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TRADE IN SMALL ARMS AND LIGHT WEAPONS. ARE EMBARGOES EFFECTIVE?

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Trade in Small Arms and Light Weapons.
Are embargoes effective?

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Abstract

This paper analyses the trade in Small Arms and Light Weapons (SALW) from 1990 to 2017. Our analysis relies on an unbalanced panel of 79,245 observations reporting SALW transfers between 9,275 pairs of countries. In particular, we study the impact of embargoes on trade in SALW. We test different channels through which arms embargoes may affect trade in SALW. We use a gravity model framework where we include beside traditional gravity variables also controls specific to trade in SALW. Results show that (i) embargoes reduce SALW imports of target country; (ii) there is no evidence of sanctions-busting because imports neighbor countries do not seem to be positively affected; (iii) Imports of sport arms – which can be subject to fewer restrictions - appear to be unrelated to sanctions, indicating that the trade in this type of weapon may be still quite unrestricted.

Keywords: Small arms and light weapons; Gravity model, Sanctions, Embargoes.

JEL Codes: F14; F51; H56; D74.

I. Introduction

The diffusion of Small Arms and Light Weapons (hereafter SALW) has drawn growing attention among scientists and experts. First, SALW has become a key component in the wave of civil conflicts that have characterized the international context since the end of the Cold War (Kruase and Mutimer, 2005; Benson and Ramsay, 2016). Furthermore, diffusion of small arms appears to be associated with the intensity of violent crime (Duggan, 2001; Cook and Ludwig, 2006; Ross and King, 2013) and the spread of suicide by firearms (Lang, 2013; Rodriguez and Hempstead, 2011). Definition of SALW has been elaborated by a UN panel of experts, "*small arms are those weapons designed for personal use, and light weapons are those designed for use by several persons serving as a crew. Small arms include pistols, rifles, carbines and light machine guns; light weapons include heavy machine guns, grenade launchers, portable anti-aircraft and anti-tank systems, and mortars of less than 100 mm caliber. This category of weaponry also includes ammunition and explosives: cartridges, shells and missiles, anti-personnel and anti-tank grenades, landmines and other explosives*" (UN, 1997, pp. 11–12).

This paper investigates the impact of arms embargoes on the trade in SALW between 1990 and 2017. There are no studies that deepen this topic in the literature. Related previous studies show that sanctions reduce imports of Major Conventional Weapons (MCW) only (Broska, 2008; Schulze et al., 2017). There are, however, some differences between SALW and MCW that motivate this study. First SALW are to be smuggled easily and target countries are often suspected to acquire small weapons from neighbor countries through porous borders (Erickson, 2013; Radford, 2016). In brief, it is often maintained that sanctions-busting is more likely with SALW. Therefore, in order to check for sanctions-busting, we investigate whether embargoes on neighbor countries stimulate imports from target countries. In fact, we investigate whether there is sanctions-busting in SALW trade. Moreover, the impact of sanctions may also change according to different types of SALW. Weapons dispatched under the label of "sport arms" can be less monitored and they can be shipped more easily across the globe. Therefore, we analyze separately the trade in sport and military SALW. We expect that the effectiveness of sanctions is smaller in the trade of sport arms.

We use a gravity-model framework that is commonly applied in international trade literature. In line with this strand of literature, our model combines traditional economic variables with political and military factors. Our analysis relies on an unbalanced panel of 79,245 observations reporting SALW transfers between 9,275 pairs of countries and territories from 1990 to 2017.

Results show that embargoes are effective in reducing SALW imports. In particular, sanctions reduce imports of SALW by 35%. Interestingly findings show that both UN and EU sanctions decrease trade, but the quantitative impact is different. An EU embargo determines a decrease of 39% of imports of SALW whereas in the presence of UN sanctions the negative impact is 24%. In brief, EU embargoes appear to be more effective than UN embargoes. Second, we found no evidence of sanctions-busting. Finally, figures highlight that sanctions have no effects on the trade of sport SALW.

The paper is organized as follows. Section 2 presents the previous literature. Section 3 introduces the data, whereas section 4 describes the model. In section 5 we report the results. Section 6 concludes.

II. Literature

The present paper relates to different strands of literature. It relies on the literature investigating the effectiveness of economic sanctions and, particularly, of arms embargoes.[1] Sanction's effectiveness can be measured according to different criteria. Sanctions may change or contribute to change the targeted policy; they may influence the target's power structure or its decision-making process; they can coerce the target to abide by the sender's demands (Baldwin, 1985; Brzoska, 2008; Erickson, 2013). Accordingly, there is no clear-cut assessment on sanctions performance. Hufbauer et al. (2007) estimate that sanctions are effective tools about 34% of the time. Pape (1997), however, shows out that in many of these cases sanctions were combined with the use of military force. Thus, he points out that sanctions by themselves are effective less than 5% of the time.

Previous literature also investigates senders' compliance to sanctions whose success depends on the states' willingness to effectively stop the supply of sanctioned goods to the target. Several works show how sanctions are often ineffective because of sanctions-busting (Early, 2015; Caruso, 2003). In absence of international mechanisms for the enforcement of sanctions, senders may find strong incentives to avoid their obligations.

Among economic sanctions, embargoes are frequently used in cases of war, support for terrorism, human rights violations, or nuclear weapons development. Their main goal is to restrain the target's access to weapons with which it perpetrates the crimes it is

[1] See Peksen (2019) for a comprehensive literature review on sanctions effectiveness.

accused of (Baldwin, 1997; Brozska, 2008). Despite their popularity, the previous literature agrees that arms embargoes are largely ineffective. In many cases, arms still get through to violent actors and combating forces seldom stop fighting (Tierney, 2005; Brzoska and Lopez, 2009).

Among the factors that may explain the failure of arms embargoes, sanctions-busting practices are often suspected (Boucher & Holt, 2009; Tierney, 2005; Cortright & Lopez, 2009). Recent studies, however, find evidence showing sender compliance to arms embargoes. Brozska (2008) analyzing arms embargoes between 1990 and 2005, shows that arms embargoes do reduce arms imports. Similarly, Erickson (2013) argues that arms embargoes restrain exports of both small and major conventional weapons from 1981 to 2004. Moore (2010) finds that in cases of UN arms embargoes, the majority of senders do not sell MCW to targets during the embargo.

Alternative explanations point to illicit trafficking as a potential cause of embargoes failure (Vines, 2005; Roger, 1996; Dreyfus and Marsh; 2006). Arms can illegally cross borders from neighboring countries and reach an embargoed state without been detected. This is especially evident for small arms that are small and easy to move. Empirical analyses of the subject, however, are scant due to a lack of data. Using imports of SALW from 1981 to 2004, Radford (2013) provides indirect evidence of illegal trafficking. He shows that the presence of arms embargoes in the neighboring countries stimulates imports of arms.

The present paper also refers to the studies that analyze the trade in MCW. The previous literature applied the gravity model to the study of MCW and it is empirically highlighted that political determinants are as important as economic determinants in terms of explaining the international trade of MCW. Bove et al. (2018) claimed that oil dependence is crucial in determining the volume of arms trade between two countries: oil-dependent economies are more willing to trade arms to oil-rich countries to preserve the political stability in the recipient and, in turn, to avoid the disruption of the oil trade. Martinez-Zarzoso and Johannsena (2017) implemented a gravity model combining traditional economic determinants with political and security factors. The authors employ a two least stage model ~~to~~ distinguish between the factors behind the decision to export (extensive margin) and those factors explaining the amount exported (intensive margin). Results indicated that, while political and security factors (such as a military and strategic pact) do affect the probability of two countries trading arms, they are less relevant in determining the volume of trade. Akerman and Seim (2014) used the social network analysis to show the role of political affinities in determining the MCW trade. They pointed out that political vicinity was crucial in determining the patterns of trade until the end of the Cold War. After this period, however, this factor has lost its influence. Comola (2012) investigated whether political cycles may affect arms exports using data on the top 20 major exporters over the period 1975–2004. As a result, she argued while that right-wing governments positively influence arms exports, incumbents serving the last year of their term and potentially running for re-election have the opposite effect.

A growing strand of literature on MCW also investigates the relationship between arms imports and conflict. Imports increase arms availability in a country and this, in turn, can dramatically impact both the outbreak and the intensity of a conflict. Despite the relevance of the issue for understanding the mechanisms behind conflict onset and escalation, there are few empirical studies available. Pamp et al. (2018), investigating the effect of inflows of MCW on the outbreak of intrastate conflict on a panel of 137 over the period 1949-2013, show that imports increase the probability of the onset of a civil war. Mehrl and Thurner (2020) focus on the relationship between the import of MCW and SALW and battle-related deaths in intrastate conflict, from 1989 to 2011. They found that this relationship is positive only when fighting sides have military parity and they use conventional combat tactics.

III. The Data

Data about SALW trade are drawn from the Norwegian Initiative on Small Arms Transfers (NISAT).[2] So far, the NISAT is considered as the most reliable database on small arms transfers and it provides information on bilateral transfers of SALW among 250 countries and territories[3] over the period 1962 until 2017 from multiple sources. Then, we have collected data about exports for all the countries available. We choose exports since they are usually considered more reliable than imports. The reasons are twofold. First, there is more information on exports than on imports (Small Arms Survey, 2001). Countries are more willing to declare that they are selling weapons than buying them. Second, imports may reflect trans-shipments and not the final destination of the weapons.

