Guns and Kidneys: How Transplant Tourism Finances Global Conflict*

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Abstract

This paper investigates the impact of organ trafficking on local conflict using georeferenced data on conflict events and hand-collected data on local transplant infrastructure in eight countries known for illegal transplanting. I exploit exogenous variation in kidney demand measured by the number of U.S. waiting list patients, their payment capacity, and their physical condition. Higher kidney demand increases conflict in localities with a transplanting center. Specifically, a one-standard deviation increase in the U.S. waiting list for kidneys leads to a 17% increase in the probability of conflict and a 1% increase in the number of conflict events compared to localities without transplant infrastructure. Consistent with the hypothesis that armed groups use organ trafficking to finance violent attacks, I find that non-state armed groups with transplanting capacities in their home region perform more attacks when kidney demand is higher. These attacks happen both in their home region and in other regions, spreading violence over space. My results further show that higher kidney demand is associated with an increase in suspicious payments from and to countries known for illegal organ trafficking. This corroborates the hypothesis that non-state armed groups finance their attacks by organ trade.

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).[1] 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 report to receive between USD 1,000 and USD 10,000 at most (Council of Europe 2019). International security agencies therefore worry that non-state armed groups could participate in organ 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 (ECOSOC 2006; OSCE 2013). This paper is the first to document a causal relationship between global organ demand, armed groups' involvement in transplant tourism, and non-state violent attacks. To overcome the dearth of data, I proxy a group's potential involvement in transplant tourism by the local existence of an authorized transplant facility. Almost all reported cases of illegal transplanting happened alongside legal transplants, that is, in transplant centers or hospitals which perform transplants as their daily business and by doctors officially employed by these centers (OSCE 2013). To get involved in the business of transplant tourism, non-state armed groups therefore need to collaborate with existing transplant facilities. This collaboration is most likely in groups' home region, where they are well-connected to the local population, professionals, and administrative bodies (Krause and Milliken 2009), and where they also commit a large part of their attacks.[2]

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 transplant infrastructure. I run my analyses on cells of 0.5° latitude $\times$ 0.5° longitude (about 55km $\times$ 55km at the equator), covering eight countries notorious for transplant tourism and monthly observations between 2010 and 2021.[3] To rule out reverse causality concerns, i.e., the demand for transplants and the availability of organs caused by violent conflict, I proxy exogenous variation in kidney demand with the demand for kidneys

[1] Delmonico (2009) lists few cases under which transplant tourism is legal 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 under official organ sharing programs. As the vast majority of reported cases on transplant tourism do not fulfill these conditions, I focus on the illegal cases of transplant tourism.

[2] Based on data from Raleigh et al. (2010) used in this analysis, about 30% of conflict incidences of a group happen in their home region and adjacent regions.

[3] My sample countries are Argentina, Armenia, Bulgaria, Hungary, India, Pakistan, Russia, and South Africa.

outside of my sample countries, namely by the number of U.S. waiting list patients, their payment capacity, and their ability to travel. I establish causality by including cell fixed effects to account for locality-specific features and country $\times$ month fixed effects to account for time-varying developments within the countries of my sample. Hence, I estimate the within-transplant cell panel variation in non-state violence caused by exogenous changes in kidney demand.

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° latitude $\times$ 0.5° 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 the number of 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, this effect is stronger for an increase in the number of waiting list patients with labor income. In line with my assumption that transplant tourists need to be healthy enough for a multi-day travel, an increase in the number of waiting list patients on dialysis does not affect conflict probability nor the number of conflict events in transplant cells.[4]

Subsequently, I turn to the role of non-state armed groups and investigate whether armed groups with access to transplant infrastructure perform more attacks with increasing kidney demand. I determine a group's potential involvement in transplant tourism by the existence of an authorized transplant center in their hand-collected 0.5° latitude $\times$ 0.5° 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. In particular, a one standard deviation increase in the number of waiting list patients increases an armed groups' probability of conflict by 13% and its probability of performing an attack *outside* its home region by 16% if it has a transplant center in its home region. The relationship is stronger for waiting list patients with labor income and absent for waiting list patients on dialysis. These results show that the involvement in transplant tourism allows armed groups to enhance their fighting capacities, both in their home region and abroad.

Finally, I focus on cross-border financial flows from organ recipients to non-state armed groups. To substantiate the hypothesis that proceeds from illegal transplant tourism pass the official banking system, at least in parts (c.f. Homeland Security Committee 2016), I use data

[4] Dialysis is the process of cleaning the blood from excess water, solutes, and toxins with the help of medical equipment, which patients with an acute kidney injury or an end-stage chronic kidney disease need to undergo. In North America, the treatment typically requires patients to visit a dialysis center for three times a week for 3 to 4 hours. While the urgency for receiving a kidney should be high for patients on dialysis, their condition hampers international travel, in particular to a lower-income country and a (supposedly) lower-quality hospital.

on cross-border payments reported as suspicious to the Financial Crime Enforcement Network (FinCEN), which were leaked by the International Consortium of Investigative Journalists (ICIJ) in 2020. 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 in countries without ties to transplant tourism. The results show 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, 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 but lack systematic data to prove this claim (Fraser 2016; Shelley 2018). Thereby, my paper contributes to the literature on how terrorists and armed groups finance themselves and their attacks. Most existing papers in this stream of literature focus on legal sources of finance, such as donations (Limodio 2019), oil and gas business (Financial Action Task Force 2015), or mining activities (Berman et al. 2017). Illegal activities like robbery, smuggling, fraud, or kidnapping (Makarenko 2004), by contrast, are less understood - mainly because of the data scarcity on illegal activities (OSCE 2013; ECOSOC 2006).

Second, I add to the literature on transplant tourism and illegal organ trafficking. 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, my study shows that, in addition to vulnerable donors and recipients, a third party, namely the local population, also suffers from the consequences of illegal organ trafficking.

My paper is closely related to Berman et al. (2017) who demonstrate 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 conceptual 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 an overview of the literature on organ markets and transplant tourism. In addition to scientific studies, I include anecdotal evidence from institutional reports to build my hypotheses on any existing evidence which might help to understand transplant tourism as a source of terrorist financing. I then develop six hypotheses, which are tested in Section 4 to Section 6.

2.1 The Market for Organs

Like any market, organ markets have a demand and supply side. 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. The demand for organs is thus driven by the desire for survival and, consequently, highly inelastic.

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. Supplying a kidney is therefore a viable option for most healthy individuals.

Unlike for most other markets, the free exchange of organs between donors and recipients is forbidden in almost all countries of the world.[5] 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 on the match between recipient and donor, on the waiting time, or on the urgency of the transplantation among other things (Health Resources and Service Administration 2021; Organ Procurement and Transplantation Network 2022).[6]

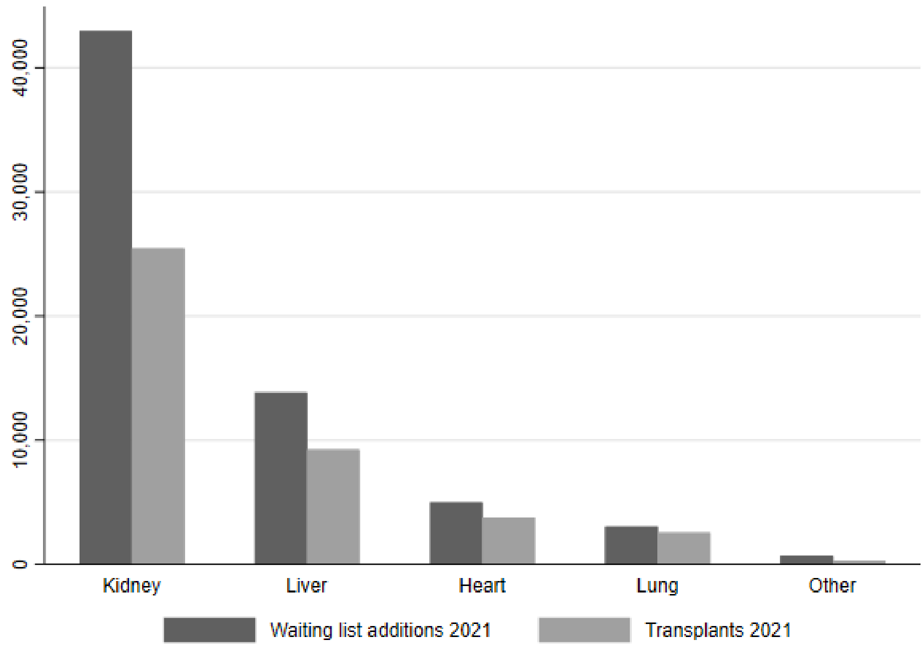
A closer look into the global statistics on waiting lists and performed transplants reveals the core problem of existing organ markets: Demand highly exceeds supply (The Economist 2008; Health Resources and Service Administration 2021). For example, as shown in Figure 1, 43,617 patients entered the U.S. waiting list for a kidney in 2021 (adding to the more than 100,000 patients already waiting in the end of 2020). In the same period, only 25,490 waiting

[5] 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 2017).

[6] There is an extensive body of research investigating optimal allocation mechanisms for organs (especially kidneys), based on game-theoretical approaches. This research strand is, however, only loosely related to my research question. See, e.g., Roth et al. (2004), Roth et al. (2005a), Roth et al. (2005b), Roth et al. (2007), Ünver (2010), Ashlagi and Roth (2012), Kessler and Roth (2014), Giwa et al. (2017) and Roth (2018).

