)	16	75
Badopal Communal Militia (India)	30	74
Bagrani Communal Militia (Pakistan)	26	69
Bagri Communal Militia (Pakistan)	26	74
Bahawalpur Communal Militia (Pakistan)	30	72
Bahmna Communal Militia (India)	30	76
Bajaur Communal Militia (Pakistan)	35	72
Bajaur Tribal Militia (Pakistan)	35	72

Actor	Home Region	
	Latitude (rounded to closest half degree)	Longitude (rounded to closest half degree)
Bajrang Dal	29	77
Bakhshapur Communal Militia (Pakistan)	29	70
Bakshi Nagar Communal Militia (India)	29	78
Balaji Communal Militia (India)	12	76
Balasore Communal Militia (India)	22	87
Balluana Communal Militia (India)	30	75
Balraj Nagar Communal Militia (India)	29	77
Bambiha Communal Militia (India)	30	75
Bangarpet Communal Militia (India)	13	78
Bangial Communal Militia (Pakistan)	33	74
Bangulzai Communal Militia (Pakistan)	29	68
Bangwar Communal Militia (Pakistan)	33	76
Bannu Communal Militia (Pakistan)	33	71
Baradari Communal Militia (India)	33	74
Barara Communal Militia (India)	30	77
Barawal Communal Militia (Pakistan)	25	73
Barhalganj Communal Militia (India)	27	84
Baruajhar Communal Militia (India)	27	92
Bavla Communal Militia (India)	28	75
Begusarai Communal Militia (India)	26	86
Beharwal Communal Militia (India)	32	75
Bengaluru Communal Militia (India)	13	78
Besant Nagar Communal Militia (India)	13	81
Betma Communal Militia (India)	23	76
BGRD: Bhartiya Gau Raksha Dal	29	77
Bhadaur Communal Militia (India)	31	76
Bhag Communal Militia (Pakistan)	29	68
Bhagat Communal Militia (Pakistan)	33	74
Bhaggapur Uttar Communal Militia (India)	32	75
Bhagwantpura Communal Militia (India)	26	75
Bhakkar Communal Militia (Pakistan)	32	71
Bhakna Khurd Communal Militia (India)	32	75
Bhalwal Communal Militia (India)	33	73
Bhambayi Communal Militia (South Africa)	-30	31
Bhan Communal Militia (Pakistan)	27	68
Bhana Mari Communal Militia (Pakistan)	34	72
Bhanada Communal Militia (India)	23	69
Bhangar Communal Militia (India)	31	75
Bharatpur Communal Militia (India)	28	78
Bhatti Communal Militia (Pakistan)	28	68
Bhayo Communal Militia (Pakistan)	28	69
Bhilgawan Communal Militia (India)	27	78
Bhurgari Communal Militia (Pakistan)	25	69
Bhut Ethnic Militia (Pakistan)	31	78
Bhutto Communal Militia (Pakistan)	28	69
Bibiwala Communal Militia (India)	30	75
Bichaula Communal Militia (India)	28	79
Bijarani Communal Militia (Pakistan)	28	69
Bijarani Tribal Militia (Pakistan)	28	69

Bijnor Communal Militia (India)	30	79
Bikkavolu Communal Militia (India)	17	82
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Binjhol Communal Militia (India)	30	77
Bishnah Communal Militia (India)	33	75
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BJD: Biju Janata Dal	21	86
BJP: Bharatiya Janata Party	29	77
BJYM: Bharatiya Janata Yuva Morcha	29	77
BLA: Baloch Liberation Army	32	66
Bori Kharak Communal Militia (Pakistan)	33	71
Borivali Communal Militia (India)	19	73
Brahmpura Communal Militia (India)	25	75
Brohi Communal Militia (Pakistan)	26	70
BSP: Bahujan Samaj Party	29	77
Bugti Communal Militia (Pakistan)	29	69
Bundi Communal Militia (India)	26	76
Buner Communal Militia (Pakistan)	32	77
Buriro Communal Militia (Pakistan)	28	69
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Chachar Communal Militia (Pakistan)	28	69
Chak 241-GB Communal Militia (Pakistan)	31	73
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Chak Seven Hundred Fifty-seven Gugera Branch Communal Militia (Pakistan)	31	74
Chakdara Communal Militia (Pakistan)	35	72
Chakri Communal Militia (Pakistan)	32	75
Challar Communal Militia (Pakistan)	25	70
Chaman Communal Militia (Pakistan)	31	67
Chamiari Communal Militia (India)	34	73
Chamkani Communal Militia (Pakistan)	34	72
Chandigarh Communal Militia (India)	31	77
Chandio Communal Militia (Pakistan)	25	67
Chandpur Communal Militia (India)	29	79
Chapri Communal Militia (Pakistan)	34	75
Charsadda Communal Militia (Pakistan)	34	72
Charwazgai Communal Militia (Pakistan)	34	71
Chattar Communal Militia (Pakistan)	33	75
Cheeka Communal Militia (India)	30	77
Chennai Communal Militia (India)	13	81
Chhajla Communal Militia (India)	30	76
Chhawla Communal Militia (India)	29	77
Chhiniwal Kalan Communal Militia (India)	31	76
Chikkade Communal Militia (India)	13	77
Chota Lahore Communal Militia (Pakistan)	34	73
Chountra Communal Militia (Pakistan)	34	73
Curcholem Communal Militia (India)	16	74
DA: Democratic Alliance	-34	19
Dabhola Communal Militia (India)	33	74