Nevertheless, we also draw data on imports since, as frequently done in the literature (see Gaulier and Zignago, 2010), we aim at

[2] The NISAT is a project established in December 1997 as a coalition of the International Peace Research Institute in Oslo (PRIO), the Norwegian Red Cross and the Norwegian Church Aid.
[3] The territories include all those regions where there has been a custom for a given period of time (for example Ryukyu Islands were occupied by the United States in 1945 and they became part of Japan only in 1972).

employing a mirror statistic strategy to impute missing exports.[4] This use of a mirroring strategy is quite important. In arms trade, it is not uncommon to find countries that did not release any information about their exports. They, however, can be tracked as declared imports in the destination countries.[5]

NISAT collects data from several sources. We have chosen to consider only data taken from the United Nations Commodity Trade Statistics Database of the UN Department of Economic and Social Affairs/UN Statistics Division (UN's ComTrade). Further details about data extraction are reported in appendix A.

Thus, the resulting dataset presents 388,385 observations indicating the value of the transfer in unit dollars, the reporter,[6] the partner, the year when the transfer took place, the type of SALW exchanged and whether the transfer is an export or an import.[7] As mentioned, SALW includes various types of weapons (see appendix A for further details about their classification). In this work, we are mainly concerned with two broader groups: sport SALW[8] and military SALW.

The data, however, present some ambiguities. First, import and export data may include cases where SALW are re-exported, re-

[4] According to a mirror statistic strategy when exports recorder by A to B are missing, the corresponding import recorded by B from A is usually taken.
[5] For example, the German Democratic Republic (DDR) declared no export but these transfers can be easily tracked as declared imports of other countries from the DDR.
[6] The code of both the reporter and the partner refers to the Correlates of War (COW) project’s classification system.
[7] Data are reported in US dollar. Data were originally reported in the currency they were recorded but NISAT converts them in US dollars using the average exchange rate of the year in question.
[8] Under PRIO assigned weapon type, three categories involve sport weapons, namely “Parts of sporting shotguns”, Sporting rifles", "Sporting shotguns". The remaining ones are categorised as military SALW.

imported, or transferred temporarily for purposes of repair or demonstration, etc. Customs data, such as Comtrade data, do not detail the context of a transfer but, they merely report whether a shipment of SALW has taken place between two customs. When possible, the NISAT highlights cases of re-imports and re-exports. In our dataset, 6,398 (about 1.6% of the total) are indicated as re-export or re-import. Moreover, the NISAT also specifies whether the transfer involves only equipment that is classified as SALW according to the 1997 UN definition or not. The goods transferred may comprise both SALW and other equipment or the description of the transfer does not detail the types of weapon traded. In our sample 297,983 observations (about 76 % of the total) are categorized as cases of exclusively SALW transfers while the remaining ones can contain also conventional weapons.

Considering different types of weapons, we found that ambiguities are not randomly distributed. Table 1 below shows their distribution in total, military and sport SALW. The share of cases labeled as re-export or re-import on total observations for sport SAWL is slightly larger than that of military weapons. Further details about disaggregated data descriptions are reported in appendix B.

[Table 1 about here]

So far, the data presented reports the disaggregated values of exports (and imports). To compute our variables of interest, we need to sum the transfers for each pair of countries in a year so to have only one observation (for exports and imports).

We also distinguish between transfers of military weapons and sport weapons. Therefore, before aggregating the data, in addition to the variable reporting the values of all the transfers of SALW we also create other two variables indicating either the value of sport arms' transfers or that of military weapons. Furthermore, we also construct an alternative sample for total, sport and military weapons excluding ambiguous transfers that we detected when describing the disaggregated data (see table 1). Eventually, we summed those observations indicating different exports (or imports) of total, sport and military SALW between the same pair of countries in the same year for both the samples (with and without ambiguities).

In these data, we still have both exports and imports between pairs. To impute missing exports, therefore, we use the corresponding mirroring imports, while we delete the remaining ones.[9] Finally, we deflated the arms trade values at constant 2010 US$ by using the CPI deflator.[10] Tables 2 below presents descriptive statistics for the three variables we obtain (total, sport, and military SALW transfer) with or without ambiguities. Three key aspects are noteworthy. First, the data are skewed, as in the other trade variables. Second, military SALW presents a larger standard deviation than sport SALW. Third, the variables including ambiguities have the largest maximal values. When we exclude ambiguities, the values of the transfers are significantly smaller.

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[9] To implement the mirroring procedure, we first gave the same direction to the flows. In the original data, exports are described as the transfer of SALW from the reporter to the partner country whereas imports indicate the flow to the reporter from the partner country. Therefore, we define the origin of the flow which is, in the exports, the reporter country and, in the imports, the partner. Similarly, the destination is the partner nation in exports and the reporter in imports.

[10] The formula used to deflate SALW transfers is SALW2010 = (SALWt*CPI2010)/CPIt. CPI is drawn from http://www.multpl.com/cpi/table

[Table 2 about here]

There are also differences in the two samples when considering the pairs of trading partners with the largest flows of SALW.[11] As shown in Table 3, in the sample with ambiguities the three largest pairs involve the USA and Japan, Taiwan and Canada. This is true for both total and military SALW. When considering sport arms only the pairs of countries with the largest trade flows are those having the USA as market and three traditional exporters such as Italy and Brazil. The figure for sport SALW does not change in the sample without ambiguities. The pair Italy-USA, however, become also the one with the largest total flows and the third in Military flows.

[Table 3 about here]

The data are unbalanced over time. There are 9,275 pairs over countries trading SALW.[12] Only a small number are available over all the period. The largest number of pairs appears only once. Table 4 reports the number of pairs in the dataset and the number of years they have a recorded transfer available.

[Table 4 about here]

Independent variables

Data about the explanatory variables are collected from different sources (See table 5). Data on arms embargoes come from

[11] Values on transfers between trading partners are obtained summing all the SALW trade flows between pairs.

[12] Please note that gravity data are directed. Therefore, we may have both the value of trade from A to B as well the one from B to A.

SIPRI which provides information on embargoes implemented by the UN and the EU or by other groups of nations. Then, we construct three variables indicating whether a state is subject to an embargo in a given year. First, we select embargoes by the UN (both mandatory and non-mandatory). Secondly, we single out EU sanctions and finally, we use all the embargoes including also those implemented by other groups of nations.

GDP per capita at constant 2010 US$ is drawn from the World Bank. World Bank also reports the importer's total military expenditure in current US$ and we deflated it in constant 2010 US$. The urban population and male population are expressed as shares of the total population. The polity IV indicator is collected from the Polity IV Project by Marshall et al. (2018).

We draw data on civil conflicts from the list of Center for Systemic Peace (CSP) Major Episodes of Political Violence, 1946-2018 (Marshall, 2020). It collects information about armed conflict defined as "*the systematic and sustained use of lethal violence by organized groups that result in at least 500 directly-related deaths over the course of the episode*" (Marshall, 2020, p.1). We create a dummy variable indicating whether a state has an episode of civil violence and/or a civil war in a given year.

Grounding on data about civil conflict and sanctions, we create two variables referring to the characteristics of the importer's neighborhood. Data about neighboring countries are drawn from COW Direct Contiguity Data, Version 3.20, which identifies direct contiguity relationships between countries over the period 1816-2016. Contiguity relationships comprise both land and sea contiguity. We focus only on land contiguity and for each importer we first identify its neighboring countries. Then, we verify whether these countries are under embargo (maintaining the differences between UN and EU embargoes) and if they have a civil conflict inside its borders. The resulting two variables indicate one the number of importers' neighboring countries that are targeted with sanctions and the other the number of neighbors that had civil unrest. For instance, China in 1992 had 5 neighboring countries under embargo. Bilateral variables are gathered from CEPII database (Head et al., 2010).[13]

[Table 5 about here]

IV. The model

Our econometric analysis uses a gravity model to investigate the relationship between arms embargoes and bilateral flows of SALW. The introduction of this model dated back to Isard (1954) and Tinbergen (1962) and it is now standard practice to use the gravity equation to estimate the effect of several economic, cultural and political factors on trade (Head and Mayer, 2014; Baltagi et al., 2014). We adopt a gravity framework to analyze how embargoes impact on inflows of SALW. We also control for several factors that may either stimulate or deter arms trade. Formally, our gravity equation takes the following form:

$$\begin{aligned} lnSALW_{itj} = {} & \beta_0 + \beta_1\, EMB_{it} + \beta_2\, Neighbour's\, EMB_{it} + \beta_3\, GDP_{it} \\ & + \beta_4\, GDP_{jt} + \beta_5\, D_{jt} + \beta_6 diff\ pol_{ij} + \beta_7\, G_{ijt} + \delta_{ijt} + \tau \\ & + \varepsilon_{ijt} \end{aligned}$$

[13] Gravity variables consist of a set of bilateral impediments or facilitating factors of trade. They capture those features that are specific to a pair of countries and that explain the volume of trade between these two countries while the importer and exporter's characteristics describe the propensity of trade/attractiveness of the single country. They are time-invariant and time-variant. The use of pair fixed effects does not allow the use of time-invariant pair variables.