Figure 1: U.S. waiting lists additions and transplants performed 2021

This figure shows the number of patients added to the U.S. waiting list for different organs in 2021 and the number of patients from the waiting list receiving an organ in 2021. Data is from the Organ Procurement and Transplantation Network.



list patients received a kidney. Consequently, more than half of all U.S. patients die on the waiting list before having received an organ (Astier 2020). Worldwide, the WHO assumes that only one in ten patients in need receives a kidney by legal means (The Economist 2008).

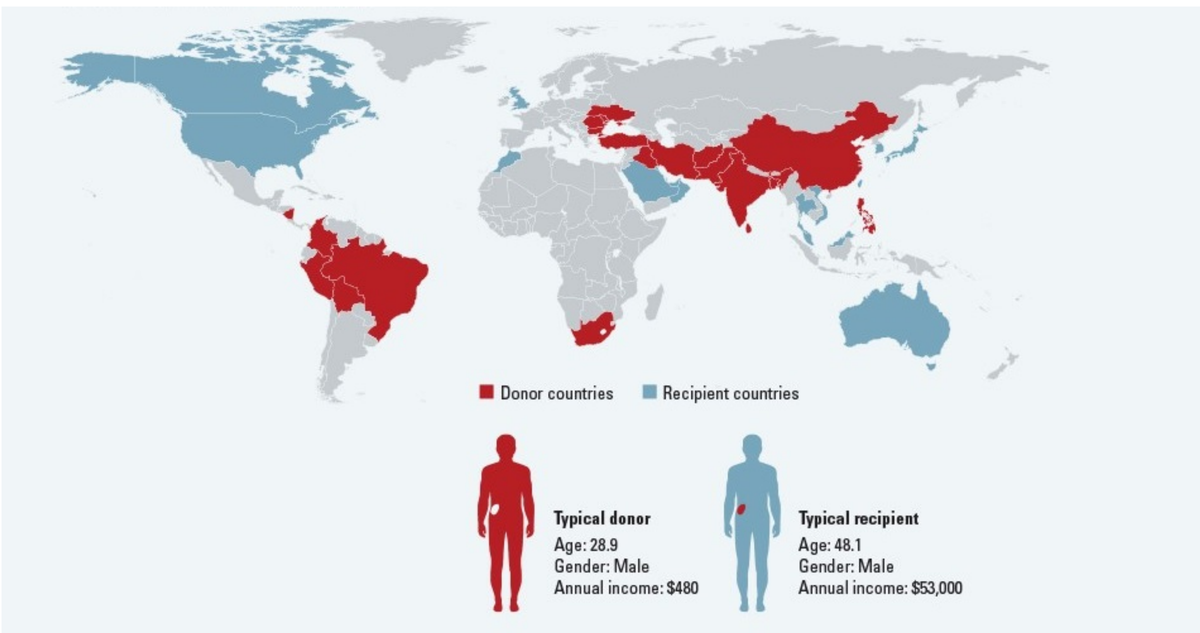
2.2 Organ Black Markets and Transplant Tourism

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 (OSCE 2013). The black market for organs is expected to be specifically vivid for living donations, given the willingness of people in need to make quick money by selling "spare" organs or organ parts. As 75% of the illegal trade is over kidneys (Hazell 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 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.

Figure 2: The global market for kidneys

This figure was compiled by Der Spiegel based on data from Coalition for Organ Failure Solutions, Organ Watch, and the European Society for Organ Transplantation. It visualizes anecdotal evidence from newspaper articles, security agency reports and case studies on global transplant tourism.



2.2.1 Kidney Donors in Black Markets

Research on illegal organ donors shows that most of them consider 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 that expected economic benefits did not materialize for a sample of 305 individuals who sold their kidney in Chennai, India, in the 1990s and 2000s: 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 surveyed donors 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., doctors who took out kidneys without the patient's knowledge during another surgery (Scheper-Hughes 2000), or criminals who killed for organs (Expansión 2014). Judging from newspaper articles and existing case studies, forced transplants are a minority of reported illegal organ trafficking cases (OSCE 2013). As my setting does not allow me to distinguish between voluntary and forced donation and both provide non-state armed groups an opportunity to finance violent attacks, I remain neutral about the question whether donation was forced out of circumstances or organs were taken without consent. Possible revenues from forced organ removal from prisoners after their execution, however, accrue to the government, rather than to non-state groups. I therefore remove China from my analysis, where this practice used to be most common (Allison et al. 2015).

2.2.2 Kidney Recipients in Black Markets

Although most existing studies focus on the weak position of illegal kidney donors, kidney recipients might also suffer unfavorable 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 the University of California, Los Angeles (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.'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. Transplant 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. This research implies that, while U.S. based recipients should prefer to receive an organ through the official list, organ scarcity induces patients to search for an alternative abroad, notwithstanding the expected inferior conditions.

2.2.3 The Role of Non-State Groups

Regardless 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 more than 20 times as high as the compensation received by the donor: The Council of Europe (2019) reports that recipients pay between USD 100,000 and USD 200,000 for a kidney, while donors receive between USD 1,000 and USD 10,000, at most.[7] Deducting the costs of the surgery - costs for a legal, professional kidney transplant in India, for instance, range from USD 8,500 to USD 14,000 (ClinicSpots 2022) - results in profit margins of 1000%, or higher. Existing literature is ambiguous on who absorbs most of this profit: While newspaper articles have identified doctors and hospital as beneficiaries, middlemen or brokers are assumed to capture most of the profit (Council of Europe 2019).

In line with Fraser (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 handle 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 (see Appendix H).

2.3 Hypotheses

I start from the assumption that non-state armed groups are financially constrained (c.f. Berman et al. 2017). Security experts suspect that, in addition to donations (Limodio 2019), oil and gas business (Financial Action Task Force 2015), and mining activities (Berman et al. 2017), armed groups use proceeds from illegal organ trade to finance attacks (Homeland

[7]From the donors' perspective, this is still a large sum making paid donation a valid option, e.g., compared to an average yearly income of of about 700 USD of the bottom 50% in India (Chancel et al. 2021). From the recipients perspective, this is still a decent price, given the average total costs of an official kidney transplant in the U.S. of over USD 400,000 (Bentley and Ortner 2020)

Security Committee 2016). Accordingly, I expect that the more organs can be sold in a given time and the higher their price, the higher the probability of an attack and the higher the number of attacks.

As I cannot observe the supply of organs, I assume it to be constant, on average. The probability and number of violent attacks should thus be positively influenced by organ demand. Organ demand depends, 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 the waiting list, the higher the probability of an attack and the more attacks are performed in locations with transplant infrastructure.

Hypothesis 2: The relationship between conflict and organ demand is stronger for waiting list patients with a higher income.

Hypothesis 3: The relationship between conflict and organ demand is weaker for waiting list patients who are unable to travel.

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 also test if the total number of a group's attacks, both in its home region and in all regions outside its home region, increases with higher kidney demand:

Hypothesis 4 : The larger the number of patients on the waiting list, the higher the probability and number of attacks by groups whose home region has transplant infrastructure.

Hypothesis 5: The larger the number of patients on the waiting list, the higher the probability and number of attacks by groups whose home region has transplant infrastructure performed outside *their home region.*

Payments between broker and donor mainly occur cash on the spot and in local currency. Transfers between recipient and broker are, however, cross-border payments and require currency clearing. It is unclear how these payments are made. Security experts, e.g., in the Homeland Security Committee (2016), suspect that most of these payments are made via official bank transfers. Bain and Mari (2018) also assume that surgeons, anesthetists and nurses, laboratories or medical facilities, but also individual brokers receive payments for illegal transplants on their usual bank accounts. In the context of the financing of armed groups, one illegal transplant should 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 a final hypothesis:

Hypothesis 6: The larger the number of people on the waiting list, the more suspicious payments are made to and from localities with transplant infrastructure.

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 known for transplant tourism activities, i.e., Argentina, Armenia, Bulgaria, Hungary, India, Pakistan, Russia, and South Africa (Cohen 2003; Council of Europe 2019; Goyal et al. 2002; Scheper-Hughes 2000; Scheper-Hughes 2003; ECOSOC 2006; OSCE 2013) . Following Berman et al. (2017), I define a locality as a subnational unit of 0.5° latitude $\times$ 0.5° 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 larger (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 4 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 data used and show descriptive statistics of my sample. A summary of all variable definitions and sources is provided in Appendix B.

3.1 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).[8] 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, ACLED records political violence without a battle-related deaths threshold. This is important in my setting because local, small groups usually do not kill that many people in one attack.

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 violent conflict events in

[8] Armed Conflict Location & Event Data Project (ACLED); acleddata.com

which non-state actors participate in my analysis. This embraces the event types "Battles", except for battles in which the "Government regains territory",[9] "Explosions/Remote violence", except for "Air/drone strikes"[10], and "Violence against civilians". I do not include events from the category "Protests", as they are defined as non-violent, nor of the category "Riots", which, though violent, are defined as mostly spontaneous actions by unorganized, unaffiliated members of society. "Strategic developments", pooling activities like "Agreements", "Arrests", or "Looting/property destruction" are also not included, as the financial necessities for these activities are not obvious.

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 has 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 this number is skewed to the right, I use the logarithm of the number of conflict events plus 1.

Reported cases of transplant tourism suggest that organ recipients pay close to the operation date, either shortly before or shortly after the transplant (OSCE 2013). Based on Berman et al. (2017), I further assume that armed groups carry out attacks quickly after having enough money to do so. Accordingly, my main specification measures kidney demand and non-state violent attacks in the same month. However, my results are robust to measuring attacks for a rolling window of the 12 months following the month when kidney demand is measured (Appendix D) and to aggregating data on a yearly level (Appendix E).