Dabri Communal Militia (India)	30	80
Daharki Communal Militia (Pakistan)	28	70
Dandeli Communal Militia (India)	15	75
Dargai Communal Militia (Pakistan)	35	72
Darrang Communal Militia (India)	27	93
Darya Gali Communal Militia (Pakistan)	34	74
Datewas Communal Militia (India)	30	76
Dedo Communal Militia (Pakistan)	31	77
Deh Nau Abad Communal Militia (Pakistan)	31	75
Dehri Communal Militia (India)	29	77
Dera Bugti Communal Militia (Pakistan)	29	69
Dera Ghazi Khan Communal Militia (Pakistan)	30	71
Detho Communal Militia (Pakistan)	28	69
Devidaspura Communal Militia (India)	32	73
Dhari Communal Militia (India)	30	80
Dhobiana Basti Communal Militia (India)	30	75
Dhoke Mangtal Communal Militia (Pakistan)	34	73
Dhotian Communal Militia (India)	32	75
Dhulian Communal Militia (India)	25	88
Dina Ki Mandi Communal Militia (India)	27	78
Dir Communal Militia (Pakistan)	35	72
DMK: Dravida Munnetra Kazhagam	13	81
Dobandai Communal Militia (Pakistan)	35	73
Doboka Communal Militia (India)	26	93
Dogar Communal Militia (Pakistan)	32	75
Dohkih Communal Militia (Pakistan)	28	77
Doom Dooma Communal Militia (India)	28	96
Dubli Communal Militia (India)	31	75
Dudhai Communal Militia (India)	24	70
Dulehar Communal Militia (India)	32	76
Dungian Communal Militia (India)	32	75
DYFI: Democratic Youth Federation of India	29	77
EFF: Economic Freedom Fighters	-26	28
English Bazar Communal Militia (India)	25	88
Faisalabad Communal Militia (Pakistan)	32	73
Faizalabad Communal Militia (Pakistan)	33	73
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Farman Communal Militia (Pakistan)	32	77
Farrukhabad Communal Militia (India)	28	80
Fateh Jang Communal Militia (Pakistan)	34	73
Fateh Khankhel Tribal Militia (Pakistan)	33	71
Fatehgarh Jattan Communal Militia (India)	31	77
Fatehpur Communal Militia (India)	26	81
Fatuwala Communal Militia (Pakistan)	28	72
Ferozewala Communal Militia (Pakistan)	32	75
Gabol Communal Militia (Pakistan)	28	69
Gadarpur Communal Militia (India)	29	80
Ga-Molepo Communal Militia (South Africa)	-24	30
Gandi Khan Khel Communal Militia (Pakistan)	33	71
Garhi Sheru Communal Militia (India)	31	76
Garja Communal Militia (Pakistan)	30	79
Gawara Communal Militia (India)	26	74

GERB: Citizens for European Development of Bulgaria	43	24
Ghariaala Communal Militia (India)	30	72
Gharo Communal Militia (Pakistan)	28	67
Gharota Communal Militia (India)	32	76
Ghatkopar Communal Militia (India)	19	73
Ghaziabad Communal Militia (India)	29	78
Ghazipur Communal Militia (India)	26	84
Ghotki Communal Militia (Pakistan)	28	70
Ghuman Communal Militia (India)	31	76
Ghuman Kalan Communal Militia (India)	31	76
Ghundi Communal Militia (Pakistan)	33	72
Gill Kalan Communal Militia (India)	31	76
GJM: Gorkha Janmukti Morcha	27	89
Gojra Communal Militia (Pakistan)	31	73
Gopang Ethnic Militia (Pakistan)	28	69
Goth Surab Khan Communal Militia (Pakistan)	30	67
Gotyibeni Communal Militia (South Africa)	-32	29
Gujar Khan Communal Militia (Pakistan)	34	74
Gujjar Communal Militia (Pakistan)	31	75
Gujrani Communal Militia (Pakistan)	29	76
Gujranwala Communal Militia (Pakistan)	32	74
Gul Imam Communal Militia (Pakistan)	33	71
Guligram Communal Militia (Pakistan)	35	73
Gundala Communal Militia (India)	15	78
Gupchani Communal Militia (Pakistan)	26	69
Guwahati Communal Militia (India)	26	92
Halepoto Communal Militia (Pakistan)	25	69
Hanjarwal Communal Militia (Pakistan)	32	75
Harban Communal Militia (Pakistan)	36	74
Hariharpara Communal Militia (India)	24	89
Hasil Faqir Bozdar Communal Militia (Pakistan)	27	69
Haud Communal Militia (India)	28	76
Helenvale Communal Militia (South Africa)	-34	26
Hisar Communal Militia (India)	29	76
HM: Hizb-ul-Mujahideen	35	74
HNA: Hmar National Army	23	93
Hoskote Communal Militia (India)	13	78
Husri Communal Militia (Pakistan)	15	75
Hussain Basti Communal Militia (India)	30	73
Hussainpura Communal Militia (India)	32	75
Hyderabad Communal Militia (India)	18	79
HYV: Hindu Yuva Vahini	27	84
Idgah Maidan Communal Militia (India)	17	75
IFP: Inkatha Freedom Party	-30	31
IJT: Islami Jamiat-e-Talaba	32	75
Imphal Communal Militia (India)	25	94
INC: Indian National Congress	29	77
IPFT: Indigenous Peoples Front of Tripura	24	92
IUML: Indian Union Muslim League	13	81
IYC: Indian Youth Congress	29	77
Jabbowal Communal Militia (India)	32	76
Jaffarabad Communal Militia (Pakistan)	32	75

