Trade Liberalization and Political Violence: Evidence from North-South Cooperation*

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Abstract

How does trade liberalization affect political violence? Theory suggests two opposite effects. If trade openness increases average income, the opportunity cost of engaging in violence increases, decreasing the supply of internal conflict. On the contrary, if trade liberalization produces a rise in contestable income, violence may increase as gains from appropriation are higher (so called *rapacity effect*). Our paper explores the micro-foundations of this trade-conflict nexus. We focus on the reduction of tariffs on agricultural imports from South countries to North countries. As tariffs drop, South countries experience a positive demand shock that builds on their comparative advantage. We combine variation in agricultural tariffs over time with differences in crop suitability across districts within South countries. Our approach rests upon the observation that differences in agro-climatic conditions within the country generate exogenous variation in suitability to produce different crops. Using 9km$\times$9km cells as unit of observations, we test if, as North-South trade liberalization is implemented, the levels of political violence and instability change differentially in those districts that are more suitable to produce liberalized crops. Our analysis covers 27 South countries and all their PTAs signed with major North trading entities between 1995 and 2014. We find robust evidence that PTAs increase economic output in areas suitable to grow crop and strong support for the rapacity effect.

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1 Introduction

Does trade liberalization affect internal political violence? Theory suggests two opposite effects (Becker 1968, Grossman 1991). On the one hand, if trade openness increases average income, the opportunity cost of engaging in violence increases accordingly, decreasing the supply of internal conflict (so called *opportunity cost effect*). On the other hand, if trade liberalization produces a rise in contestable income, violence may increase as gains from appropriation are higher (so called *rapacity effect*).

Existing empirical evidence has produced mixed results. Several studies have find evidence consistent with the opportunity cost effect (Miguel, Satyanath, and Sergenti 2004, Bruckner and Ciccone 2010; Dube and Vargas 2013; Bazzi and Blattman 2014; Blattman and Annan 2016). However, other studies have also find support for the rapacity effect (Dube and Vargas 2013; Mayer and Thoenig, 2016; Pinto and Zhu, 2017). In short, the question of how trade liberalization affects internal warfare remains largely unanswered.

This paper studies empirically the micro-foundations of the trade-conflict nexus. Providing sound evidence of the impact of trade liberalization is challenging for several reasons. For one, trade liberalization policies are typically adopted within the framework of national development strategies, and are therefore informed by the economic and political environment. In particular, political stability is crucial in the design and implementation of trade agreements. As a result, a reverse causal path exists, from political violence to trade liberalization.

To overcome these challenges, we focus on the reduction of tariffs on agricultural imports from South countries to North countries. As tariffs drop, South countries experience a positive demand shock that builds on their comparative advantage. We combine variation in agricultural tariffs over time with differences in crop suitability across districts within South countries. Our approach rests upon the observation that differences in agro-climatic conditions within the country generate exogenous variation in suitability to produce different crops. Using 9km$\times$9km cells as unit of observations, we test if, as North-South trade liberalization is implemented, the levels of political violence change differentially in those districts that are more suitable to produce liberalized crops. Our analysis cover 27 South countries and all their PTAs signed with major trading entities between 1995 and 2014.

To carry out this fine-grained empirical analysis, we combine data from several sources. We use agro-climatic-based estimates of crop suitability at the sub-national level with data on agricultural tariffs, deriving a time-varying measure of export exposure at the cell level.[1] Moreover, we use luminosity as a proxy of GDP, following recent contributions in economics (Henderson et al 2012, Michalopoulos and Papaioannou 2013, Costinot and Donaldson 2017). To the best of our knowledge, we are the first to assemble this extensive mass of micro-level data to analyze the trade-conflict nexus for a relative large number of countries.

Our main results are two-fold. First, we find strong evidence that North-South PTAs increase the economic output of cells with high crop suitability significantly more than the economic output of cells with low crop suitability. The magnitude of the effect is quite remarkable; in South countries, the economic output value would have been 2.2 percent lower in absence of the trade agreement with major trading entities. Second, we find strong support for the *rapacity effect*. According to the estimates, the effects of PTAs that we investigate account for an increase of 10 percent of the total number of violent events in South countries in the period under investigation.

We contribute to the literature on the trade-conflict nexus along several dimensions. First, while previous studies have mostly explored the effect of trade on inter-state conflict, our paper focuses on the impact of trade agreements on intra-state conflicts, which has been largely overlooked by the previous literature. Second, focusing on preferential liberalization allows us to bring governments preferences into the picture. In studying the opportunity cost channel as a determinant of political violence, economists and political scientists have traditionally focused on changes in international commodity prices as shocks to economic activity. These are determined by the interaction of demand and supply at the global level, with little role for government intervention. On the contrary, trade agreements are policy tools on which governments have direct control. Therefore, our analysis provides clear policy implication useful to governments implementing trade liberalization.

Third, from a policy point of view, our results are timely and important. To facilitate trade, governments in both developed and developing countries have implemented a large number of trade agreements. Our analysis shows that these policies are effective from a purely economic point of view. However, we demonstrate also that trade agreements come with a dangerous side effect politically. Our findings should warn politicians and policy-makers that trade liberalization may jeopardize political stability, exactly in those areas in which trade openness works the most. In this regard, our research is in line with recent evidence from the US (Autor et al 2016).