Figure 3 shows the spatial distribution of conflict events in my sample countries in a heat map. 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.

Group-Level Conflict Events

In my second analysis, I investigate whether armed groups increase their overall number of attacks with higher kidney demand if their home region has transplant infrastructure. To do so, I transform the dataset to 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 headquarters, or

[9] In the context of conflicts between the government and armed groups, events in which "Government regains territory" are mostly government operations to fight back armed groups. The timing of these operations is independent of the armed group and should therefore be unrelated to its financing.

[10] I assume that air/drone strikes are predominantly used by government forces. The non-state armed group targeted in these strikes might fight back, but has no power over the timing of the event.

Figure 3: Spatial distribution of conflict events and transplant centers

This figure shows a heatmap of non-state violent conflicts from The Armed Conflict Location & Event Data Project (ACLED) that happened in my sample countries between 2010 and March 2021. Deeper colors indicate a higher frequency of conflict. The map further shows hand-collected transplant centers as red dots.

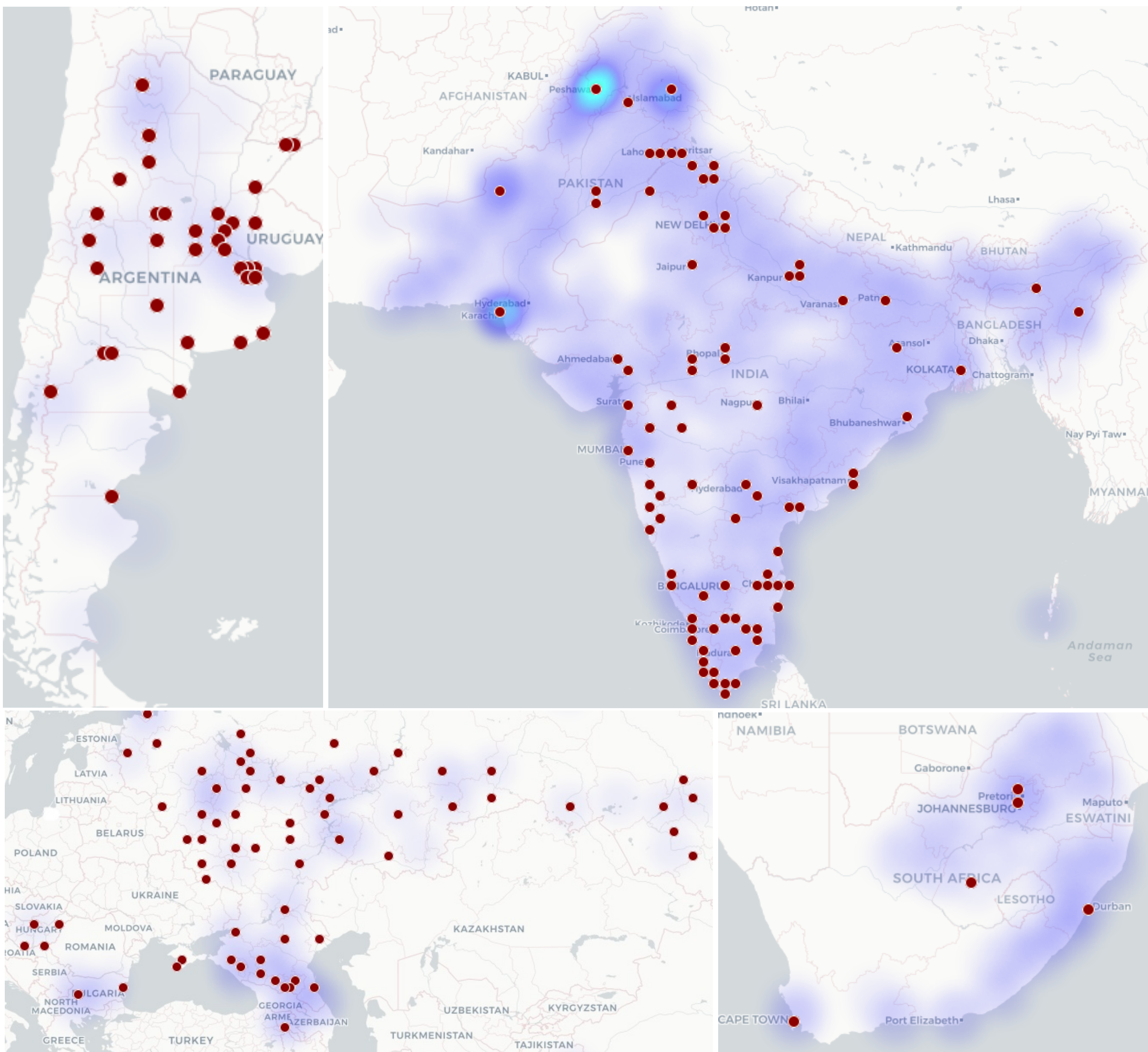
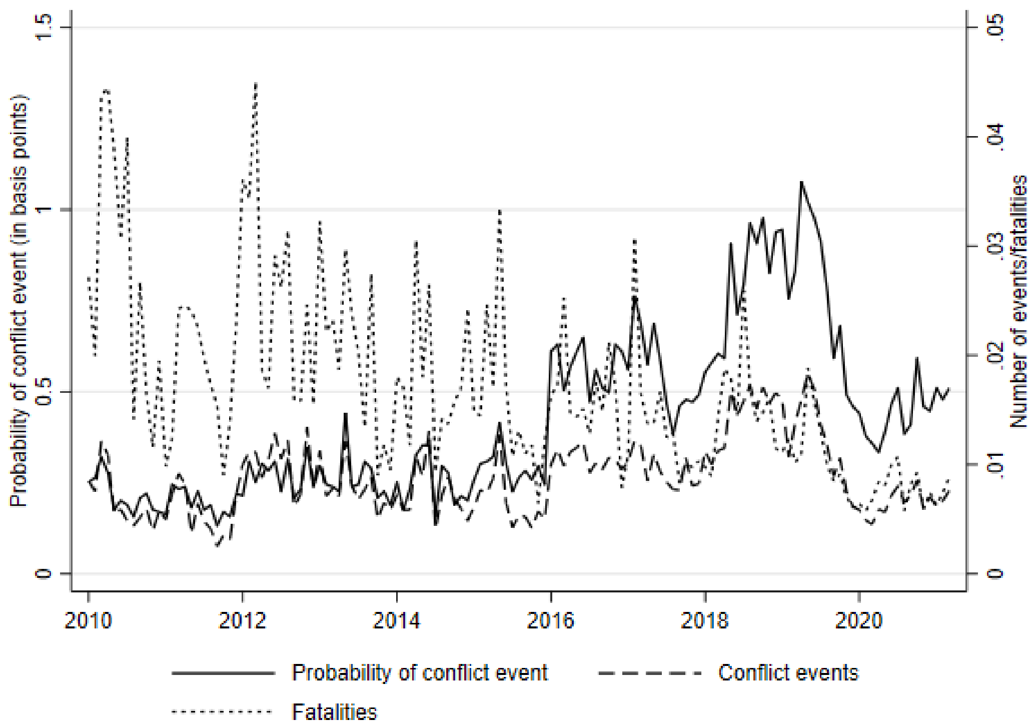


Figure 4: Probability of conflict, conflict events and fatalities

This figure shows the average probability of a conflict event, the number of events and the number of fatalities in an 0.5° latitude × 0.5 longitude cell in my sample. Data is from The Armed Conflict Location & Event Data Project (ACLED).



(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 online sources to determine these locations. I provide a list of all groups of the analysis and their manually determined home region in Appendix H.

3.2 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 transplantation via email. For some countries that I would have liked to include 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 emails. Appendix A gives an overview of the data sources for authorized transplant centers in my sample.

Given the location obtained via a manual Google Maps search, I assign each transplant center to a 0.5° latitude $\times$ 0.5 longitude cell. The variable *Transplant center* equals one if at least one authorized transplant center is located in a cell. I assume that transplant infrastructure is constant over my sample period as, in most countries, no information is available about when a transplant center first received or when it lost its authorization. Since it is unlikely that an armed group establishes an authorized transplant center with the sole aim to finance an increase of (already planned) attacks, reverse causality should not pose a problem here. There is also no indication that any state would establish transplant centers preemptively in the expectation of increasing attacks. Figure 3 shows the distribution of transplant centers in my sample countries as red dots.

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

For my country-level analyses on the relationship between suspicious payments and transplant infrastructure, I create two variables that identify 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, according to data from the Global Observatory on Donation and Transplantation (GODT). This variably is time-varying. To check for the robustness of the result, I define a country to be a *Trafficking country* if it is involved in organ trafficking, according to a list compiled on the Wikipedia page for "Organ trade" based on different sources.

3.3 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 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 labor income when entering the waiting list. Third, the variable *Waiting list patients on dialysis* proxies for patients' inability to travel. Patients with an acute kidney injury or an end-stage chronic kidney disease need to undergo dialysis, a process of cleaning the blood from excess water, solutes, and toxins with the help of medical equipment. In North America, the treatment typically requires patients to visit a dialysis center for three times a week for 3 to 4 hours. While the urgency for receiving a kidney should be high for patients on dialysis, their condition hampers international travel, in particular to a lower-income country and a (supposedly) lower-quality hospital. To calculate this variable, I use the number of people on the U.S. waiting list for a kidney who need dialysis in a given month. Figure 5 shows the number of waiting list patients, the subset of patients with labor income and the subset of patients under dialysis over my sample period.