Jagirani Communal Militia (Pakistan)	28	68
Jagti Communal Militia (India)	33	75
Jagtial Communal Militia (India)	19	79
Jaintia Communal Militia (India)	26	93
Jaipur Communal Militia (India)	27	76
Jakhrani Communal Militia (Pakistan)	29	70
Jakhrani Tribal Militia (Pakistan)	29	70
Jalalpur Communal Militia (India)	27	83
Jalbandi Communal Militia (Pakistan)	28	68
Jammu Communal Militia (India)	33	75
Jampur Communal Militia (Pakistan)	30	71
Jamrud Communal Militia (Pakistan)	34	72
Jamshedpur Communal Militia (India)	23	86
Jandola Communal Militia (Pakistan)	33	70
Janwari Communal Militia (Pakistan)	27	69
Jaranwala Communal Militia (Pakistan)	32	74
Jat Communal Militia (Pakistan)	17	76
Jatli Communal Militia (Pakistan)	33	73
Jatoi Communal Militia (Pakistan)	30	71
Jawaki Ara Khel Communal Militia (Pakistan)	34	72
JD(S): Janata Dal (Secular)	13	78
JD(U): Janata Dal (United)	29	77
JeM: Jaish-e-Mohammad	30	72
Jewan Gondal Communal Militia (Pakistan)	22	71
Jewar Communal Militia (India)	28	78
Jhal Magsi Communal Militia (Pakistan)	29	68
Jhang Communal Militia (Pakistan)	34	73
Jhansi Communal Militia (Pakistan)	26	79
Jhark Communal Militia (Pakistan)	32	72
Jl: Jamaat-e-Islami	32	75
JJMP: Jharkhand Jan Mukti Parishad	24	86
Jokhio Communal Militia (Pakistan)	25	68
JSMM: Jeay Sindh Muttahida Mahaz	26	69
JSQM: Jeay Sindh Qaumi Movement	26	69
JUD: Jamaat-ud-Dawa	32	75
JUL-F: Jamiat Ulema-e-Islam-Fazl	32	71
Kabirwala Communal Militia (Pakistan)	31	72
Kahna Nau Communal Militia (Pakistan)	32	75
Kahuta Communal Militia (Pakistan)	34	74
Kaimganj Communal Militia (India)	28	80
Kakori Communal Militia (India)	27	81
Kalhoru Communal Militia (Pakistan)	26	69
Kali Dinga Communal Militia (India)	33	74
Kaliachak Communal Militia (India)	25	88
Kaliasot Communal Militia (India)	23	78
Kallar Communal Militia (Pakistan)	10	77
Kamali Banda Communal Militia (Pakistan)	33	71
Kamboke Communal Militia (India)	32	75
Kamoke Communal Militia (Pakistan)	32	74
Kandari Communal Militia (Pakistan)	19	76
Kandhkot Communal Militia (Pakistan)	28	69
Kanpur Dehat Communal Militia (India)	27	80