Here, $SALW_{itj}$ is the log of the value of flows of SALW from the exporter, i.e. country i, to the importer, i.e. country j. EMB_{it} is a dummy variable that indicates if the importer is under embargo. It controls for the effectiveness of sanctions in reducing the target's imports in SALW. $Neighbour's\, EMB_{it}$ reports the number of importer's neighbors under embargo. It accounts for the presence of illegal trafficking in SALW trade.

GDP_{it} and GDP_{jt} refers respectively to the exporter's and the importer's GDP per capita (constant 2010US$), which traditionally proxy for countries' economic size. D_{jt} is a vector comprising a set of importer's characteristics that may affect the demand of SALW. First, we include the level of military expenditures to check for a likely complementarity. Other factors explaining the demand for arms are the share of the urban population and the male population over the total. According to a stream of literature, large urban concentration increases crime rates (see for example World Bank, 2011). Similarly, a high ratio of the male population over the total population may bring civil unrest. To face these threats, governments may need to buy new light weapons.

A key factor in explaining the demand for SALW are also civil conflicts. Civil conflicts are mainly fought with small weapons. Thus, we account for the presence of civil conflict in the importing country. However, to check for sanctions-busting we use the number of neighbor countries fighting a civil war as further control for the demand of SALW. Furthermore, we include the level of democracy of the importer. As suggested by De Soysa et al. (2010), autocracies and regimes involved in human rights repression need small arms to support their police forces. Finally, (G_{ij}) is a vector of time-variant gravity variables that are two binary variables taking value 1 if i and

j have a common currency or have regional trade agreements (RTAs) in force. δ_{ijt} are country-pair fixed effects which account for time-invariant bilateral factors influencing arms trade flows. τ is year-fixed effects while ε_{ijt} the error term.

V. Results

V.1 Baseline results

In this section we present estimates from regressing total trade of SALW over the period 1990-2017 (see table 6). First, there is a negative and significant relationship between embargoes on the target countries and the inflows of SALW. Figures show that, when the importer is under arms embargo, imports of SALW decrease by 35%. We interpret this result as evidence of the effectiveness of sanctions in reducing inflows of SALW. This result is in line with the literature on conventional weapons (Broska, 2008; Erickson, 2013; Schulze et al., 2017). The analysis of UN and EU sanctions shows that their impact is different. The imposition of an EU embargo on the importer leads to a decrease of 39% in its imports. In the case of the UN, the impact of sanctions is 24%. Plausibly, the EU imposes to its member states compliance as well as the punishment of free riders. The coefficient for embargoes on neighbor countries is not significant so providing no evidence of sanctions-busting.

Furthermore, results are also in line with our hypotheses about the importer's characteristics that drive inflows of SALW. The coefficient for military expenditures is positive and significant: an increase of 1% in military expenditures rises imports of SALW of nearly 0.4%. This figure highlights a complementarity between military expenditures and SALW inflows.

Civil conflict is positively correlated with imports of SALW: namely the presence of civil conflict in the importer country is associated with an increase of about 20% in the volume of its arms imports. This figure confirms what the literature has already highlighted. The wave of civil conflicts that broke off after the end of the Cold War was largely fought with light weapons. Thus, it is reasonable to expect that a rise in inflows of SALW in war zones. No evidence, however, suggests any link between neighbors at war and imports of small arms. The importer's level of democracy is also unrelated to the trade of SALW. Similarly, the coefficient for political similarities between the exporter and the importer is not significant. This figure indicates that the nature of the importer's government is not conducive to explaining its demand for arms.

Among gravity variables, the coefficient for importer's GDP per capita is positive and significant: this in line with the literature about the gravity model which argues that the economic dimension of the importer is a proxy for its demand. In detail, an increase of 1% in the GDP is correlated with a rise of about 0.4 % in SALW imports. Surprisingly, figures also show a negative association between the exporter GDP and the flows of SALW. We believe this result can be linked to the composition of the word supply of SALW. Since the '90, some developing countries have become relevant exporters of SALW. Brazil, for instance, is the 6th larger SALW exporter over the period 1990-2017. The emergence of these new exporters has reduced the weight that the richest countries had on the market.

Interestingly we found a positive and significant relationship between SALW inflows and the importer's share of the male population. In detail, when there is an increase of 1% in this share, the SALW imports rise by about 6%. We interpret this figure as evidence that in presence of large shares of the male population, governments buy more arms for their police forces to prevent civil unrest. Surprisingly, the coefficient for the share of the importer's urban population is negative and significant with elasticities of about 1.2. This figure suggests the existence of scale economies in arming the police recruitment.

[Table 6 about here]

V.2 Types of arms

Hereafter, we run estimations splitting our data between sport and military weapons. Relevant differences emerge. Tables 7- 8 report the results. First, the impact of sanctions changes according to the type of arms analyzed. Figures show that while embargoes reduce of about 36% imports of military arms, there is no significant relationship with sports weapons. Sanctions seem to be ineffective in limiting trade in sport arms. Plausibly, these weapons are less monitored, and can easily arrive in target countries without any restriction by the international community.

Furthermore, our analysis suggests that sport arms are far from being used only for civilian activities but, they are linked to key aspects of the military. The coefficient of the importer's military expenditure is positive and significant with an elasticity of 0.4. Moreover, the presence of civil conflict in the importer leads to an increase of 37% in its imports of sport arms. It is noteworthy that the coefficient of civil conflict is significantly lower when considering the trade in military weapons. Here, the increase in inflows of SALW associated with the presence of civil conflict is about 23%.

A second relevant difference in the trade of sport and military weapons lies in the association between countries' economic dimensions and their trade. When analyzing sport arms, the coefficient of the importer's GDP per capita is positive and significant with an elasticity of 1.1. Conversely, in the analysis of military weapons, the association is not significant. The interpretation of these figures suggests that in the trade of military weapons, the demand for this commodity is not driven by wealth. Furthermore, also when we observe the exporter's economic dimension, wealth considerations are not relevant. For military arms, there is a negative but weakly significant association between the exporter's GDP and its exports while this association is not significant for sport arms.

[Table 7 and 8 about here]

V.3 Robustness checks

To test the robustness of our results we implement three types of checks. First, we drop from our analysis the observations reported as ambiguous in the original dataset which mainly refer to transfers also including conventional weapons.[14] As highlighted in the data section, the exclusion of these observations changes some key features. Estimates, however, show that our main results are robust (see table 9). There are, however, three key differences. Firstly, the estimated impact of sanctions on arms imports is significantly weaker. When excluding ambiguities, the reduction in imports of SALW due to the imposition of an embargo (total or EU) is on average 10 points lower. The figure for UN sanctions is not significant.

[14] Please remember that the trade in sport arms does not include this form of ambiguities. Thus, we do not run this robustness check for sport arms

Secondly, the coefficient for civil conflict is higher in the sample with no ambiguities. If considering total SALW, the increase in its imports associated with the presence of civil conflict is 38%. In the trade of military weapons, the rise in imports is 42%. Thirdly, the coefficient for the exporter's GDP is not significant.

Furthermore, we drop separately destination countries with a population below 40% (table 11), 60% (table 12) and 80% (table 13) of the median of population. Finally, in the third group of checks, we progressively remove outliers, namely values of export below 1% and above 99% (table 14), below 5% and above 95% (table 15) and below 10% and above 90% of exports (table 16). Estimates confirm the negative relationship between embargoes and imports of SALW. The coefficients of the other regressors have all the same sign and their magnitudes are alike to general results. Few exceptions are notable. First, when excluding underpopulated countries[15], the exporter's

[15] The list of countries we exclude in these checks is: Albania, American Samoa, Andorra, Antigua & Barbuda, Armenia ,Aruba, Austria, Azerbaijan, Bahamas, Bahrain, Barbados, Belize, Benin, Bermuda, Bhutan, Bolivia, Bosnia-Herzegovina, Botswana, British Virgin Islands, Brunei, Bulgaria, Burundi, Cape Verde, Cayman Islands, Central African Republic, Chad, Comoros, Congo (Republic of), Costa Rica, Croatia, Curacao, Cyprus, Denmark, Djibouti, Dominica, Dominican Republic, East Timor, El Salvador, Equatorial Guinea, Eritrea, Estonia, Faroe Islands, Fiji, Finland, French Polynesia, Gabon, Gambia, Georgia, Gibraltar, Greenland, Grenada, Guam, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong, Iceland, Ireland, Israel, Jamaica, Jordan, Kiribati, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho, Liberia, Libya, Lithuania, Luxembourg, Macao, Macedonia, Maldive Islands, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Micronesia (Federated States of), Moldova, Mongolia, Montenegro, Namibia, Nauru, New Caledonia, New Zealand, Nicaragua, Niger, Northern Marianas Islands, Norway, Oman, Palau, Panama, Papua New Guinea, Paraguay, Qatar, Rwanda, Samoa/Western Samoa (former), San Marino, SaoTome-Principe, Senegal, Serbia/Yugoslavia (former) /Serbia & Montenegro, Seychelles, Sierra Leone, Singapore, Sint Maarten, Slovakia, Slovenia, Solomon Islands, Somalia, St. Kitts-Nevis, St. Lucia, St. Vincent and the Grenadines, Surinam, Swaziland, Sweden, Switzerland, Tajikistan, Togo, Tonga Islands, Trinidad and Tobago, Tunisia, Turkmenistan, Turks and Caicos, Tuvalu, United Arab Emirates, Uruguay, Vanuatu, West Bank, Zambia

GDP is not significant. Furthermore, the impact of the male population skyrockets. Conversely, when dropping outliers, the coefficient for the male population decreases from 5%in table 14 to 2% in table 16.