As can be seen from Panel (A) in Figure 5, in the long run, the number of waiting list patients seems relatively stable. However, as Panel (B) shows, the number varies considerably on a monthly basis. As all my regressions include cell or group fixed-effects, what matters for my analysis is the change over time. Aggregating waiting list data on a yearly level eliminates much of the variation, which is why I use the monthly specification in my main analyses.[11] [12]

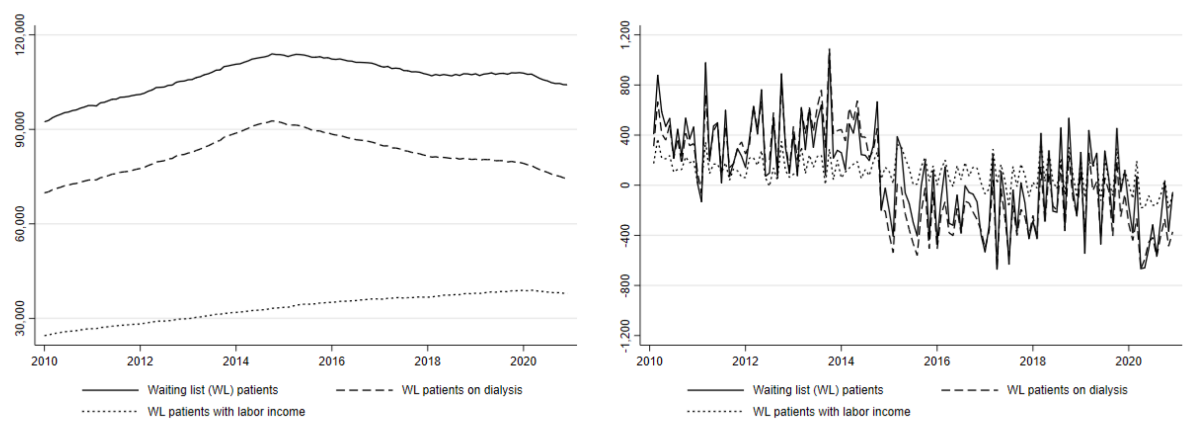
[11] My results are robust to using yearly data and to measuring conflict events in the rolling window of 12 months after kidney demand is measured.

[12] One might wonder what happens to patients registered on the U.S. waiting list after having obtained an organ via a transplant tourism agreement. Due to 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 C1 in Appendix C shows different reasons under which patients exit the list. Reasons that could subsume recipients leaving the list after a successful transplant tourism operation are highlighted in red.

Figure 5: Demand for kidneys on the U.S. waiting list

This figure shows the number of patients on the U.S waiting list for kidneys, the number of patients on the U.S. waiting list for kidneys who had labor income when entering the waiting list, and the number of patients on the U.S. waiting list for kidneys who are on dialysis. Panel (A) shows the absolute number, panel (B) presents monthly changes. Data is from The Armed Conflict Location & Event Data Project (ACLED).

Panel (A) Panel (B)



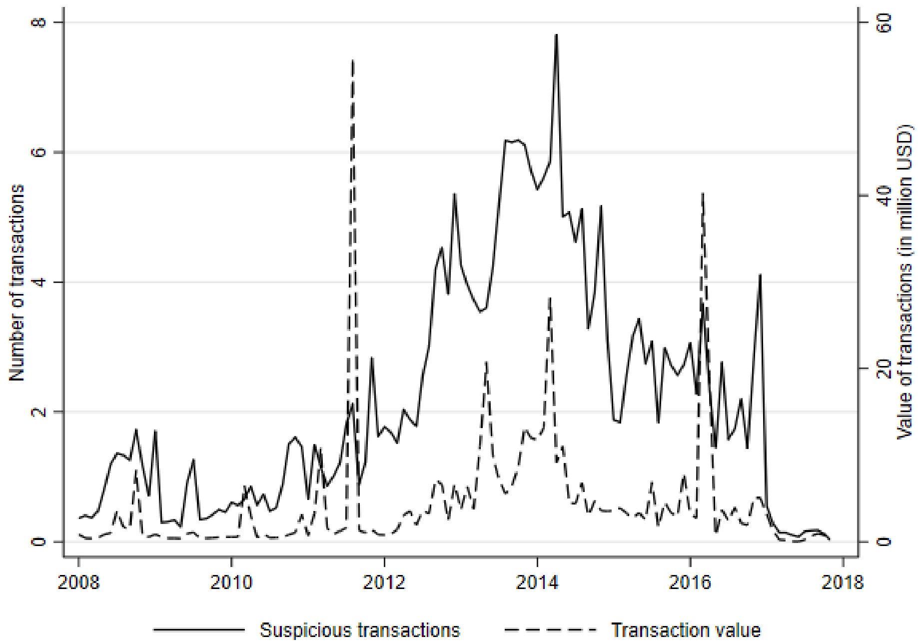
3.4 Suspicious Payments

To measure *Suspicious payments* from and to countries potentially involved in transplant tourism, I draw on available data from 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 available countries 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 the number of payments. The average number of suspicious payments from and to a country from 2008 to 2018 is shown in Figure 6.

Figure 6: Suspicious Payments

This figure shows the average number of suspicious payments from and to a country of my sample and the average transferred value. Payments are defined as suspicious if they have been reported to the U.S. Financial Crime Enforcement Network (FinCen) by a global correspondent bank. The (non-representative) sample of FinCen data was leaked by the International Consortium of Investigative Journalists (ICIJ) in 2020.



3.5 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, G and B in the analysis on suspicious payments in Section 6.

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, G and B are used in the analysis on suspicious payments in Section 6.

	N	Mean	SD	Median	Min	Max
Panel A: Cell-month level						
Conflict 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
$\mid$ Events > 0	9,592	2.17	3.45	1	1	62
Panel B: Month level						
Kidney demand over 135 months						
Waiting list patients	2,143,260	106,554	5,347	107,526	92,409	113,951
with labor income	2,143,260	33,409	4,290	34,506	24,538	38,952
on dialysis	2,143,260	81,857	6,025	81,015	69,849	92,709
Panel C: Cell level						
Transplant infrastructure 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
Panel D: Group-month level						
Conflict 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
$\mid$ Events > 0	1,633	1.88	1.95	1	1	20
Prob. of conflict outside home region in %	97,605	1.25	11	0	0	100
Number of events outside home region	97,605	.0251	.3227	0	0	20
$\mid$ Events outside home region > 0	1,219	2.017	2.09	1	1	20
Panel E: Group level						
Transplant infrastructure at home region 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
Panel F: Country-month level						
Financial transactions from and to 105 countries over 291 months						
Suspicious payments	17,850	1.46	7.15	0	0	162
Panel G: Country level						
Transplant infrastructure in 105 (21) countries						
Transplant country	21	0.6364	0.4923	0	0	1
Trafficking country	105	0.1981	0.4005	0	0	1

4 The Impact of Organ Demand on Local Conflict

I now turn to the empirical analysis of how organ demand impacts local conflict. I first discuss my identification strategy and then report results of different specifications.

4.1 Methodological Issues

Establishing a causal relationship between global organ demand on local conflict involves several 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 are needed and the more organs can be acquired. This implies the same, positive correlation as my proposed hypothesis. To address this concern, I exploit variation in U.S. organ demand, which is exogenous to local conflict in my sample countries.

The second concern refers to a potential spurious correlation 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 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 the U.S. waiting list for kidneys, the number of those patients who have entered the waiting list with labor income, or the number of waiting list patients on dialysis, respectively. FE_i are cell fixed effects, FE_{ct} are additional fixed effects which can vary at different levels (e.g., month and country $\times$ month).

β_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, compared to those without a transplant center.

I use a linear probability model to estimate the effect of kidney demand on the probability of conflict and a log-linear model to estimate the effect of kidney demand on the number of conflict events. I favor linear over nonlinear estimators, also for the binary outcome variable, as I include several dimensions of fixed effects. I provide robustness checks using nonlinear estimators, namely conditional logit and Poisson pseudo-maximum-likelihood estimators in Appendix F.

As visible in Figure 3, both conflicts and transplant centers are locally clustered. I therefore apply a spatial HAC correction which allows for both cross-sectional spatial and location-specific serial correlation, building on Conley (1999) and Hsiang et al. (2011). Following Berman et al. (2017), I restrict spatial correlation to 500 km and assume serial correlation to only vanish in infinity (i.e., 100,000 months). Accordingly, I do not constrain the temporal decay for the Newey-West/Bartlett kernel which weights serial correlation across time periods.

One further concern with fixed effects models of (relatively) rare events data is that the elimination of no-event units from the sample may result in biased marginal effects (Cook et al. 2020). Applying the penalized maximum likelihood fixed effects estimator proposed by Cook et al. (2020) shows that correcting for this issue does not significantly alter my results (Appendix G). I do not use Cook et al. (2020)'s estimator for my main specification as it does not allow for the extensive correction for spatial and serial clustering applied in my main analyses.

Existing evidence is unclear about the exact timing of events. Armed groups could wait with their attacks some months after receiving the money. Therefore, in addition to regressing conflict events on kidney demand of the same month, I run an alternative specification of events aggregated from month t, i.e., the month when kidney demand is measured, to month $t+11$, i.e., one year after kidney demand is measured (Appendix D). I provide robustness checks using yearly data in Appendix E.

A final issue concerns the definition of different dimensions of kidney demand: Both the number of waiting list patients with labor income when entering the waiting list and those on dialysis are a subset of total waiting list patients. As such, they proxy for the total number of waiting list patients. Given a positive effect from kidney demand on conflict, any non-orthogonal subset of the number of total kidney demand should yield higher regression coefficients, by design. To address this issue and obtain comparable coefficients, I standardize the three waiting list variables in all my analyses.