Kapoor Singh Wala Communal Militia (India)	32	75
Karachi Communal Militia (Pakistan)	25	67
Karmatanr Communal Militia (India)	24	87
Karur Communal Militia (India)	11	78
Katlang Communal Militia (Pakistan)	35	72
Katohar Communal Militia (Pakistan)	32	76
Katra Communal Militia (India)	26	86
KCP: Kangleipak Communist Party	25	94
Khadoli Communal Militia (India)	20	73
Khairpur Communal Militia (Pakistan)	28	69
Khan Garh Communal Militia (Pakistan)	31	76
Khanpur Communal Militia (India)	26	86
Khanpur Communal Militia (Pakistan)	26	86
Khanpur Mahar Communal Militia (Pakistan)	28	70
Kharal Communal Militia (Pakistan)	26	73
Kharan Communal Militia (Pakistan)	25	77
Khari Dhand Communal Militia (Pakistan)	26	70
Kharral Communal Militia (Pakistan)	30	73
Khaskheli Communal Militia (Pakistan)	28	69
Khatauli Communal Militia (India)	30	78
Khati Communal Militia (Pakistan)	30	80
Kheda Communal Militia (India)	23	73
Khiala Kalan Communal Militia (India)	32	75
Khokhar Communal Militia (India)	27	75
Khokhar Communal Militia (Pakistan)	27	75
Khosa Communal Militia (Pakistan)	31	76
Khoso Communal Militia (Pakistan)	26	70
Khoso Tribal Militia (Pakistan)	26	70
Khuleka Communal Militia (South Africa)	-29	32
Khumari Communal Militia (Pakistan)	22	80
Khuzdar Communal Militia (Pakistan)	28	67
Khyber Communal Militia (Pakistan)	37	75
Killi Pathan Goth Communal Militia (Pakistan)	26	69
KNF: Kuki National Front	25	94
Kohat Communal Militia (Pakistan)	34	72
Koliwad Communal Militia (India)	16	76
Kolkata Communal Militia (India)	23	89
Korangi Communal Militia (Pakistan)	25	67
Kot Addu Communal Militia (Pakistan)	31	71
Kot Hassan Khan Communal Militia (Pakistan)	32	72
Kot Momin Communal Militia (Pakistan)	32	73
Kotla Doom Communal Militia (India)	32	75
Kotli Communal Militia (Pakistan)	32	77
Kotri Communal Militia (Pakistan)	26	69
Kotwali Communal Militia (India)	30	79
Kozhikode Communal Militia (India)	11	76
Krugersdorp Communal Militia (South Africa)	-26	28
Kumbakonam Communal Militia (India)	11	80
Kurar Communal Militia (India)	19	73
Kurram Communal Militia (Pakistan)	33	71
KwaZulu-Natal Communal Militia (South Africa)	-29	31
Laghari Communal Militia (Pakistan)	32	72



Laheriasarai Communal Militia (India)	26	86
Lahian Communal Militia (India)	32	75
Lahore Communal Militia (Pakistan)	32	75
Lakher Communal Militia (Pakistan)	28	76
Lakki Marwat Communal Militia (Pakistan)	33	71
Lakshimpur Communal Militia (India)	25	87
Lalru Communal Militia (India)	31	77
Landhi Communal Militia (Pakistan)	26	69
Langah Communal Militia (Pakistan)	32	75
Larkana Communal Militia (Pakistan)	28	68
Lasbela Communal Militia (Pakistan)	26	67
Lashari Communal Militia (Pakistan)	31	74
Lasi Goth Communal Militia (Pakistan)	25	67
Lathi Communal Militia (Pakistan)	27	72
Lehian Communal Militia (India)	32	75
LeT: Lashkar-e-Taiba	32	75
Lingapura Communal Militia (India)	13	78
Lisana Communal Militia (India)	28	77
Lodra Communal Militia (Pakistan)	21	83
Loharka Kalan Communal Militia (India)	32	75
Los Monos Gang	-33	-61
Ludhiana Communal Militia (India)	31	76
Lyari Communal Militia (Pakistan)	25	67
Machhi Communal Militia (Pakistan)	26	70
Machhrauli Communal Militia (India)	29	77
Machi Communal Militia (Pakistan)	25	94
Magangangozi Communal Militia (South Africa)	-29	30
Magsi Communal Militia (Pakistan)	24	76
Mahar Communal Militia (Pakistan)	30	79
Mahesar Communal Militia (Pakistan)	20	83
Maho Dheri Communal Militia (Pakistan)	34	72
Mahsud Communal Militia (Pakistan)	33	70
Mahua Khera Communal Militia (India)	27	78
Maidan Communal Militia (Pakistan)	23	89
Mainpuri Communal Militia (India)	27	79
Malgin Communal Militia (Pakistan)	34	72
Malik Din Khel Tribal Militia (Pakistan)	34	71
Malikpur Communal Militia (Pakistan)	26	88
Malir Communal Militia (Pakistan)	25	67
Malpur Communal Militia (Pakistan)	25	74
Maluwal Communal Militia (India)	32	75
Mambapur Communal Militia (India)	18	78
Mamelodi Communal Militia (South Africa)	-26	29
Mananwala Communal Militia (Pakistan)	32	74
Manesar Communal Militia (India)	29	77
Manga Mandi Communal Militia (Pakistan)	32	74
Mangrio Communal Militia (Pakistan)	25	67
Mano Chak Communal Militia (Pakistan)	33	74
Manwal Communal Militia (India)	33	75
Mardan Communal Militia (Pakistan)	34	72
Maregaon Communal Militia (India)	20	79
Mari Kamboke Communal Militia (India)	32	75