[Tables 9-16 about here]

VI. Conclusion

This paper investigates the impact of arms embargoes on the world trade in SALW between 1990 and 2017. The main results we would claim for this work are: (i) sanctions reduce imports of SALW by 35%. Interestingly, findings show that both UN and EU sanctions decrease trade but the quantitative impact is different. An EU embargo determines a decrease of 39% of imports whereas in the presence of UN sanctions the negative impact is 24%.

We have also investigated the existence of sanctions-busting by considering imports of neighbor countries as indirect signals of sanctions-busting. In fact, we found no evidence of sanctions-busting. Finally, estimations highlight that sanctions have no effects on the trade of sport SALW. That is, labeling of small arms really marks a difference. These results appear to be robust. First, when considering ambiguities in the data, the main results do not substantially change. In fact, we have run a set of robustness checks and all main results are confirmed.

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Tables and references

Table 1: Ambiguities (1990-2017)

	Small Arms only		Re-export		Re-import		Total
	Num	*%*	*Num*	*%*	*num*	*%*	*num*
Total SALW	297,983	76	6,398	1.65	46	0.01	388,385
Sport SALW	87,389	100	1,467	1.68	11	0.01	87,389
Military SALW	210,594	69	4,931	1.64	35	0.01	300,996

Table 2. SALW transfers in constant 2010 US$ (1990-2017)

Variable	Obs.	Mean	Std. Dev.	Min	Max
Total SALW	79,245	2,631,929	20,800,000	0	1,420,000,000
Sport SALW	79,245	297,364	3,195,495	0	191,000,000
Military SALW	79,245	2,334,565	20,000,000	0	1,420,000,000
Total SALW (no ambiguities)	70,466	1,194,997	7,010,257	0.892	280,000,000
Sport SALW (no ambiguities)	70,466	330,108	3,335,103	0	191,000,000
Military SALW (no ambiguities)	70,466	864,889	4,939,683	0	175,000,000

Table 3: Top 3 largest trading partner in constant 2010 US$ (1990-2017)

	Ambiguities			No Ambiguities	
Origin	Destination	Total SALW	Origin	Destination	Total SALW
USA	Japan	11,650,000,000	Italy	USA	4,490,000,000
USA	Taiwan	7,735,000,000	USA	Canada	3,243,000,000
USA	Canada	7,168,000,000	Germany	USA	2,579,000,000
		Sport SALW			Sport SALW
Italy	USA	2,787,000,000	Italy	USA	2,787,000,000
Brazil	USA	1,926,000,000	Brazil	USA	1,926,000,000
Japan	USA	1,112,000,000	Japan	USA	1,112,000,000
		Military SALW			Military SALW
USA	Japan	11,610,000,000	USA	Canada	2,343,000,000

USA	Taiwan	7,731,000,000	Germany	USA	2,193,000,000
USA	UK	6,791,000,000	Italy	USA	1,702,000,000

Table 4: Pairs of trading countries over time

No of pairs	No of years
6,383	1-10
1,373	11-20
1,011	21-30
508	28

Table 5: Descriptive statistics

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
SALWij	Flows of SALW (constant 2010 US$)	79,242	10.912	2.987	-0.114	21.072
Sport SALWij	Flows of sport SALW (constant 2010 US$)	35,496	10.471	2.442	-0.089	19.068
Military SALWij	Flows of military SALW (constant 2010 US$)	70,748	10.814	3.043	-0.114	21.072
Embargoj	1 if the importer is under embargo, 0 otherwise	79,245	0.041	0.199	0	1
Neighbours embargoj	The number of importer's neighbours under embargo	79,245	0.403	0.806	0	5
UN embargoj	1 if the importer is under UN embargo, 0 otherwise	79,245	0.018	0.134	0	1
Neighbours UN embargoj	The number of importer's neighbours under an UN embargo	79,245	0.181	0.474	0	3
EU embargoj	1 if the importer is under EU embargo, 0 otherwise	79,245	0.037	0.188	0	1
Neighbors EU embargoj	The number of importer's neighbours under EU embargo	79,245	0.355	0.717	0	5
GDPpci (ln)	Exporter's GDP per capita (constant 2010 US$)	77,444	9.881	1.091	5.170	11.626
GDPpcj (ln)	Importer's GDP per capita (constant 2010 US$)	76,292	9.258	1.424	5.102	11.626
Milexj (ln)	Importer's military expenditure (constant 2010 US$)	70,074	21.671	2.214	10.790	27.274
Urban popj (ln)	Importer's urban population (% of total population)	78,123	4.118	0.408	1.689	4.605
Male popj (ln)	Importer's population, male (% of total population)	76,654	3.908	0.056	3.816	4.340
Civil conflictj	1 if the importer has a civil conflict	79,245	0.042	0.201	0	1
Neighbors civil conflictj	The number of importer's neighbours having a civil conflict	79,245	0.201	0.487	0	3
Polityj	Importer's polity score	71,838	6.064	5.712	-10	10
Diff polityij		69,601	4.712	5.774	0	20
Common currencyij	1 if common currency, 0 otherwise	78,593	0.047	0.211	0	1

Free Tradeij	1 if free trade agreement, 0 otherwise	71,399	0.307	0.461	0	1

Table 6. Results

	(1)	(2)	(3)	(4)	(5)	(6)
Embargo j	-0.427***	-0.436***				
	(0.120)	(0.120)				
Neighbors embargo j	0.023	0.002				
	(0.033)	(0.034)				
UN embargo j			-0.297†	-0.297†		
			(0.170)	(0.171)		
Neighbors UN embargo j			-0.100†	-0.113*		
			(0.053)	(0.054)		
EU embargo j					-0.481***	-0.488***
					(0.132)	(0.132)
Neighbors EU embargo j					0.036	0.012
					(0.035)	(0.036)
GDPpc i (ln)	-0.186†	-0.278*	-0.203†	-0.284*	-0.183†	-0.280*
	(0.109)	(0.128)	(0.110)	(0.129)	(0.109)	(0.128)
GDPpc j (ln)	0.378**	0.380**	0.401***	0.412**	0.374**	0.370**
	(0.116)	(0.134)	(0.116)	(0.135)	(0.116)	(0.134)
Milex j (ln)	0.521***	0.383***	0.513***	0.371***	0.520***	0.384***
	(0.042)	(0.046)	(0.042)	(0.046)	(0.042)	(0.046)
Urban pop j (ln)	-1.044***	-1.207***	-0.993***	-1.136***	-1.035***	-1.195***
	(0.280)	(0.294)	(0.280)	(0.294)	(0.281)	(0.295)
Male pop j (ln)	7.559***	6.143***	8.030***	6.712***	7.480***	6.032**
	(1.826)	(1.852)	(1.837)	(1.866)	(1.825)	(1.851)
Civil conflict j	0.209*	0.199*	0.197*	0.185*	0.201*	0.190*
	(0.092)	(0.092)	(0.091)	(0.092)	(0.092)	(0.092)
Neighbors civil conflict j	0.015	0.001	0.011	-0.003	0.012	-0.003
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Polity j	0.002	0.004	0.004	0.007	0.002	0.004
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Diff polity ij	0.001	0.000	0.001	-0.000	0.001	0.000
	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
Constant	-27.026***	-16.881*	-28.935***	-19.370*	-26.736***	-16.408*
	(7.136)	(7.674)	(7.173)	(7.736)	(7.134)	(7.673)
Time dummy	No	Yes	No	Yes	No	Yes
Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,316	58,316	58,316	58,316	58,316	58,316
Number of id_pair	6,574	6,574	6,574	6,574	6,574	6,574
R2 within	0.017	0.021	0.016	0.020	0.017	0.021
R2 overall	0.053	0.034	0.052	0.035	0.054	0.033
R2 betweenness	0.016	0.005	0.014	0.005	0.016	0.005

Clustered Robust standard errors at pair level in parentheses. ***p<0.001, **p<0.01 *p<0.05 †p<0.1