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 90.77 basis points in the model with month fixed effects, and by 73.63 basis points in the model with month $\times$ country fixed-effects, respectively. Compared to a base probability of conflict of 5.38% 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 stronger for waiting list patients who have entered the list with labor income. A one standard deviation increase in the number of patients with income leads to an increase of conflict of 2.44 or 1.90 percentage points, on average, which is an increase of 45 or 35%, 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.

In line with the idea that receiving an organ in a transplant tourism agreement requires the recipient to be healthy enough for traveling, coefficients for waiting list patients on dialysis are insignificant and small.

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 0.7%, respectively, as compared to non-transplant cells. Like for the extensive margin, the effect is stronger for waiting list patients with income: On average, the number of events in a cell with transplant infrastructure increases by 1.8 or 1.4% with a one standard-deviation increase in waiting list patients with income. Again, the effect is insignificant for waiting list patients on dialysis like hypothesized in Hypothesis 3.

Taken together, these results are in line with Hypothesis 1, 2, and 3: Conflicts increase with a rising kidney demand in cells with transplant infrastructure, both in the extensive and the intensive margin. This effect is stronger for waiting list patients with income and absent for waiting list patients on dialysis.

Table 2: The impact of organ demand on conflict probability

This table reports coefficients of a linear probability model regressing a binary conflict variable on the interaction between transplant infrastructure and kidney demand (see equation (1)). Conley (1999) standard errors, allowing for spatial correlation within a 500 km radius and for infinite serial correlation, are shown in parenthesis. The sample consists of monthly observations of 15,876 cells of 0.5° latitude × 0.5° 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° latitude × 0.5° 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. Models (1), (3), and (5) include cell and month fixed effects, models (2), (4), and (6) include cell and country × month fixed effects.

	Dependent variable: Probability of conflict (in basis points]					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center						
× waiting list (WL) patients	90.77***	73.63***				
	(16.29)	(15.80)				
× WL patients with income			244.05***	189.78***		
			(37.28)	(35.28)		
× WL patients on dialysis					0.87	5.48
					(14.04)	(13.73)
Observations	2,143,125	2,142,180	2,143,125	2,142,180	2,143,125	2,142,180
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country × month FEs	No	Yes	No	Yes	No	Yes
Base prob. transplant cells	538.4	538.4	538.4	538.4	538.4	538.4
R-squared	0.00	0.00	0.00	0.00	0.00	0.00

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

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

This table reports coefficients of a linear regression of the log number of local conflict events on the interaction between transplant infrastructure and kidney demand (see equation (1)). Conley (1999) standard errors, allowing for spatial correlation within a 500 km radius and for infinite serial correlation, are shown in parenthesis. The sample consists of monthly observations of 15,876 cells of 0.5° latitude × 0.5° longitude, covering 8 countries between 2010 and 2021. The dependent variable is the logged number of conflict events in a given month. Independent variables are the binary variable $Transplant\ center$, indicating the existence of an authorized transplant center in an 0.5° latitude × 0.5° 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. Models (1), (3), and (5) include cell and month fixed effects, models (2), (4), and (6) include cell and country × month fixed effects.

	Dependent variable: Log conflict events					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center						
× waiting list (WL) patients	0.009^{***}	0.007^{***}				
	(0.00)	(0.00)				
× WL patients with income			0.018^{**}	0.014^{*}		
			(0.01)	(0.01)		
× WL patients on dialysis					0.003	0.003
					(0.00)	(0.00)
Observations	2,143,125	2,142,180	2,143,125	2,142,180	2,143,125	2,142,180
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country × month FEs	No	Yes	No	Yes	No	Yes
Mean log events transplant cells	0.07	0.07	0.07	0.07	0.07	0.07
R-squared	0.00	0.00	0.00	0.00	0.00	0.00

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

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 examine if increased financial capabilities of local armed groups are responsible for these attacks. The results show that armed groups whose home region has a transplant center increase their attacks with increasing kidney demand, both in their home region and outside their home region.

5.1 Methodological Issues

As detailed in Section 3, in the following, I focus on the number of attacks performed by a certain group conditional on the existence of a transplant infrastructure in its home region. In particular, I run the following specification for armed groups j in country c and month t:

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

$Conflict_{jt}$ 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 the number of patients on the U.S. waiting list for kidneys, the number of those patients who have entered the waiting list with labor income, or the number of waiting list patients on dialysis, respectively. FE_j are group fixed effects, FE_{ct} are additional fixed effects which can vary at different levels (e.g., month and country $\times$ month).

β_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, compared to those without a transplant center. To account for within-group correlation and serial correlation, I cluster standard errors by group and month, using two-way clustering. Like in the previous section, I standardize the waiting list variables.

5.2 Results

Table 4 reports the results of regressing a group's conflict probability on the interaction between kidney demand and transplant infrastructure. A one standard deviation increase in the number of waiting list patients increases the probability of conflict of a group with transplant infrastructure by 28.37 basis points or 27.43 basis points, respectively, compared to a group without transplant infrastructure at home. In comparison to a transplant group's base probability of conflict of 2.17 or 2.18%, this is an increase of 13%.

As hypothesized, coefficients are larger for an increase in the number of waiting list patients who have entered the list with labor income: A one standard-deviation increase in the number of these patients is associated with an increase in conflict probability of 59.34 or 64.20 basis points, respectively, compared to groups without a transplant center at home. This is a 27 or 29% increase compared to the base probability.

A higher number of waiting list patients on dialysis, again, has no disproportionate impact on violence of groups with and without transplant infrastructure at home.

Table 5 reports the results for the intensive margin of conflict, i.e., the coefficients of regressing a group's log number of attacks on the interaction between transplant infrastructure and kidney demand. Higher kidney demand is positively associated with the number of conflict events of groups with a transplant center at home. However, due to the relatively large uncertainty around the estimate, the effect is insignificant for the number of all waiting list patients and only significant at the 10% level for those patients with labor income. A one standard-deviation increase in the number of waiting list patients with income increases the number of conflict by approximately 0.7%. For waiting list patients on dialysis, coefficients are insignificant and small.

These results are in line with the idea that groups use revenues from transplant tourism to carry out attacks (Hypothesis 4), increasing both the group's extensive and intensive margin of conflict. To investigate whether armed groups use the transplant infrastructure at home to finance attacks in other cells (Hypothesis 5), I consider a group's attacks *outside its home region* as the dependent variables in the following. Table 5 and Table 6 present the results from this analysis.[13]

The base probability of a conflict outside a group's home region of 1.61% increases significantly by 25.60 or 24.70 basis points with a one standard deviation increase in patients on the waiting list for groups with a transplant center at home. This is a percentage increase of 16 or 14%, respectively. The effect is larger for patients who entered the waiting list with income: A one standard-deviation increase in the number of these patients increases the base probability by 51.55 or 55.86 basis points, an increase of 32 or 35%, respectively. For waiting list patients on dialysis, the effect is insignificant and small.

Table 7 reports the results for the intensive margin. A one standard deviation increase in the number of waiting list patients leads to an increase in the number of outside attacks of

[13]Conflicts outside the group's home region are a subset of all conflicts. Coefficients in Table 6 and Table 7 should therefore, by design, be smaller than in Table 4 and Table 5, given that the hypothesized mechanism is at work. This is the case in my analyses.

approximately 0.2%, a one standard deviation increase of the number of waiting list patients with income by 0.6 or 0.7%, respectively. For waiting list patients on dialysis the effect does not significantly deviate from zero.

Overall, my results lend support to Hypothesis 5: An increase in kidney demand increases the probability of conflict and the number of conflict outside a group's home region more for those groups with a transplant center at home than for groups without such center in their home region. This indicates that armed groups, indeed, make use of transplant infrastructure at home to finance attacks, both at their home region and abroad.

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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country × 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						
× waiting list (WL) patients	28.37**	27.43**				
	(13.84)	(13.48)				
× WL patients with income			59.34**	64.20**		
			(29.61)	(29.86)		
× WL patients on dialysis					6.91	3.58
					(13.56)	(12.69)
Observations	95,715	95,580	95,715	95,580	95,715	95,580
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country × month FEs	No	Yes	No	Yes	No	Yes
Base prob. transplant groups	216.98	217.94	216.98	217.94	216.98	217.94
R-squared	0.12	0.13	0.12	0.13	0.12	0.13

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

Table 5: 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country × month fixed effects. Standard errors are two-way clustered by group and month and shown in parentheses.

	Dependent variable: Group's log conflict events					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center at home region						
× waiting list (WL) patients	0.002	0.002				
	(0.00)	(0.00)				
× WL patients with income			0.007*	0.007*		
			(0.00)	(0.00)		
× WL patients on dialysis					-0.000	-0.000
					(0.00)	(0.00)
Observations	95,715	95,580	95,715	95,580	95,715	95,580
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country × month FEs	No	Yes	No	Yes	No	Yes
Mean log events transplant groups	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

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

Table 6: 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. 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 basis points)					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center at home region						
$\times$ waiting list (WL) patients	25.60**	24.70**				
	(12.73)	(12.29)				
$\times$ WL patients with income			51.55*	55.86*		
			(29.01)	(29.32)		
$\times$ WL patients on dialysis					6.46	3.45
					(12.25)	(11.39)
Observations	95,715	95,580	95,715	95,580	95,715	95,580
Group 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 groups	160.60	161.32	160.60	161.32	160.60	161.32
R-squared	0.16	0.16	0.16	0.16	0.16	0.16

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 7: The impact of organ demand on a group's number of conflict events outside its home region

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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country × month fixed effects. Standard errors are two-way clustered by group and month and shown in parentheses.