Mari Tribal Militia (Pakistan)	31	76
Marri Tribal Militia (Pakistan)	31	76
Maryamzai Communal Militia (Pakistan)	34	72
Masaurhi Communal Militia (India)	26	85
Mastala Communal Militia (Pakistan)	33	73
Mathia Hata Communal Militia (India)	27	84
Mayo Gardens Communal Militia (Pakistan)	32	75
Mazari Communal Militia (Pakistan)	30	78
Mdantsane Communal Militia (South Africa)	-33	28
Mehar Communal Militia (Pakistan)	27	68
Mehar Shah Communal Militia (Pakistan)	32	71
Mehatpur Communal Militia (India)	31	76
Mehma Sawai Communal Militia (India)	31	75
Memon Communal Militia (Pakistan)	25	67
Memon Goth Communal Militia (Pakistan)	25	68
Mengal Communal Militia (Pakistan)	30	68
Mevasa Communal Militia (India)	24	71
Mhlwazini Communal Militia (South Africa)	-29	30
Mianwali Communal Militia (Pakistan)	33	72
Mirza Nawaz Communal Militia (Pakistan)	34	73
Mitraon Communal Militia (India)	29	77
MNS: Maharashtra Navnirman Sena	19	73
Moga Communal Militia (India)	31	75
Mohan Garden Communal Militia (India)	29	77
Morbi Communal Militia (India)	23	71
MPN: Neuquen People's Movement	-39	-70
MQM: Muttahida Qaumi Movement	25	67
MQM-H: Mohajir Qaumi Movement-Haqiqi	25	67
MQM-L: Muttahida Qaumi Movement-London	25	67
MSF: Muslim Students Federation	13	81
Msinga Communal Militia (South Africa)	-29	31
Mughal Communal Militia (Pakistan)	32	75
Muhtsar Communal Militia (India)	31	75
Muneer Communal Militia (Pakistan)	25	67
Munnekolala Communal Militia (India)	13	78
Murhu Communal Militia (India)	23	86
Murree Communal Militia (Pakistan)	34	74
Nabha Communal Militia (India)	31	76
Nacho Communal Militia (India)	29	94
Nagpur Communal Militia (India)	21	79
Nahali Communal Militia (India)	22	75
Nai Abadi Communal Militia (Pakistan)	34	73
Naich Communal Militia (Pakistan)	30	72
Naik Muhammad Communal Militia (Pakistan)	25	67
Naik Ziarat Communal Militia (Pakistan)	31	68
Nainital Communal Militia (India)	30	80
Nainwal Communal Militia (India)	29	77
Nakur Communal Militia (India)	30	78
Nand Nagri Communal Militia (India)	29	78
Nangal Communal Militia (India)	32	77
Nankana Sahib Communal Militia (Pakistan)	32	74
Narayanpur Communal Militia (India)	26	87

Nasirpur Communal Militia (India)	31	77
Nathpura Communal Militia (India)	23	75
Nathuwala Communal Militia (Pakistan)	31	75
Naurang Communal Militia (Pakistan)	31	75
Nawada Communal Militia (India)	25	86
Nawan Killi Communal Militia (Pakistan)	32	75
Nayagarh Communal Militia (India)	20	85
Ndibela Communal Militia (South Africa)	-34	19
NDPP: Nationalist Democratic Progressive Party	26	94
New Fatehgarh Communal Militia (India)	21	86
New Gurnam Nagar Communal Militia (India)	28	77
Nimbahera Communal Militia (India)	25	75
Nizamani Communal Militia (Pakistan)	25	69
Noida Communal Militia (India)	29	78
Noor Muhammad Communal Militia (Pakistan)	26	70
Noorpur Basti Communal Militia (Pakistan)	27	83
Nothia Communal Militia (Pakistan)	34	72
NSCN: National Socialist Council of Nagaland	26	94
NSCN-IM: National Socialist Council of Nagaland-Isak Muivah	26	94
NSCN-K: National Socialist Council of Nagaland-Khaplang	26	94
NSCN-KK: National Socialist Council of Nagaland-Khango Konyak	26	94
NSCN-K-NK: National Socialist Council of Nagaland-Khaplang-Nyemlang Konyak	26	94
NSCN-K-YA: National Socialist Council of Nagaland-Khaplang-Yung Aung	26	94
NSCN-R: National Socialist Council of Nagaland-Reformation	26	94
NSCN-U: National Socialist Council of Nagaland-Unification	26	94
NSUI: National Students Union of India	29	77
Ntsimbini Communal Militia (South Africa)	-33	29
NUM: National Union of Mineworkers	-26	28
NUMSA: National Union of Metalworkers of South Africa	-26	28
Nusrat Pur Communal Militia (Pakistan)	34	73
Nuzvid Communal Militia (India)	17	81
Oghi Communal Militia (Pakistan)	35	73
Okara Communal Militia (Pakistan)	31	74
Okhla Communal Militia (India)	29	78
Orakzai Communal Militia (Pakistan)	34	71
Orangi Communal Militia (Pakistan)	25	67
Othwal Communal Militia (Pakistan)	33	73
PAC: People's Aman Committee	25	67
PAGAD: People Against Gangsterism and Drugs	-34	19
Pakhi Kalan Communal Militia (India)	31	75
Pakhtoon Communal Militia (Pakistan)	19	73
Pakpattan Communal Militia (Pakistan)	31	74
Palam Vihar Communal Militia (India)	29	77
Palamedu Communal Militia (India)	10	78
Palda Communal Militia (India)	23	76
Palh Communal Militia (Pakistan)	28	76
Pandra Communal Militia (India)	24	86
Panhwar Communal Militia (Pakistan)	26	69
Para Chamkani Tribal Militia (Pakistan)	34	72
Pari Bangla Communal Militia (Pakistan)	26	74
PASMA: Pan Africanist Student Movement of Azania	-34	19
Pasrur Communal Militia (Pakistan)	33	75