Table 7. Sport arms

	(1)	(2)	(3)	(4)	(5)	(6)
Embargo j	-0.159	-0.187				
	(0.150)	(0.146)				
Neighbors embargo j	0.016	-0.023				
	(0.038)	(0.038)				
UN embargo j			-0.041	-0.066		
			(0.243)	(0.236)		
Neighbors UN embargo j			-0.206**	-0.200**		
			(0.069)	(0.070)		
EU embargo j					-0.151	-0.170
					(0.159)	(0.157)
Neighbors EU embargo j					0.008	-0.028
					(0.039)	(0.040)
GDPpc i (ln)	-0.025	0.019	-0.041	0.018	-0.026	0.018
	(0.133)	(0.151)	(0.133)	(0.151)	(0.133)	(0.151)
GDPpc j (ln)	1.087***	1.122***	1.091***	1.128***	1.091***	1.124***
	(0.138)	(0.160)	(0.136)	(0.159)	(0.138)	(0.160)
Milex j (ln)	0.497***	0.416***	0.496***	0.408***	0.497***	0.416***
	(0.050)	(0.053)	(0.050)	(0.053)	(0.050)	(0.053)
Urban pop j (ln)	-1.263***	-1.382***	-1.215***	-1.319***	-1.254***	-1.353***
	(0.362)	(0.380)	(0.359)	(0.378)	(0.362)	(0.380)
Male pop j (ln)	6.540***	4.799*	6.958***	5.316**	6.535***	4.793*
	(1.901)	(1.989)	(1.912)	(1.997)	(1.901)	(1.989)
Civil conflict j	0.363**	0.316*	0.358**	0.307*	0.358**	0.309*
	(0.130)	(0.129)	(0.130)	(0.128)	(0.129)	(0.128)
Neighbors civil conflict j	-0.047	-0.041	-0.045	-0.038	-0.047	-0.043
	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
Polity j	0.003	-0.001	0.003	0.001	0.003	-0.000
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Diff polity ij	-0.002	-0.011	-0.001	-0.011	-0.002	-0.011
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Constant	-30.423***	-25.390**	-32.060***	-27.523**	-30.442***	-25.494**
	(7.364)	(8.452)	(7.388)	(8.464)	(7.371)	(8.456)
Time dummy	No	Yes	No	Yes	No	Yes
Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,732	27,732	27,732	27,732	27,732	27,732
Number of id pair	3,752	3,752	3,752	3,752	3,752	3,752
R2 within	0.050	0.118	0.051	0.118	0.050	0.118
R2 overall	0.082	0.090	0.082	0.090	0.082	0.090
R2 betweenness	0.033	0.034	0.033	0.034	0.033	0.034

Clustered Robust standard errors at pair level in parentheses. ***p<0.001, **p<0.01 *p<0.05 †p<0.1

Table 8. Military arms

	(1)	(2)	(3)	(4)	(5)	(6)
Embargo j	-0.446***	-0.442***				
	(0.130)	(0.130)				
Neighbors embargo j	0.049	0.026				
	(0.037)	(0.038)				
UN embargo j			-0.371*	-0.358†		
			(0.187)	(0.189)		
Neighbors UN embargo j			0.025	0.014		
			(0.059)	(0.059)		
EU embargo j					-0.476**	-0.461**
					(0.145)	(0.146)
Neighbors EU embargo j					0.059	0.029
					(0.038)	(0.039)
GDPpc i (ln)	-0.217†	-0.252†	-0.230†	-0.255†	-0.214†	-0.253†
	(0.121)	(0.143)	(0.122)	(0.143)	(0.121)	(0.143)
GDPpc j (ln)	0.060	0.156	0.084	0.187	0.059	0.153
	(0.127)	(0.145)	(0.127)	(0.146)	(0.127)	(0.145)
Milex j (ln)	0.544***	0.368***	0.539***	0.359***	0.541***	0.367***
	(0.046)	(0.050)	(0.046)	(0.051)	(0.046)	(0.050)
Urban pop j (ln)	-1.127***	-1.190***	-1.115***	-1.163***	-1.127***	-1.184***
	(0.308)	(0.326)	(0.309)	(0.327)	(0.309)	(0.326)
Male pop j (ln)	7.218***	5.969**	7.475***	6.303**	7.172***	5.904**
	(1.987)	(2.007)	(1.997)	(2.018)	(1.986)	(2.006)
Civil conflict j	0.228*	0.215*	0.213*	0.199*	0.219*	0.206*
	(0.097)	(0.097)	(0.096)	(0.097)	(0.097)	(0.097)
Neighbors civil conflict j	0.052	0.027	0.045	0.021	0.047	0.023
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
Polity j	0.004	0.008	0.005	0.009	0.004	0.008
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Diff polity ij	0.005	0.002	0.004	0.002	0.005	0.002
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)
Constant	-22.786**	-14.037†	-23.844**	-15.510†	-22.586**	-13.748†
	(7.759)	(8.332)	(7.791)	(8.375)	(7.757)	(8.334)
Time dummy	No	Yes	No	Yes	No	Yes
Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,955	51,955	51,955	51,955	51,955	51,955
Number of id pair	6,208	6,208	6,208	6,208	6,208	6,208
R2 within	0.013	0.019	0.012	0.018	0.013	0.019
R2 overall	0.038	0.025	0.038	0.026	0.038	0.025
R2 betweenness	0.015	0.006	0.014	0.006	0.015	0.006

Clustered Robust standard errors at pair level in parentheses. ***p<0.001, **p<0.01 *p<0.05 †p<0.1

Table 9. Total SALW, no ambiguities

VARIABLES	(1) lncexpc	(2) lncexpc	(3) lncexpc	(4) lncexpc	(5) lncexpc	(6) Lncexpc
Embargo j	-0.287*	-0.302*				
	(0.122)	(0.122)				
Neighbors embargo j	0.012	-0.017				
	(0.032)	(0.033)				
UN embargo j			-0.165	-0.171		
			(0.171)	(0.172)		
Neighbors UN embargo j			-0.113*	-0.121*		
			(0.055)	(0.055)		
EU embargo j					-0.357**	-0.367**
					(0.134)	(0.134)
Neighbors EU embargo j					0.013	-0.020
					(0.034)	(0.035)
GDPpc i (ln)	0.104	0.010	0.090	0.005	0.108	0.008
	(0.102)	(0.121)	(0.102)	(0.121)	(0.102)	(0.121)
GDPpc j (ln)	0.428***	0.447***	0.444***	0.468***	0.424***	0.438***
	(0.111)	(0.131)	(0.110)	(0.132)	(0.111)	(0.131)
Milex j (ln)	0.533***	0.381***	0.526***	0.370***	0.534***	0.384***
	(0.042)	(0.046)	(0.042)	(0.046)	(0.042)	(0.046)
	(1.802)	(1.853)	(1.805)	(1.856)	(1.803)	(1.855)
Civil conflict j	0.349***	0.331***	0.339***	0.320***	0.345***	0.326***
	(0.095)	(0.096)	(0.095)	(0.096)	(0.095)	(0.096)
Neighbors civil conflict j	0.042	0.023	0.039	0.021	0.040	0.020
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Constant, demographic and political controls	YES	YES	YES	YES	YES	YES
Time dummy	No	Yes	No	Yes	No	Yes
Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52,106	52,106	52,106	52,106	52,106	52,106
Number of id_pair	5,952	5,952	5,952	5,952	5,952	5,952
R2 within	0.024	0.030	0.024	0.030	0.024	0.030
R2 overall	0.082	0.072	0.081	0.072	0.082	0.072
R2 betweenness	0.036	0.026	0.035	0.026	0.037	0.026

Clustered Robust standard errors at pair level in parentheses. ***p<0.001, **p<0.01 *p<0.05 †p<0.1

Table 10. Military arms, no ambiguities

VARIABLES	(1) lncexpc_ml	(2) lncexpc_ml	(3) lncexpc_ml	(4) lncexpc_ml	(5) lncexpc_ml	(6) lncexpc_ml
Embargo j	-0.276*	-0.272*				
	(0.138)	(0.137)				
Neighbors embargo j	0.032	0.005				
	(0.036)	(0.037)				
UN embargo j			-0.161	-0.157		
			(0.200)	(0.201)		
Neighbors UN embargo j			0.023	0.017		
			(0.061)	(0.061)		
EU embargo j					-0.351*	-0.325*
					(0.156)	(0.155)

Neighbors EU embargo j					0.035	-0.003
					(0.038)	(0.039)
GDPpc i (ln)	0.071	0.078	0.062	0.076	0.075	0.077
	(0.119)	(0.140)	(0.119)	(0.140)	(0.119)	(0.140)
GDPpc j (ln)	0.057	0.236	0.076	0.257†	0.054	0.232
	(0.126)	(0.149)	(0.125)	(0.148)	(0.125)	(0.149)
Milex j (ln)	0.561***	0.358***	0.556***	0.350***	0.561***	0.361***
	(0.048)	(0.051)	(0.048)	(0.052)	(0.047)	(0.051)
Civil conflict j	0.379***	0.358***	0.367***	0.343**	0.375***	0.354***
	(0.103)	(0.104)	(0.103)	(0.104)	(0.104)	(0.105)
Neighbors civil conflict j	0.117*	0.085†	0.113*	0.081†	0.115*	0.082†
	(0.049)	(0.049)	(0.049)	(0.049)	(0.048)	(0.049)
Constant, demographic and political controls	YES	YES	YES	YES	YES	YES
Time dummy	No	Yes	No	Yes	No	Yes
Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,637	44,637	44,637	44,637	44,637	44,637
Number of id_pair	5,494	5,494	5,494	5,494	5,494	5,494
R2 within	0.016	0.025	0.016	0.025	0.017	0.025
R2 overall	0.069	0.077	0.069	0.076	0.070	0.077
R2 betweenness	0.034	0.031	0.033	0.031	0.034	0.031