	Dependent variable: Log conflict events outside home region					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center at home region						
× waiting list (WL) patients	0.002*	0.002*				
	(0.00)	(0.00)				
× WL patients with income			0.006	0.007*		
			(0.00)	(0.00)		
× WL patients on dialysis					0.000	-0.000
					(0.00)	(0.00)
Observations	95,715	95,580	95,715	95,580	95,715	95,580
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country × month FEs	No	Yes	No	Yes	No	Yes
Mean log events transplant groups	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

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

6 Organ Demand, Transplant Infrastructure, and Suspicious Payments

In this section, I investigate the link between kidney demand, transplant infrastructure and suspicious payments. The results are in line with the idea that (at least some) payments for transplant tourism are transferred via the official banking system.

6.1 Methodological Issues

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

I include country and month fixed effects to adjust for unobserved country characteristics that are constant over time and for time-varying developments common to all countries. Specifically, for each country c in month t, I estimate the following model:

$$\begin{aligned} Payments_{ct} = \beta_0 + \beta_1 Transplant\ Infrastructure_{ct} \times Kidney\ Demand_t \\ + \beta_2 Transplant\ Infrastructure_{ct} + FE_c + FE_t + \epsilon_{ct} \end{aligned} \tag{3}$$

$Payments_{ct}$ is the log number of suspicious payments from and to country c in a given month. $Transplant\ Infrastructure_{ct}$ is either the time-varying variable $Transplant\ country_{ct}$, i.e., a dummy if the country has performed an above-median number of kidney transplant in a given year, or the variable $Trafficking\ country_c$, i.e., a dummy if the country is known for organ trafficking, according to a Wikipedia list compiled by different sources.

β_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 suspicious payments from and to a country with, compared to a country without transplant infrastructure. To account for within-country correlation and serial correlation, I cluster standard errors by country and month, using two-way clustering. As in the previous sections, I standardize all waiting list variables.

6.2 Results

Table 8 reports the results of the analyses. The significantly positive coefficient of the interaction between $Transplant\ country$ and $Kidney\ demand$ indicates that payments from and to countries with an above-average transplanting activity increase more with an increase in U.S. kidney demand, as compared to other countries. In particular, a one standard deviation increase in the number of waiting list patients is associated with 24.8% more suspicious payments from and to transplant countries. The effect is somewhat smaller, 17.1%, for waiting list patients who have entered the waiting list with labor income. For waiting list patients on dialysis, this effect is also present: A one standard deviation increase in waiting list patients on dialysis is associated with 18.2% more suspicious payments from and to countries that transplant.

Results are similar for the alternative definition of transplant infrastructure: A one standard deviation increase in waiting list patients is associated with 24.9% more suspicious payments to and from $Trafficking\ countries$. Coefficients are a little smaller for an increase in the number of patients with labor income or the number of patients on dialysis.

Note that suspicious payments of my sample are a small, non-representative 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 countries reported in Table 8 should not be interpreted.

The reported correlations are in line with Hypothesis 6 that higher kidney demand induces more suspicious payments from and to transplant countries. This is consistent with the notion that transplant tourism is, at least partly, processed via the official banking system. However, due to the high aggregation level and the inconsistent result for waiting list patients on dialysis, these associations should not be interpreted causally.

Table 8: Organ demand, transplant infrastructure, and suspicious payments

This table reports OLS coefficients of the regression of the log number 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. All models include country and month fixed effects. Standard errors are two-way clustered by country and month and shown in parentheses.

	Dependent variable: Log suspicious payments					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant country						
Transplant country	-0.171*	0.037	-0.074			
	(0.10)	(0.08)	(0.09)			
× waiting list (WL) patients	0.259**					
	(0.12)					
× WL patients with income		0.171**				
		(0.07)				
× WL patients on dialysis			0.182**			
			(0.09)			
Trafficking country						
× waiting list (WL) patients				0.249**		
				(0.12)		
× WL patients with income					0.165**	
					(0.08)	
× WL patients on dialysis						0.187**
						(0.09)
Observations	9,357	8,836	9,246	17,850	16,275	17,325
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean log payments transplant countries	0.50	0.54	0.51	0.49	0.54	0.51
R-squared	0.57	0.51	0.53	0.49	0.46	0.47

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

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° latitude $\times$ 0.5° 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 from the U.S. waiting list for kidneys, I find a significant and sizable effect of higher kidney demand on the extensive and intensive margin of local conflict for localities with transplant infrastructure. Further, I show that groups with transplant infrastructure at their home region perform more 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 from 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.

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A Sources for Authorized Transplant Centers

Table A1 lists the sources for authorized transplant centers in the countries of my sample. I determined the exact coordinates for each center with the help of Google Maps.

Table A1: Sources for authorized transplant centers

Country	Source for authorized transplant centers
Argentina	https://www.argentina.gob.ar/salud/incucai/organismos-jurisdiccionales
Armenia	https://www.mohanfoundation.org/transplant-centres/index.asp
Bulgaria	https://iamn.bg/en/transplantations/statistics-organ-transplantation-by-healthcare
Hungary	https://www.ovsz.hu/en/organ-coordination-office/accessibilities
India	https://www.mohanfoundation.org/transplant-centres/index.asp
Pakistan	https://applications.emro.who.int/emhj/v16/supp/16$_{S2}010_{1}59_{1}66.pdf?ua = 1$
Russia	https://www.transpl.ru
South Africa	Direct contact with ministry of health

B Variable Definitions

Table B1: Definition and sources of all variables

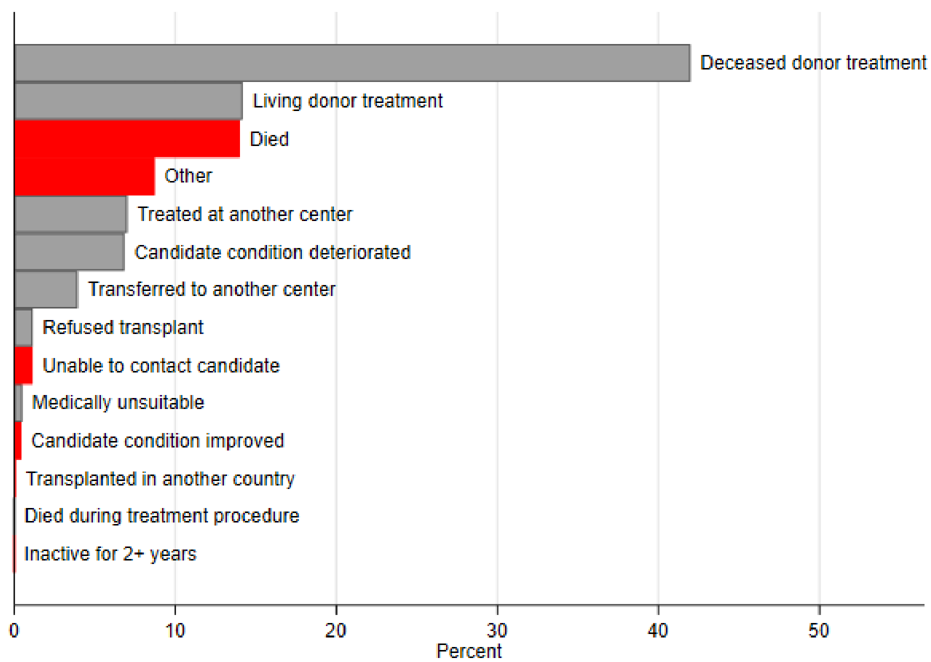
Variable	Definition	Source
Panel A: Cell-month level		
Conflict dummy	Binary variable indicating if at least one conflict event happened in a 0.5° latitude × 0.5° longitude cell in a month	The Armed Conflict Location & Event Data Project (ACLED)
Number of events	Number of conflicts happening in a 0.5° latitude × 0.5° longitude cell in a month, log-ed in analyses	ACLED
Panel B: Month level		
Waiting list patients	Number of people on the waiting list in a given month	United Network of Organ Sharing Standard Transplant Analysis Research file (UNOS Star File)
Waiting list patients with labor income	Number of people on the waiting list in a given month who indicated that they have a labor income when entering the waiting list	UNOS Star File
Waiting list patients on dialysis	Number of people on the waiting list who are on dialysis in a given month	UNOS Star File
Panel C: Cell level		
Transplant Center	Binary variable indicating if there is at least one authorized transplant center in a 0.5° latitude × 0.5° longitude cell	Manual collection based on sources listed in Appendix A
Panel D: Group-month level		
Conflict dummy	Binary variable indicating if a non-state armed group was involved in a conflict event in a given month	ACLED
Number of events	Number of conflict events an armed group was involved in in a given month, log-ed in analyses	ACLED
Conflict dummy outside home region	Binary variable indicating if a non-state armed group was involved in a conflict event outside its home region in a given month	ACLED
Number of events outside home region	Number of conflict events outside a group's home region, log-ed in analyses	ACLED
Panel E: Group level		
Transplant center	Binary variable indicating if there is at least one transplant center in the 0.5° latitude × 0.5° longitude home region of an armed group	Manual collection based on sources given in Appendix A
Home region	0.5° latitude × 0.5° longitude cell in which an armed group (i) has its headquarters, or (ii) was founded, or (iii) the ethnic affiliation of a group is based, or (iv) the community mentioned in a group's name is based.	Manual collection using Wikipedia and other online sources
Panel F: Country-month level		
Suspicious payments	Number of payments from and to a country that have been flagged as 'suspicious' to the Financial Crime Enforcement Network (FinCen) by a global correspondent bank	International Consortium of Investigative Journalists (ICJA) (Leaked from FinCeN)
Panel G: Country level		
Transplant country	Binary variable indicating if country has performed an above-median number of transplants in a year	Global Observatory on Donation and Transplantation (GODT)
Trafficking country	Binary variable indicating if country is listed as known for organ trafficking	Wikipedia page "Organ Trade" (based on various sources)

C Transplant Tourists on U.S. Waiting Lists

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 C1 shows different reasons under which patients exit the list. Stated reasons which could include successful transplant tourists are marked in red.