Patakpur Communal Militia (India)	28	77
Pathan Communal Militia (Pakistan)	33	76
Patna Communal Militia (India)	26	85
Peerwala Communal Militia (Pakistan)	31	78
Peshawar Communal Militia (Pakistan)	34	72
Peshwar Communal Militia (Pakistan)	34	72
Petlurivaripalem Communal Militia (India)	16	80
Phagwara Communal Militia (India)	31	76
Phulgran Communal Militia (Pakistan)	34	73
Phulwari Communal Militia (India)	26	85
Pindi Bhattian Communal Militia (Pakistan)	32	74
Pipariya Communal Militia (India)	25	86
Pipli Communal Militia (India)	31	79
Pirmahal Communal Militia (Pakistan)	31	73
PLA: People's Liberation Army of Manipur	25	94
PML-F: Pakistan Muslim League-Functional	25	67
PML-N: Pakistan Muslim League-Nawaz	32	75
Port Blair Communal Militia (India)	12	93
Powat Communal Militia (India)	31	77
PPP: Pakistan Peoples Party	34	73
Pratapgarh Communal Militia (India)	26	82
PSF: People's Student Federation	34	73
PSF: Peoples Students Federation	34	73
PSF: Pukhtoon Students Federation	34	72
PSP: Pak Sarzameen Party	25	67
PTI: Pakistan Tehreek-i-Insaf	34	73
Pundar Communal Militia (India)	31	78
Pursapur Communal Militia (India)	17	78
Qambar Shahdadkot Communal Militia (Pakistan)	28	68
Qambrani Communal Militia (Pakistan)	28	68
Quetta Communal Militia (Pakistan)	30	67
QWP: Qaumi Watan Party	34	72
Radhanpur Communal Militia (India)	24	72
Raiganj Communal Militia (India)	26	88
Raipur Communal Militia (India)	21	82
Raisani Communal Militia (Pakistan)	30	67
Raiwind Communal Militia (Pakistan)	31	74
Rajar Communal Militia (Pakistan)	19	73
Rajeev Colony Communal Militia (India)	18	80
Rajeev Nagar Communal Militia (India)	29	78
Rajjar Communal Militia (Pakistan)	34	72
Rajpar Communal Militia (Pakistan)	23	70
Rajpura Communal Militia (India)	31	77
Rakkathampatti Communal Militia (India)	11	79
Ram Nagar Communal Militia (India)	27	76
Rampur Communal Militia (India)	29	79
Rampuram Communal Militia (India)	18	83
Ranchi Communal Militia (India)	24	86
Ranchi Communal Militia (india)	24	86
Randfontein Communal Militia (South Africa)	-26	28
Randhawa Communal Militia (Pakistan)	30	77
Ranewali Communal Militia (India)	32	75

Rangar Communal Militia (Pakistan)	32	77
Rangia Communal Militia (India)	27	92
Rani Bagh Communal Militia (India)	29	77
Rani Majra Communal Militia (India)	31	77
Rasulpur Communal Militia (India)	23	88
Rawalpindi Communal Militia (Pakistan)	34	73
Rawat Communal Militia (Pakistan)	34	73
Rehti Communal Militia (India)	23	78
Remuna Communal Militia (India)	22	87
RJD: Rashtriya Janata Dal	29	77
Rodala Communal Militia (Pakistan)	26	73
RSS: Rashtriya Swayamsevak Sangh	21	79
Rupawas Communal Militia (India)	26	74
Rureke Kalan Communal Militia (India)	31	76
Rustenburg Communal Militia (South Africa)	-26	27
Sadar Communal Militia (Pakistan)	26	83
Saddar Communal Militia (Pakistan)	25	67
Sadiqabad Communal Militia (Pakistan)	29	70
Sadozai Communal Militia (Pakistan)	27	66
Saharanpur Communal Militia (India)	30	78
Sahiwal Communal Militia (Pakistan)	31	73
Salarpur Communal Militia (India)	27	83
Salempur Communal Militia (India)	27	84
Samundri Communal Militia (Pakistan)	31	73
SAMWU: South African Municipal Workers Union	-26	28
Sangatpura Communal Militia (India)	30	74
Sangna Communal Militia (India)	32	75
Sango Romana Communal Militia (India)	31	75
Sanjrani Communal Militia (Pakistan)	29	70
Santipur Communal Militia (India)	24	89
Saraikeela Communal Militia (India)	23	86
Sargani Communal Militia (Pakistan)	31	71
Sarthal Communal Militia (India)	25	77
Sasaram Communal Militia (India)	25	84
SASCO: South Africa Students Congress	-26	28
Sasoli Communal Militia (Pakistan)	32	76
SATAWU: South African Transport and Allied Workers Union	-26	28
Satghara Communal Militia (Pakistan)	31	74
Sawai Madhopur Communal Militia (India)	26	77
Sawaich Kamalu Communal Militia (India)	30	75
SDPI: Social Democratic Party of India	29	77
Sethar Communal Militia (Pakistan)	27	68
Shadbagh Communal Militia (Pakistan)	25	67
Shah Hassan Khel Communal Militia (Pakistan)	34	72
Shahdadpur Communal Militia (Pakistan)	26	69
Shahdara Communal Militia (Pakistan)	29	78
Shaheed Udam Singh Nagar Communal Militia (India)	31	76
Shaheeda Banda Communal Militia (Pakistan)	34	71
Shahjahanpur Communal Militia (India)	28	80
Shahpur Bela Communal Militia (India)	26	82
Shahpur Communal Militia (India)	26	85
Shahzad Communal Militia (Pakistan)	32	75