Clustered Robust standard errors at pair level in parentheses. ***p<0.001, **p<0.01 *p<0.05 †p<0.1

Table 11. Excluding destination countries with population below 80% of the median

VARIABLES	(1) lncexp	(2) lncexp	(3) Lncexp	(4) lncexp	(5) lncexp	(6) Lncexp
Embargo j	-0.306*	-0.354*				
	(0.151)	(0.151)				
Neighbors embargo j	0.003	-0.024				
	(0.041)	(0.042)				
UN embargo j			-0.387†	-0.364		
			(0.222)	(0.223)		
Neighbors UN embargo j			-0.164**	-0.181**		
			(0.061)	(0.061)		
EU embargo j					-0.316†	-0.385*
					(0.176)	(0.177)
Neighbors EU embargo j					0.017	-0.013
					(0.044)	(0.045)
GDPpc i (ln)	-0.024	-0.150	-0.043	-0.154	-0.022	-0.153
	(0.137)	(0.161)	(0.137)	(0.161)	(0.138)	(0.162)
GDPpc j (ln)	0.514**	0.444*	0.512**	0.451*	0.510**	0.432*
	(0.168)	(0.192)	(0.165)	(0.191)	(0.168)	(0.192)
Milex j (ln)	0.507***	0.385***	0.517***	0.395***	0.505***	0.384***
	(0.056)	(0.062)	(0.056)	(0.062)	(0.055)	(0.062)
Civil conflict j	0.201*	0.194*	0.195*	0.184†	0.193*	0.186†
	(0.096)	(0.096)	(0.095)	(0.095)	(0.096)	(0.096)
Neighbors civil conflict j	0.006	-0.020	0.001	-0.022	0.003	-0.023

	(1)	(2)	(3)	(4)	(5)	(6)
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
Constant, demographic and political controls	YES	YES	YES	YES	YES	YES
Time dummy	No	Yes	No	Yes	No	Yes
Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,887	37,887	37,887	37,887	37,887	37,887
Number of id_pair	4,239	4,239	4,239	4,239	4,239	4,239
R2 within	0.017	0.021	0.017	0.021	0.017	0.021
R2 overall	0.053	0.024	0.052	0.027	0.053	0.023
R2 betweenness	0.023	0.008	0.022	0.009	0.023	0.008

Clustered Robust standard errors at pair level in parentheses. ***p<0.001, **p<0.01 *p<0.05 †p<0.1

Table 12. Excluding destination countries with population below 60% of the median

VARIABLES	(1) lncexp	(2) lncexp	(3) Lncexp	(4) lncexp	(5) lncexp	(6) Lncexp
Embargo j	-0.383**	-0.410**				
	(0.141)	(0.142)				
Neighbors embargo j	0.030	0.006				
	(0.038)	(0.039)				
UN embargo j			-0.364†	-0.358†		
			(0.189)	(0.191)		
Neighbors UN embargo j			-0.113*	-0.133*		
			(0.056)	(0.057)		
EU embargo j					-0.431**	-0.467**
					(0.162)	(0.163)
Neighbors EU embargo j					0.040	0.012
					(0.040)	(0.041)
GDPpc i (ln)	-0.100	-0.182	-0.119	-0.187	-0.095	-0.184
	(0.130)	(0.154)	(0.130)	(0.154)	(0.130)	(0.154)
GDPpc j (ln)	0.429**	0.417*	0.428**	0.430*	0.430**	0.408*
	(0.157)	(0.180)	(0.156)	(0.181)	(0.156)	(0.180)
Milex j (ln)	0.515***	0.386***	0.519***	0.388***	0.512***	0.385***
	(0.053)	(0.059)	(0.053)	(0.059)	(0.053)	(0.059)
Civil conflict j	0.205*	0.199*	0.194*	0.187*	0.197*	0.192*
	(0.094)	(0.095)	(0.094)	(0.094)	(0.094)	(0.095)
Neighbors civil conflict j	0.029	0.000	0.022	-0.004	0.025	-0.003
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
Constant, demographic and political controls	YES	YES	YES	YES	YES	YES
Time dummy	No	Yes	No	Yes	No	Yes
Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,291	42,291	42,291	42,291	42,291	42,291
Number of id_pair	4,712	4,712	4,712	4,712	4,712	4,712
R2 within	0.015	0.019	0.015	0.019	0.015	0.019
R2 overall	0.049	0.032	0.048	0.034	0.049	0.031
R2 betweenness	0.018	0.009	0.017	0.009	0.019	0.008

Clustered Robust standard errors at pair level in parentheses. ***p<0.001, **p<0.01 *p<0.05 †p<0.1

Table 13. Excluding destination countries with population below 40% of the median

VARIABLES	(1) lncexp	(2) lncexp	(3) Lncexp	(4) lncexp	(5) lncexp	(6) Lncexp
Embargo j	-0.359**	-0.382**				
	(0.134)	(0.134)				
Neighbors embargo j	0.041	0.016				
	(0.036)	(0.038)				
UN embargo j			-0.300†	-0.299†		
			(0.173)	(0.174)		
Neighbors UN embargo j			-0.100†	-0.119*		
			(0.056)	(0.057)		
EU embargo j					-0.396**	-0.426**
					(0.151)	(0.152)
Neighbors EU embargo j					0.050	0.022
					(0.038)	(0.040)
GDPpc i (ln)	-0.131	-0.203	-0.149	-0.209	-0.128	-0.205
	(0.123)	(0.145)	(0.123)	(0.145)	(0.123)	(0.145)
GDPpc j (ln)	0.398**	0.421**	0.406**	0.441**	0.399**	0.416*
	(0.141)	(0.162)	(0.141)	(0.163)	(0.141)	(0.162)
Milex j (ln)	0.550***	0.410***	0.553***	0.409***	0.548***	0.409***
	(0.049)	(0.054)	(0.049)	(0.055)	(0.049)	(0.054)
Civil conflict j	0.202*	0.198*	0.192*	0.187*	0.194*	0.190*
	(0.093)	(0.094)	(0.093)	(0.093)	(0.093)	(0.094)
Neighbors civil conflict j	0.031	0.008	0.024	0.003	0.027	0.005
	(0.047)	(0.048)	(0.047)	(0.047)	(0.047)	(0.047)
Constant, demographic and political controls	YES	YES	YES	YES	YES	YES
Time dummy	No	Yes	No	Yes	No	Yes
Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,179	48,179	48,179	48,179	48,179	48,179
Number of id_pair	5,409	5,409	5,409	5,409	5,409	5,409
R2 within	0.015	0.019	0.015	0.019	0.015	0.019
R2 overall	0.045	0.032	0.045	0.034	0.045	0.032
R2 betweenness	0.015	0.008	0.014	0.008	0.016	0.008

Clustered Robust standard errors at pair level in parentheses. ***p<0.001, **p<0.01 *p<0.05 †p<0.1

Table 14. Excluding values of export below 1% and above 99% of exports

VARIABLES	(1) lncexp	(2) lncexp	(3) Lncexp	(4) lncexp	(5) lncexp	(6) Lncexp
Embargo j	-0.366**	-0.383**				
	(0.116)	(0.117)				
Neighbors embargo j	0.023	0.001				
	(0.033)	(0.034)				
UN embargo j			-0.291†	-0.298†		
			(0.167)	(0.168)		
Neighbors UN embargo j			-0.070	-0.080		
			(0.051)	(0.052)		

EU embargo j					-0.402**	-0.420**
					(0.128)	(0.128)
Neighbors EU embargo j					0.030	0.005
					(0.034)	(0.035)
GDPpc i (ln)	-0.111	-0.250*	-0.124	-0.254*	-0.108	-0.252*
	(0.105)	(0.123)	(0.106)	(0.124)	(0.105)	(0.123)
GDPpc j (ln)	0.448***	0.387**	0.465***	0.412**	0.447***	0.380**
	(0.112)	(0.130)	(0.112)	(0.131)	(0.112)	(0.130)
Milex j (ln)	0.511***	0.382***	0.505***	0.372***	0.510***	0.383***
	(0.041)	(0.045)	(0.042)	(0.045)	(0.041)	(0.045)
Civil conflict j	0.271**	0.257**	0.261**	0.246**	0.263**	0.249**
	(0.090)	(0.090)	(0.089)	(0.090)	(0.090)	(0.090)
Neighbors civil conflict j	0.025	0.009	0.022	0.006	0.022	0.006
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
Constant, demographic and political controls	YES	YES	YES	YES	YES	YES
Time dummy	No	Yes	No	Yes	No	Yes
Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57,206	57,206	57,206	57,206	57,206	57,206
Number of id_pair	6,513	6,513	6,513	6,513	6,513	6,513
R2 within	0.020	0.024	0.019	0.024	0.020	0.024
R2 overall	0.056	0.032	0.055	0.033	0.056	0.032
R2 betweenness	0.019	0.006	0.018	0.006	0.020	0.006

Clustered Robust standard errors at pair level in parentheses. ***p<0.001, **p<0.01 *p<0.05 †p<0.1