Figure C1: Reasons for being removed from the U.S. waiting list for kidneys

This figure shows the percentage of removals from the U.S. waiting list kidneys for different reasons. Reasons that could subsume recipients leaving the list after a successful transplant tourism operation are marked in red. Data comes from the UNOS Star files.



D Robustness: Conflict Probability and Events within a Rolling Window of 12 Months

To account for the possibility that armed groups delay attacks for several months after the money inflow from a transplant, Table D1 to Table D6 show all my analyses with an alternative definition of the conflict variable: The $Conflict\ dummy_{it}$ is one if a conflict happened in month t when kidney demand is measured, or in any of the following 11 months $t+1$ to $t+11$. $Conflict\ events_{it}$ are summed up from month t to month $t+11$. All other variables are as defined in Section 3 and in Appendix B. The regression equations are specified in Section 4 and Section 5.

Table D1: The impact of organ demand on conflict probability over the next 12 months

This table reports coefficients of a linear probability model regressing a binary conflict variable on the interaction between transplant infrastructure and kidney demand (see equation (1)). Conley (1999) standard errors, allowing for spatial correlation within a 500 km radius and for infinite serial correlation, are shown in parenthesis. The sample consists of monthly observations of 15,876 cells of 0.5° latitude × 0.5° longitude, covering 8 countries between 2010 and 2021. The dependent variable is a binary variable indicating if a conflict took place between month t and month t+11. Independent variables are the binary variable $Transplant\ center$, indicating the existence of an authorized transplant center in an 0.5° latitude × 0.5° 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. Models (1), (3), and (5) include cell and month fixed effects, models (2), (4), and (6) include cell and country × month fixed effects.

	Dependent variable: Probability of conflict (in basis points)					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center						
× waiting list (WL) patients	394.20***	256.12***				
	(49.52)	(41.10)				
× WL patients with income			972.45***	691.38***		
			(90.33)	(78.47)		
× WL patients on dialysis					45.65	6.25
					(37.68)	(34.25)
Observations	2,143,125	2,142,180	2,143,125	2,142,180	2,143,125	2,142,180
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country × month FEs	No	Yes	No	Yes	No	Yes
Base prob. transplant cells	1722.57	1722.57	1722.57	1722.57	1722.57	1722.57
R-squared	0.00	0.00	0.00	0.00	0.01	0.01

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

Table D2: The impact of organ demand on the number of conflict events over the next 12 months

This table reports coefficients of a linear regression of the log number of local conflict events on the interaction between transplant infrastructure and kidney demand (see equation (1)). Conley (1999) standard errors, allowing for spatial correlation within a 500 km radius and for infinite serial correlation, are shown in parenthesis. The sample consists of monthly observations of 15,876 cells of 0.5° latitude × 0.5° longitude, covering 8 countries between 2010 and 2021. The dependent variable is the logged number of conflict events that took place from month t to month t+11. Independent variables are the binary variable $Transplant\ center$, indicating the existence of an authorized transplant center in an 0.5° latitude × 0.5° 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. Models (1), (3), and (5) include cell and month fixed effects, models (2), (4), and (6) include cell and country × month fixed effects.

	Dependent variable: Log conflict events					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center						
× waiting list (WL) patients	0.065***	0.048***				
	(0.01)	(0.01)				
× WL patients with income			0.125***	0.093***		
			(0.02)	(0.02)		
× WL patients on dialysis					0.026***	0.020***
					(0.01)	(0.01)
Observations	2,143,114	2,142,169	2,143,114	2,142,169	2,143,114	2,142,169
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country × month FEs	No	Yes	No	Yes	No	Yes
Mean log events transplant cells	0.30	0.30	0.30	0.30	0.30	0.30
R-squared	0.00	0.00	0.00	0.00	0.01	0.01

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

Table D3: The impact of organ demand on a group's conflict probability over the next 12 months

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 from month t to month t+11. 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. 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)					
Transplant center at home region						
$\times$ waiting list (WL) patients	109.70*	119.86**				
	(55.97)	(55.88)				
$\times$ WL patients with income			101.79	132.72*		
			(74.02)	(69.30)		
$\times$ WL patients on dialysis					80.80	80.42
					(61.44)	(61.25)
Observations	95,715	95,580	95,715	95,580	95,715	95,580
Group 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 groups	1388.07	1394.24	1388.07	1394.24	1388.07	1394.24
R-squared	0.19	0.21	0.19	0.21	0.19	0.21

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

Table D4: The impact of organ demand on a group's number of conflict events over the next 12 months

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 from month t to month t+11. 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country × month fixed effects. Standard errors are two-way clustered by group and month and shown in parentheses.

	Dependent variable: Group's log conflict events					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center at home region						
× waiting list (WL) patients	0.017*	0.019**				
	(0.01)	(0.01)				
× WL patients with income			0.025*	0.028**		
			(0.01)	(0.01)		
× WL patients on dialysis					0.010	0.010
					(0.01)	(0.01)
Observations	95,704	95,569	95,704	95,569	95,704	95,569
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country × month FEs	No	Yes	No	Yes	No	Yes
Mean log events transplant groups	0.16	0.16	0.16	0.16	0.16	0.16
R-squared	0.34	0.36	0.34	0.35	0.34	0.36

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

Table D5: The impact of organ demand on a group's conflict probability outside its home region over the next 12 months

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 from month t to month t+11. 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country × 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 basis points)					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center at home region						
× waiting list (WL) patients	54.82	61.65				
	(49.82)	(49.22)				
× WL patients with income			23.97	48.00		
			(71.47)	(68.99)		
× WL patients on dialysis					44.81	43.39
					(48.30)	(47.37)
Observations	95,715	95,580	95,715	95,580	95,715	95,580
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country × month FEs	No	Yes	No	Yes	No	Yes
Base prob. transplant groups	882.99	886.91	882.99	886.91	882.99	886.91
R-squared	0.22	0.23	0.22	0.23	0.22	0.23

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

Table D6: The impact of organ demand on a group's number of conflict events outside its home region over the next 12 months

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 from month t to month t+11. 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country × month fixed effects. Standard errors are two-way clustered by group and month and shown in parentheses.

	Dependent variable: Log conflict events outside home region					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center at home region						
× waiting list (WL) patients	0.014*	0.015*				
	(0.01)	(0.01)				
× WL patients with income			0.017	0.021		
			(0.01)	(0.01)		
× WL patients on dialysis					0.008	0.008
					(0.01)	(0.01)
Observations	95,704	95,569	95,704	95,569	95,704	95,569
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No
Country × month FEs	No	Yes	No	Yes	No	Yes
Mean log events transplant groups	0.11	0.11	0.11	0.11	0.11	0.11
R-squared	0.39	0.40	0.39	0.40	0.39	0.40

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

E Robustness: Conflict and Kidney Demand, Yearly Analysis

To account for the possibility that payments are made some month before or after the transplant and that armed groups delay their attacks after the inflow from a transplant tourist operation, Table E1 to Table E6 show all my analyses on a cell-year level: The $Conflict\ dummy_{it}$ indicates if a conflict took place in cell i in year t, $Conflict\ events_{it}$ are summed up over year t for each cell. Conflict variables are regressed on the interaction of transplant infrastructure and beginning-of-the-year kidney demand. All other variables are as defined in Section 3 and in Appendix B. The regression equations are specified in Section 4 and Section 5.

Table E1: The impact of organ demand on conflict probability (yearly panel)

This table reports coefficients of a linear probability model regressing a binary conflict variable on the interaction between transplant infrastructure and kidney demand (see equation (1)). Conley (1999) standard errors, allowing for spatial correlation within a 500 km radius and for infinite serial correlation, are shown in parenthesis. The sample consists of yearly observations of 15,876 cells of 0.5° latitude × 0.5° longitude, covering 8 countries between 2010 and 2021. The dependent variable is a binary variable indicating if a conflict took place in a given year. Independent variables are the binary variable $Transplant\ center$, indicating the existence of an authorized transplant center in an 0.5° latitude × 0.5° 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis in the beginning of the year. Models (1), (3), and (5) include cell and year fixed effects, models (2), (4), and (6) include cell and country × year fixed effects.

	Dependent variable: Probability of conflict (in basis points)					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center						
× waiting list (WL) patients	452.17***	300.16***				
	(75.15)	(54.54)				
× WL patients with income			922.11***	648.35***		
			(99.86)	(81.34)		
× WL patients on dialysis					147.47**	84.45
					(72.58)	(51.55)
Observations	190,500	190,416	190,500	190,416	190,500	190,416
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No	Yes	No
Country × year FEs	No	Yes	No	Yes	No	Yes
Base prob. transplant cells	1647.38	1647.38	1647.38	1647.38	1647.38	1647.38
R-squared	0.00	0.00	0.00	0.00	0.01	0.01

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

Table E2: The impact of organ demand on the number of conflict events (yearly panel)

This table reports coefficients of a linear regression of the log number of local conflict events on the interaction between transplant infrastructure and kidney demand (see equation (1)). Conley (1999) standard errors, allowing for spatial correlation within a 500 km radius and for infinite serial correlation, are shown in parenthesis. The sample consists of yearly observations of 15,876 cells of 0.5° latitude × 0.5° longitude, covering 8 countries between 2010 and 2021. The dependent variable is the logged number of conflict events in a given year. Independent variables are the binary variable $Transplant\ center$, indicating the existence of an authorized transplant center in an 0.5° latitude × 0.5° 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis in the beginning of the year. Models (1), (3), and (5) include cell and year fixed effects, models (2), (4), and (6) include cell and country × year fixed effects.