Shalozan Communal Militia (Pakistan)	34	70
Shamli Communal Militia (India)	30	78
Shankarpura Communal Militia (India)	27	78
Shatabgarh Communal Militia (India)	31	77
Sheikhabad Communal Militia (Pakistan)	34	72
Sherani Communal Militia (Pakistan)	31	70
Sher-e-Bengal	24	88
Shikarpur Communal Militia (Pakistan)	28	78
Shopian Communal Militia (India)	34	75
Shyampur Communal Militia (India)	30	78
Sialkot Communal Militia (Pakistan)	33	75
Sihala Communal Militia (Pakistan)	31	76
Sikandarpur Communal Militia (India)	34	73
SIMI: Students Islamic Movement of India	28	78
Sincha Communal Militia (India)	34	75
Siyahlala Communal Militia (South Africa)	-34	19
Siyal Communal Militia (Pakistan)	32	77
SKM: Sikkim Krantikari Morcha	28	89
SMP: Sipah-e-Muhammad Pakistan	32	75
Sohana Communal Militia (India)	31	77
Sohna Communal Militia (India)	29	77
Solangi Communal Militia (Pakistan)	25	70
Sonari Communal Militia (India)	27	95
Sorada Communal Militia (India)	20	85
Soraon Communal Militia (India)	26	82
SP: Samajwadi Party	29	77
Sperkai Tribal Militia (Pakistan)	33	70
Spinwam Communal Militia (Pakistan)	33	71
Srivaikuntam Communal Militia (India)	9	78
SSP: Sipah-e-Sahaba Pakistan	34	73
Sukkur Communal Militia (Pakistan)	28	69
Sultanpur Lodhi Communal Militia (India)	31	75
Suppi Communal Militia (India)	27	86
Surab Communal Militia (Pakistan)	29	67
Surajpur Communal Militia (India)	24	83
Swabi Communal Militia (Pakistan)	34	72
Swat Communal Militia (Pakistan)	35	72
Syed Bachal Shah Communal Militia (Pakistan)	28	68
Tablighi Jamaat	30	78
Tahir Shah Communal Militia (Pakistan)	32	75
Tajori Communal Militia (Pakistan)	33	71
Talaja Communal Militia (India)	22	72
Talpur Communal Militia (Pakistan)	30	76
Talwandi Sabo Communal Militia (India)	30	75
Tando Bago Communal Militia (Pakistan)	25	69
Tando Yousuf Communal Militia (Pakistan)	26	69
Tapriyan Communal Militia (India)	25	77
Tareen Communal Militia (Pakistan)	30	72
Tarn Taran Communal Militia (India)	32	75
Tarsikka Communal Militia (India)	32	75
TDP: Telugu Desam Party	18	79
Teghani Communal Militia (Pakistan)	28	69

Tehrik-e-Tuhafaz Pakistan	34	73
Thaheem Communal Militia (Pakistan)	25	67
Thakarwal Communal Militia (India)	31	76
Thanjavur Communal Militia (India)	11	79
Thari Mirwah Communal Militia (Pakistan)	26	69
Thikriwala Communal Militia (Pakistan)	32	74
Tiljala Communal Militia (India)	23	89
Tiwaripur Communal Militia (India)	26	82
TLP: Tehreek-e-Labbaik Pakistan	32	75
TMC: Trinamool Congress Party	23	89
TMCP: Trinamool Chhatra Parishad	23	89
Township Communal Militia (Pakistan)	32	75
TRS: Telangana Rashtra Samithi	18	79
Tughlaqabad Communal Militia (India)	29	78
Tulsinagar Communal Militia (India)	17	80
Tushura Communal Militia (India)	21	84
Ubha Communal Militia (India)	30	76
Uch Sharif Communal Militia (Pakistan)	29	71
Udaka Communal Militia (India)	28	78
UDM: United Democratic Movement	-26	28
Uggoke Communal Militia (Pakistan)	31	76
ULA/AA: United League of Arakan/Arakan Army	25	98
Umrani Communal Militia (Pakistan)	29	68
Urmar Communal Militia (Pakistan)	32	76
Urmar Payan Communal Militia (Pakistan)	34	72
Usta Muhammad Communal Militia (Pakistan)	28	68
Uttam Nagar Communal Militia (India)	29	77
Vadodara Communal Militia (India)	23	73
Vehari Communal Militia (Pakistan)	30	73
VHP: Vishwa Hindu Parishad	29	77
Vishnupur Communal Militia (India)	23	88
Wali Muhammad Communal Militia (Pakistan)	30	72
Wankaner Communal Militia (India)	23	71
Wapda Town Communal Militia (Pakistan)	30	72
Warah Communal Militia (Pakistan)	32	71
Wazirwala Communal Militia (Pakistan)	33	72
Welkom Communal Militia (South Africa)	-28	27
Xolobeni Communal Militia (South Africa)	-31	30
Yaqubi Communal Militia (Pakistan)	34	73
Yar Hussain Communal Militia (Pakistan)	34	73
Yazman Communal Militia (Pakistan)	29	72
YSRCP: Yuvajana, Sramika, Rythu Congress Party	17	81
Zhob Communal Militia (Pakistan)	32	70
Ziarat Communal Militia (Pakistan)	31	68