Table 15. Excluding values of export below 5% and above 95% of exports

VARIABLES	(1) lncexp	(2) lncexp	(3) Lncexp	(4) lncexp	(5) lncexp	(6) Lncexp
Embargo j	- 0.385***	- 0.404***				
	(0.111)	(0.112)				
Neighbors embargo j	0.023	0.008				
	(0.030)	(0.031)				
UN embargo j			-0.221	-0.234		
			(0.163)	(0.164)		
Neighbors UN embargo j			-0.066	-0.071		
			(0.049)	(0.050)		
EU embargo j					- 0.451***	- 0.474***
					(0.121)	(0.122)
Neighbors EU embargo j					0.034	0.016
					(0.032)	(0.033)
GDPpc i (ln)	-0.004	-0.204†	-0.020	-0.209†	0.000	-0.206†
	(0.096)	(0.112)	(0.097)	(0.113)	(0.096)	(0.112)
GDPpc j (ln)	0.562***	0.421***	0.586***	0.457***	0.557***	0.409***
	(0.103)	(0.121)	(0.103)	(0.122)	(0.103)	(0.121)
Milex j (ln)	0.449***	0.335***	0.440***	0.322***	0.448***	0.336***
	(0.039)	(0.042)	(0.039)	(0.042)	(0.039)	(0.042)
Civil conflict j	0.264**	0.250**	0.252**	0.237**	0.256**	0.241**

	(0.088)	(0.088)	(0.087)	(0.088)	(0.088)	(0.088)
Neighbors civil conflict j	0.010	-0.004	0.006	-0.008	0.007	-0.007
	(0.040)	(0.040)	(0.039)	(0.040)	(0.040)	(0.040)
Constant, demographic and political controls	YES	YES	YES	YES	YES	YES
Time dummy	No	Yes	No	Yes	No	Yes
Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52,458	52,458	52,458	52,458	52,458	52,458
Number of id_pair	6,218	6,218	6,218	6,218	6,218	6,218
R2 within	0.026	0.030	0.025	0.030	0.026	0.030
R2 overall	0.043	0.024	0.042	0.025	0.044	0.024
R2 betweenness	0.019	0.007	0.018	0.006	0.020	0.007

Clustered Robust standard errors at pair level in parentheses. ***p<0.001, **p<0.01 *p<0.05 †p<0.1

Table 16. Excluding: excluding values of export below 10% and above 90% of exports

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	lncexp	lncexp	Lncexp	lncexp	lncexp	Lncexp
Embargo j	-0.373***	-0.398***				
	(0.099)	(0.099)				
Neighbors embargo j	0.010	0.003				
	(0.029)	(0.030)				
UN embargo j			-0.236†	-0.260†		
			(0.138)	(0.138)		
Neighbors UN embargo j			-0.046	-0.048		
			(0.048)	(0.048)		
EU embargo j					-0.438***	-0.471***
					(0.111)	(0.111)
Neighbors EU embargo j					0.022	0.013
					(0.031)	(0.031)
GDPpc i (ln)	0.001	-0.248*	-0.011	-0.251*	0.005	-0.249*
	(0.088)	(0.103)	(0.088)	(0.103)	(0.088)	(0.103)
GDPpc j (ln)	0.638***	0.416***	0.656***	0.445***	0.632***	0.402***
	(0.096)	(0.112)	(0.096)	(0.112)	(0.096)	(0.112)
Milex j (ln)	0.336***	0.256***	0.327***	0.243***	0.337***	0.258***
	(0.037)	(0.040)	(0.037)	(0.040)	(0.037)	(0.040)
Civil conflict j	0.232**	0.217**	0.220**	0.203**	0.225**	0.209**
	(0.078)	(0.079)	(0.078)	(0.078)	(0.078)	(0.079)
Neighbors civil conflict j	0.024	0.016	0.020	0.011	0.021	0.013
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Constant, demographic and political controls	YES	YES	YES	YES	YES	YES
Time dummy	No	Yes	No	Yes	No	Yes
Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,468	46,468	46,468	46,468	46,468	46,468
Number of id_pair	5,842	5,842	5,842	5,842	5,842	5,842

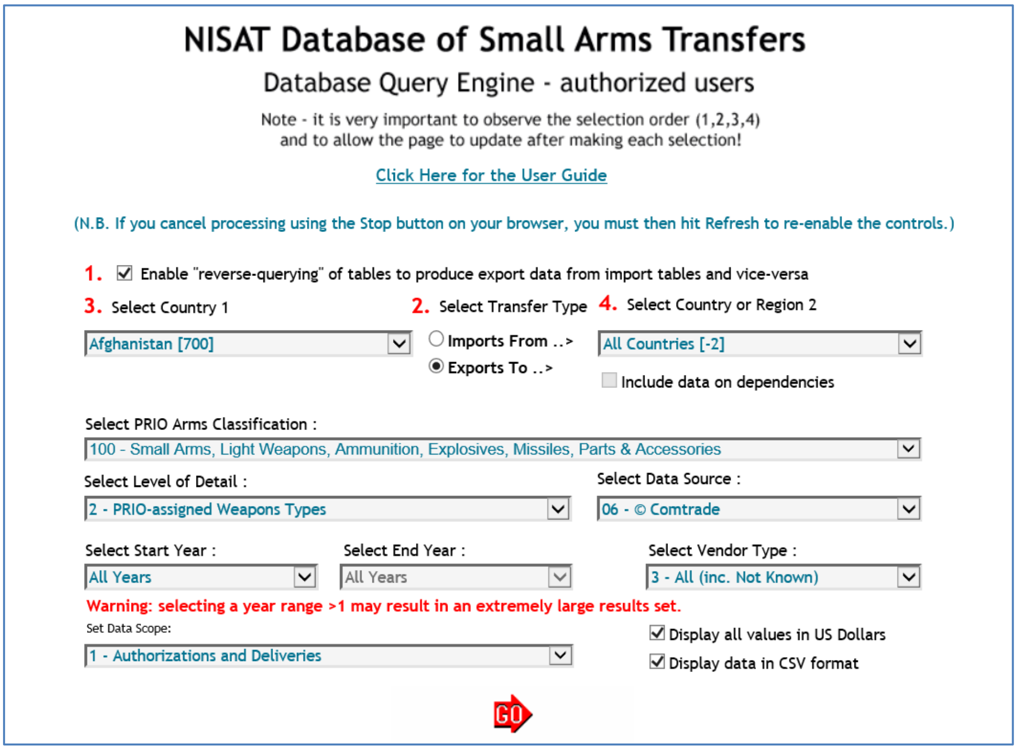
R2 within	0.027	0.031	0.026	0.030	0.027	0.031
R2 overall	0.028	0.014	0.027	0.014	0.029	0.014
R2 betweenness	0.013	0.003	0.012	0.003	0.013	0.003

Clustered Robust standard errors at pair level in parentheses. ***p<0.001, **p<0.01 *p<0.05 †p<0.1

Appendix A: data extraction

The NISAT allows the researcher to select different options when looking for SALW trade data. Figure A1 below details the options we selected.

Figure A1: Selected option



First of all, we enable reverse-querying procedure This procedure facilitates the use of a mirroring strategy using a mirroring: when looking for a given country's exports, it also searches for all other countries' imports from that country.

Secondly, we select the most comprehensive searching code (code 100) including all types of SALW. This NISAT allows to select transfers according to the type of SALW traded. However, since some data sources provide only general descriptions of the arms, the use of this tool may leave out some potentially interesting transfers.

Furthermore, we select the PRIO description of the weapon types. This choice is motivated by the need to compare data among countries and sources. Lacking a common global standard for classifying small arms and light weapons[16], a wide range of descriptions of SALW is usually provided when recording a transfer. To deal with this puzzle, the NISAT ascribes each weapon transferred to a PRIO weapon type based on the already mentioned 1997 UN panel of experts' report.

NISAT distinguishes between government sales or sales by commercial companies. Furthermore, it also reports if the transfer was simply authorized or if it was delivered to the destination country. Transfer of SALW may need an export license that is the government department in charge and has to grant permission to export. The presence of authorization, however, does not automatically imply that the arms will be delivered. *Furthermore, in some cases, there may be a considerable delay between the authorization and the delivery. In the UK, for instance, licenses are valid for two years.* NISAT also provides information about the transfer whose authorization was refused. Selecting the COMTRADE as the only data source automatically excludes both granted authorizations and refusals as well as the distinction between government and commercial sales.

Data were extracted automatically using python: we created a code that for every reporter in the database searched the data, keeping fixed all the other criteria, as described in figure A1 above. The data searched were in CSV format and they were organized in a primary dataset, reporting the exports from the reporter to all its partners, and in a secondary dataset, indicating the imports to the reporter

[16] Apart from the 1997 UN panel of experts' report, there exist many other regional (OSCE, EU) global (Wassenaar) and a myriad of national definitions.

from its partner. When there was no data on exports, there was only a secondary dataset. For a few countries, no data were recorded by the Comtrade. Please note that Viet Nam and Yemen were reported in the database twice. Once searched, the data were copied in a txt file: we organized this process in two stages. First, we instructed Python to start copying data from the heading of the primary dataset, indicating the name of the variables, to the second heading marking the beginning of the secondary dataset. Then also data from this point to the end of the data were copied. In doing so, we were careful to maintain the distinction in rows corresponding to different observations (extracting the text as a unique string would have made it difficult to reconstruct the original data structure).