	Dependent variable: Log conflict events					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center						
× waiting list (WL) patients	0.070***	0.052***				
	(0.01)	(0.01)				
× WL patients with income			0.116***	0.085***		
			(0.02)	(0.02)		
× WL patients on dialysis					0.038***	0.030***
					(0.01)	(0.01)
Observations	190,500	190,416	190,500	190,416	190,500	190,416
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No	Yes	No
Country × year FEs	No	Yes	No	Yes	No	Yes
Mean log events transplant cells	0.28	0.28	0.28	0.28	0.28	0.28
R-squared	0.00	0.00	0.00	0.00	0.01	0.01

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

Table E3: The impact of organ demand on a group's conflict probability (yearly panel)

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 yearly 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 year. 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis in the beginning of the year. Models (1), (3), and (5) include actor and year fixed effects, models (2), (4), and (6) include actor and country $\times$ year fixed effects. Standard errors are two-way clustered by group and year 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	130.79	138.20				
	(88.97)	(94.49)				
$\times$ WL patients with income			125.77*	154.47**		
			(61.67)	(55.67)		
$\times$ WL patients on dialysis					94.86	92.36
					(111.83)	(117.36)
Observations	8,508	8,496	8,508	8,496	8,508	8,496
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No	Yes	No
Country $\times$ year FEs	No	Yes	No	Yes	No	Yes
Base prob. transplant groups	1382.74	1388.89	1382.74	1388.89	1382.74	1388.89
R-squared	0.20	0.22	0.20	0.22	0.20	0.22

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

Table E4: The impact of organ demand on a group's number of conflict events (yearly panel)

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 yearly 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis in the beginning of the year. Models (1), (3), and (5) include actor and month fixed effects, models (2), (4), and (6) include actor and country $\times$ year fixed effects. Standard errors are two-way clustered by group and year and shown in parentheses.

	Dependent variable: Group's log conflict events					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center at home region						
$\times$ waiting list (WL) patients	0.019	0.020				
	(0.01)	(0.01)				
$\times$ WL patients with income			0.024	0.028*		
			(0.01)	(0.01)		
$\times$ WL patients on dialysis					0.013	0.013
					(0.01)	(0.02)
Observations	8,508	8,496	8,508	8,496	8,508	8,496
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No	Yes	No
Country $\times$ year FEs	No	Yes	No	Yes	No	Yes
Mean log events transplant groups	0.15	0.15	0.15	0.15	0.15	0.15
R-squared	0.34	0.35	0.34	0.35	0.34	0.35

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

Table E5: The impact of organ demand on a group's conflict probability outside its home region (yearly panel)

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 yearly 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 year. 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis in the beginning of the year. Models (1), (3), and (5) include actor and year fixed effects, models (2), (4), and (6) include actor and country × year fixed effects. Standard errors are two-way clustered by group and year and shown in parentheses.

	Dependent variable: Group's probability of conflict outside home region (in basis points)					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center at home region						
× waiting list (WL) patients	65.10	70.60				
	(60.48)	(62.36)				
× WL patients with income			50.05	72.94		
			(74.64)	(67.07)		
× WL patients on dialysis					43.11	40.66
					(71.67)	(74.22)
Observations	8,508	8,496	8,508	8,496	8,508	8,496
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No	Yes	No
Country × year FEs	No	Yes	No	Yes	No	Yes
Base prob. transplant groups	877.58	881.48	877.58	881.48	877.58	881.48
R-squared	0.22	0.24	0.22	0.24	0.22	0.24

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

Table E6: The impact of organ demand on a group's number of conflict events outside its home region (yearly panel)

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 yearly 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. Models (1), (3), and (5) include actor and year fixed effects, models (2), (4), and (6) include actor and country × year fixed effects. Standard errors are two-way clustered by group and year and shown in parentheses.

	Dependent variable: Log conflict events outside home region					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center at home region						
× waiting list (WL) patients	0.016	0.016				
	(0.01)	(0.01)				
× WL patients with income			0.019	0.022		
			(0.01)	(0.01)		
× WL patients on dialysis					0.010	0.010
					(0.01)	(0.01)
Observations	8,508	8,496	8,508	8,496	8,508	8,496
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No	Yes	No
Country × year FEs	No	Yes	No	Yes	No	Yes
Mean log events transplant groups	0.11	0.11	0.11	0.11	0.11	0.11
R-squared	0.38	0.38	0.38	0.38	0.38	0.39

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

F Robustness: Conflict Probability and Kidney Demand, Nonlinear Estimators

Table F1 and Table F2 report the results of regressing a binary conflict variable on the interaction between transplant infrastructure and kidney demand using a conditional logit model (Table F1) and a Poisson pseudo-maximum-likelihood model (Table F2).

Table F1: The impact of organ demand on conflict probability (Logit regression)

This table reports coefficients of a conditional logit 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° latitude × 0.5° 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° latitude × 0.5° 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. All models include cell and month fixed effects. Standard errors are reported in parenthesis.

	Dependent variable: Probability of conflict		
	(1)	(2)	(3)
Transplant center			
× waiting list (WL) patients	0.165***		
	(0.05)		
× WL patients with income		0.505***	
		(0.18)	
× WL patients on dialysis			-0.012
			(0.06)
Observations	142,020	142,020	142,020
Cell fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table F2: The impact of organ demand on conflict probability (Poisson pseudo-maximum-likelihood regression)

This table reports coefficients of a Poisson psuedo-maximum likelihood 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° latitude × 0.5° 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° latitude × 0.5° 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. All models include cell and month fixed effects. Standard errors are reported in parenthesis.

	Dependent variable: Probability of conflict		
	(1)	(2)	(3)
Transplant center			
× waiting list (WL) patients	0.047		
	(0.06)		
× WL patients with income		0.137	
		(0.15)	
× WL patients on dialysis			-0.007
			(0.04)
Observations	142,020	142,020	142,020
Cell fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Base prob. transplant cells	0.05	0.05	0.05
R-squared			

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

G Robustness: Conflict Probability and Events with Penalized Maximum Likelihood Fixed-Effects Estimator

Cook et al. (2020) raise the concern that marginal effects can be biased in fixed effects models of rare events data. To address this concern, I re-run my analyses using the penalized maximum likelihood fixed effects estimator suggested by Cook et al. (2020) in this Appendix. I do not use Cook et al. (2020)'s estimator for my main specification as it does not allow for the extensive correction for spatial and serial clustering applied in my main analyses. At the time of writing [April 29] I only present the results for India, the country with most conflict events and transplant centers. Analyses on the entire sample are computationally highly demanding and are still running on our University server.

Table G1: The impact of organ demand on conflict probability (Penalized maximum likelihood fixed effects estimator)

This table reports coefficients of regressing a binary conflict variable on the interaction between transplant infrastructure and kidney demand (see equation (1)) using Cook et al. (2020)'s penalized maximum likelihood fixed effects estimator. The sample consists of monthly observations of 1,175 cells of 0.5° latitude × 0.5° longitude in India 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° latitude × 0.5° 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 who had labor income when entering the waiting list, and (iii) patients on the U.S. waiting list for a kidney on dialysis. All models include cell fixed effects, models (2), (4), and (6) include month fixed effects, in addition. Standard errors are reported in parenthesis.

	Dependent variable: Probability of conflict					
	(1)	(2)	(3)	(4)	(5)	(6)
Transplant center						
× waiting list (WL) patients	0.405***	0.173				
	(0.049)	(0.118)				
× WL patients with income			2.397***	0.190		
			(0.121)	(0.168)		
× WL patients on dialysis					-0.071*	0.129
					(0.043)	(0.082)
Observations	158,625	158,625	158,625	158,625	158,625	158,625
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	Yes	No	Yes	No	Yes

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

H Sample of Non-State Armed Groups and their Home Region

Table H1 list all non-state armed groups of my sample for which the home region could be determined. Group names are from the Armed Conflict Location & Event Data Project (ACLED). A group's home region is defined 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 online sources to determine these locations.

Table H1: Sample of non-state violent groups and their home region

This table reports my sample of non-state violent groups and their home region. Group names are from the Armed Conflict Location & Event Data Project (ACLED). A group's home region is defined 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 online sources to determine these locations.

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

Actor	Home Region	
	Latitude (rounded to closest half degree)	Longitude (rounded to closest half degree)
Baba Goth Communal Militia (Pakistan)	25	67
Babanian 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
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
Bhaggupur 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
Bin Qasim Communal Militia (Pakistan)	25	67
Bindapur Communal Militia (India)	29	77
Binjhol Communal Militia (India)	30	77
Bishnah Communal Militia (India)	33	75
Bizana Communal Militia (South Africa)	-31	30
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
Bushbuckridge Communal Militia (South Africa)	-25	31
Central Kurram Communal Militia (Pakistan)	33	71
Chabba Communal Militia (India)	32	75
Chachar Communal Militia (Pakistan)	28	69
Chak 241-GB Communal Militia (Pakistan)	31	73
Chak Communal Militia (Pakistan)	28	69
Chak Hakim Communal Militia (India)	33	75
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
Curchorem 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
Faridkot Communal Militia (India)	31	75
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
Ghariala 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
Jalbani 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
JI: 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
JUI-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
Kalhoro 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
Muktsar 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
Saraikela 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