## B Sources for Authorizes Transplant Centers

Table 8: Sources for authorized transplant centers

Country	Source for authorized transplant centers
Argentina	<a href="https://www.argentina.gob.ar/salud/incuca/organismos-jurisdiccionales">https://www.argentina.gob.ar/salud/incuca/organismos-jurisdiccionales</a>
Armenia	<a href="https://www.mohanfoundation.org/transplant-centres/index.asp">https://www.mohanfoundation.org/transplant-centres/index.asp</a>
Bulgaria	<a href="https://iamn.bg/en/transplantations/statistics-organ-transplantation-by-healthcare-in">https://iamn.bg/en/transplantations/statistics-organ-transplantation-by-healthcare-in</a>
Hungary	<a href="https://www.ovsz.hu/en/organ-coordination-office/accessibilities">https://www.ovsz.hu/en/organ-coordination-office/accessibilities</a>
India	<a href="https://www.mohanfoundation.org/transplant-centres/index.asp">https://www.mohanfoundation.org/transplant-centres/index.asp</a>
Pakistan	<a href="https://applications.emro.who.int/emhj/v16/supp/16_S2010_159_166.pdf?ua=1">https://applications.emro.who.int/emhj/v16/supp/16_S2010_159_166.pdf?ua = 1</a>
Russia	<a href="https://www.transpl.ru">https://www.transpl.ru</a>
South Africa	Email to ministry of health



## C Robustness

Table 9: The impact of organ demand on a group’s number of conflict events

This table reports OLS coefficients of the regression of an armed group’s number of attacks on the interaction between transplant infrastructure and kidney demand (see equation (2)). The sample consists of monthly observations of 723 non-state armed groups between 2010 and 2021. The dependent variable is an armed group’s log number of conflicts. Independent variables are the binary variable *Transplant center*, indicating the existence of an authorized transplant center in the group’s home region, and the standardized number of (i) patients on the U.S. waiting list for a kidney, (ii) patients on the U.S. waiting list for a kidney on dialysis, and (iii) patients on the U.S. waiting list for a kidney who had a labor income when entering the waiting list. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country  $\times$  month fixed effects. Standard errors are two-way clustered by group and month and shown in parentheses.

	Dependent variable: Log group’s conflict events					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center						
$\times$ waiting list (WL) patients	0.002 (0.00)	0.002 (0.00)				
$\times$ WL patients on dialysis			-0.000 (0.00)	-0.000 (0.00)		
$\times$ WL patients with income					0.006 (0.00)	0.007 (0.00)
Observations	97,605	97,470	97,605	97,470	97,605	97,470
actor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country $\times$ month FEs	No	Yes	No	Yes	No	Yes
Mean events transplant actors	0.02	0.02	0.02	0.02	0.02	0.02
R-squared	0.18	0.18	0.18	0.18	0.18	0.18

Standard errors (two-way clustered by group and month) in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 10: The impact of organ demand on a group’s number of conflict events

This table reports OLS coefficients of the regression of an armed group’s number of attacks outside its home region on the interaction between transplant infrastructure and kidney demand (see equation (2)). The sample consists of monthly observations of 723 non-state armed groups between 2010 and 2021. The dependent variable is the log number of conflicts outside a group’s home region. Independent variables are the binary variable *Transplant center*, indicating the existence of an authorized transplant center in the group’s home region, and the standardized number of (i) patients on the U.S. waiting list for a kidney, (ii) patients on the U.S. waiting list for a kidney on dialysis, and (iii) patients on the U.S. waiting list for a kidney who had a labor income when entering the waiting list. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country  $\times$  month fixed effects. Standard errors are two-way clustered by group and month and shown in parentheses.

	Dependent variable:					
	Log Group’s conflict events outside home region					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center						
$\times$ waiting list (WL) patients	0.002 (0.00)	0.002 (0.00)				
$\times$ WL patients on dialysis			0.000 (0.00)	-0.000 (0.00)		
$\times$ WL patients with income					0.005 (0.00)	0.006 (0.00)
Observations	97,488	97,353	97,488	97,353	97,488	97,353
actor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country $\times$ month FEs	No	Yes	No	Yes	No	Yes
Mean events transplant actors	0.02	0.02	0.02	0.02	0.02	0.02
R-squared	0.21	0.21	0.21	0.21	0.21	0.21

Standard errors (two-way clustered by group and month) in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

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