Our code worked well for the reporters' samples having two headings in the dataset (206 countries out of 246). For the other nations, two cases occurred: firstly, there was no heading in the primary dataset since no data on the given country's exports were available. In this case, python just copied the secondary dataset. Secondly, no data at all were reported in the text but there was a heading. In this other case, just the heading was copied. In this regard, it is noteworthy that in the NISAT when no exports or no data at all are recorded, the heading can be included or not. As a consequence, in my dataset I have reporters with both the primary and secondary dataset, countries with a blank heading for the primary dataset and a secondary dataset, countries with no heading for the primary dataset and the data for the secondary dataset, countries with two blank headings for both the secondary and the primary dataset. I checked the cases manually to be sure that all information available was included. (see cases where just one extraction)

Finally, we tested our code by selecting 18 countries which account for about 38% of the total observations, extracting their transfers manually and comparing the sample obtained with the one we previously extracted automatically. The two samples matched at 100%.

As a result of our extraction procedure, we got 516,401 observations. The data extracted, however, present groups of observations that must be dropped. Some transfers, for instance, do not indicate the partner or the reporter country but they may either record the sum of a country's exports or imports. Other flows only report their value without any reference to their destinations or origin. In addition, some figures indicate the trade from or towards specific regions like the EU (Tot 27,203 observations). There are also instances of loops i.e. the country trade with itself (1,143 observations). Finally, the data presents some duplicates (i.e. 6,466). Once dropped these transfers we got a sample of 481,589 observations.

Appendix B: disaggregated data description

NISAT also provides information about the units of SALW transferred and their weight[17] when stated in the source. Only 25% of the observations we got record the units of the transfer (97,991 observations) while 66% of our sample indicates the weight (256,926 observations). Moreover, NISAT assesses both the accuracy and reliability of the data reported. Accuracy indicates whether the figures reported by sources are rounded or are approximations.

[17] This figure is in kilograms (Kg) except where stated.

Comtrade data have high accuracy.[18] Reliability consists both in the description of the source and a subjective judgment about its reliability. This assessment evaluates whether the source has systems in place to check data and ensure their quality. Comtrade is considered a secondary source[19] and its data are assessed as highly reliable.

Appendix c: PPML estimates

Santos Silva and Tenreyro (2006) (hereafter SST) published a seminal work which criticised the standard practice of log linearizing the gravity equation and estimating the parameters of interest by OLS. They claim that constant-elasticity models, as the gravity model, should be estimated in their multiplicative form and propose a Pseudo Poisson Maximum Likelihood (PPML) estimator an alternative to OLS techniques. PPML belongs to the class of the Generalized Linear Model (GLM) estimators and it is based on the assumption that the conditional variance is proportional to the conditional mean.

$$\mathrm{E}[Y_i|X] = \exp(x_i\beta) \propto V[Y_i|X]$$

[18] "Low: the source supplied estimates accurate to, and figures rounded to, more than the nearest USD 1000 (for example, a report that a country had exported USD 1.2 million worth of ammunition).
Medium: the source supplied estimates accurate to, and figures rounded to, USD 1000 or less (for example, a report that a country exported $59 000 worth of small arms).
High: the source supplied figures with no evident estimation, rounding or calculation" (NISAT database: public user manual, p. 17).

[19] Sources are categorised as primary: original documents produced by the party involved in the transfer (such as a government report on its arms exports); and eye witness reports. Secondary sources are information reported by a third party (such as a press report).

According to SST, PPML has two main advantages over OLS. First, it provides a natural way of dealing with zero values of the dependent variable while the log linearization excludes these values. Secondly, it produces consistent estimates of the parameters in the presence of heteroscedasticity. Basing on the Jensen inequality, SST argue that OLS estimates are not consistent because the expected value of $\ln \varepsilon_{ij}$ depends on the regressors. "*The nonlinear transformation of the dependent variable changes the properties of the error term in a nontrivial way because the conditional expectation of $ln\, \varepsilon_{ij}$ depends on the shape of the conditional distribution of ε_{ij}*" (SST, p. 644). Therefore, if the variance of the error factor ε_{ij} depends on the regressors, the expected value of $\ln \varepsilon_{ij}$ will also depend on the regressors.

PPML has an important drawback. Assuming that the conditional variance is proportional to the conditional mean does not allow to take full account of the heteroskedasticity in the model. In other words, it gives the same weight to all observations and this may not produce efficient estimates in case of overdispersion in the dependent variable. Under the assumption that $E[Y_i|X] \propto V[Y_i|X]$, "*all observations have the same information on the parameters of interest as the additional information on the curvature of the conditional mean coming from observations with large $exp(x_i\beta)$ is offset by their larger variance*" (SST, p. 645). It is noteworthy that SST claim that although the use of PPML is not optimal, it is a good compromise in absence of precise information on the pattern of heteroskedasticity. Further research, however, shows that PPML does not perform well on all trade data (Martin and Pham, 2008 and Martínez-Zarzoso 2013, Head and Mayer, 2014).

In this work we do not use PPML since we believe that the use of this technique is not in line with SALW trade data. In this regard, our argument is twofold. First, we have only three cases of zero flows in our dataset, recorded in 2017. This is due to the nature of the trade in small arms. In this type of trade, transfers may well remain unreported. Therefore, the researcher cannot easily assume that missing values are zero trade flow since the absence of information on trade in SALW between a couple of countries cannot be regarded as evidence that transfers have not taken place.

Secondly, our dependent variable shows great overdispersion. Detailed summary statistics show that the distribution of the export of SALW is positively skewed (skewness: 22.86) with heavy tail or outliers (kurtosis: 839.03). The trade in small arms involves both a great number of transfers of small economic significance with few flows comprising large quantities of arms. This distribution is common in trade data in general. Nevertheless, as far as SALW are regarded, the differences between small and large flows are larger. The values below 10% of the dependent variable are under 1000 dollars while those above 90% 2,440,508. The lowest data represent cases of small trade and even donations (for those cases that are nearly one dollar), the largest are substantial transfer of arms that occasionally occur among countries. Nearly 85% of our observations are below 1 million dollars.

We argue that giving the same weight to all these observations doesn't properly fit the functional distribution of the dependent variable. In contrast, the log of the dependent variable is approximately normal with skewness nearly zero and kurtosis close to 3. In these cases, estimates drawn from logged models are in general more accurate and robust than those based on the analysis of the original unlogged dependent variable (Manning, 1998). Further analysis reveals the relevance of the outliers in driving the results. When we use PPML on the sample where we cut off values of export below 10% and above 90%, PPML and OLS converges (Table C.1 below).

Table C.1: Results for exports in levels (excluding values of export below 10% and above 90%)

	(1)	(2)	(3)	(4)	(5)	(6)
Embargo j	-0.311**	-0.324***				
	(0.097)	(0.097)				
Neighbors embargo j	0.042†	0.036				
	(0.025)	(0.025)				
UN embargo j			-0.266†	-0.275*		
			(0.138)	(0.138)		
Neighbors UN embargo j			0.053	0.048		
			(0.046)	(0.046)		
EU embargo j					-0.382***	-0.401***
					(0.110)	(0.110)
Neighbors EU embargo j					0.050†	0.043†
					(0.026)	(0.026)
GDPpc i (ln)	0.031	-0.144	0.024	-0.145	0.037	-0.145
	(0.082)	(0.092)	(0.082)	(0.091)	(0.082)	(0.091)
GDPpc j (ln)	0.612***	0.460***	0.627***	0.481***	0.608***	0.450***
	(0.087)	(0.103)	(0.088)	(0.103)	(0.087)	(0.103)
Milex j (ln)	0.292***	0.221***	0.289***	0.215***	0.288***	0.219***
	(0.035)	(0.038)	(0.035)	(0.038)	(0.035)	(0.038)
Urban pop j (ln)	-0.569*	-0.819***	-0.562*	-0.804***	-0.554*	-0.809***
	(0.233)	(0.236)	(0.233)	(0.236)	(0.233)	(0.236)
Male pop j (ln)	4.250**	2.814*	4.316**	2.933*	4.182**	2.709*
	(1.328)	(1.363)	(1.327)	(1.362)	(1.324)	(1.361)
Civil conflict j	0.090	0.079	0.077	0.064	0.089	0.078
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
Neighbors civil conflict j	0.027	0.015	0.023	0.010	0.023	0.012
	(0.033)	(0.034)	(0.033)	(0.034)	(0.033)	(0.034)
Polity j	0.000	0.002	0.001	0.002	0.000	0.001
	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
Diff polity ij	0.001	0.002	0.001	0.002	0.001	0.002
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Constant	-13.703**	-2.271	-14.000**	-2.860	-13.440**	-1.752
	(5.167)	(5.700)	(5.164)	(5.698)	(5.158)	(5.699)
Time dummy	No	Yes	No	Yes	No	Yes
Pair fixed	Yes	Yes	Yes	Yes	Yes	Yes

effects						
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,969	44,969	44,969	44,969	44,969	44,969
Num id pairs	4,343	4,343	4,343	4,343	4,343	4,343
Pseudo R2	0.5804	0.5828	0.5801	0.5825	0.5805	0.5829

Clustered Robust standard errors at pair level in parentheses. ***p<0.001, **p<0.01 *p<0.05 †p<0.1