[1] For recent papers using on crop suitability, see Adamopoulos and Restuccia (2015) and Bustos, Caprettini and Ponticelli (2016); Costinot and Donaldson (2016).

The remainder of the paper proceeds as follows. The next section surveys the literature related to the trade-conflict nexus. Section 3 presents the conceptual framework driving the empirical analysis. Section 4 describes the data. Section 5 explains the empirical strategy, while Section 6 reports the results of the empirical analysis. Section 7 concludes.

2 Literature Review

A rich body of economics and political science research has investigated the association between economic conditions and political violence. There is large cross-country evidence that low-income levels are associated with more conflict (Fearon and Laitin 2003; Collier and Hoeffler 2004; Justino 2009; Blattman and Miguel 2010; Buhaug et al. 2011).[2] Following the seminal paper by Miguel et al. (2004) several contributions have documented the effect of economic shock on the incidence, onset and duration of conflicts providing a strong support for the opportunity cost explanation of violence (Hidalgo et al. 2010; Bohlken and Sergenti 2010).

One particularly important source of economic shocks is international trade. When countries are open to trade, they are exposed to international prices variations. Several studies have used the latter as a proxy for exogenous external income shocks (Besley and Persson 2008; Bruckner and Ciccone 2010; Fearon 2005). In particular, most of the studies test the theory that an increase in the value of export provides an incentive for the onset of a civil war and makes its continuation possible (Collier and Hoefer 2007; Collier, Hoefer and Rohner 2009). Cali and Mulabdic (2017) provides evidence cross-country evidence that depending on the type of goods for which the price changes the effect on conflict can be very different. McGuirk and Burke (2017) look in detail to the different possible effects of changes in food prices on conflict in Africa distinguishing between producer and consumer effects and between types of conflict. Their analysis document a high degree of heterogeneity in the relationship between food prices and conflict: the effect vary with the type of actor and the type and form of conflict.

While the evidence of an effect of export prices on conflict is weak at the cross-country level (Bazzi and Blattman 2013), the micro-level studies support the existence of a causal relationship (Berman and Couttenier 2016). Dube and Vargas (2013) show

[2] While we do not discuss it here, there is similarly rich literature looking at the effect of conflicts on economic outcomes. For a review see Blattman and Miguel (2010). On the effects of conflict on trade, see the seminal work by Blomberg and Hess (2006); Glick and Taylor (2010); Egger and Gassebner (2015).

that the effect of export price variations on conflict intensity in Colombia depends on the type of product. A reduction in the export price of coffee (a labor intensive good) lowers wages and increases violence (opportunity cost effect), while the increase in the price of oil (a capital intensive good) increases its value and thus the violence to capture it (rapacity effect). Other studies have found different effects. Crost and Felter (2016) find that the increase in the price of the export crop in the Philippines leads to an increase in conflict, yet this happens only in areas with low control by the insurgents.

Other cross-country studies have looked at the effect changes in the trade relations - as proxied by trade agreements - on conflict. Vicard (2012) provides empirical evidence that customs unions and common markets do reduce the probability of war between members while free trade agreements have no effect on war probabilities. Martin et al. (2008a) show that the effect of international trade on conflict is theoretically ambiguous. On one hand, international trade increases the opportunity costs of civil conflict because of the trade gains involved (for both the government and the rebels).

On the other hand, international trade may act as a substitute for internal trade during civil conflicts, reducing the opportunity cost of conflict. Trade may act as a deterrent if trade gains are put at risk during civil wars, but it may also act as an insurance if international trade provides a substitute to internal trade during civil wars. They conclude that trade openness may deter the most severe civil wars (those that destroy the largest amount of trade) but may increase the risk of lower-scale conflicts. Martin et al. (2008b) study the effect of different trade agreements on the probability of military conflicts. Using data for the 1950-2000 period, they find that the probability of conflict escalation is lower for countries that trade more bilaterally (because of the opportunity cost associated with the loss of trade gains) while countries more open to global trade have a higher probability of war (because multilateral trade openness decreases bilateral dependence to any given country and the cost of a bilateral conflict). Martin et al. (2012) argue that regional trade agreements (RTA) can promote peaceful relations by increasing the opportunity cost of conflicts. Using data from 1950 to 2000, they find that in line with the theory - country pairs with large trade gains from RTAs and more conflict in the past are more likely be part of a RTA.

Our focus is on the effect of trade liberalization on internal conflict and political violence, rather than interstate warfare. We thus regard it as complementary to the existing literature on the pacifying effects of trade agreements. Indeed, a large literature has investigated how international trade affects conflict between states as a result of increasing economic interdependence between countries. The Liberal Peace view in political science argues that increasing trade flows (together with free markets and democracy) should limit the incentive to use military force in interstate relations.[3]

Several studies find a negative correlation between trade openness and the risk of war (Oneal et al 1996; Gartzke 1998; Barbieri and Reuveny 2005; Bussmann and Schneider 2007; Gartzke 2007). However, overall the empirical evidence is mixed. Barbieri (1996) finds that economic interdependence increases the probability of militarized disputes, whereas Beck et al. (1998) find no significant effect of trade on conflict. Mansfield and Pevehouse (2000) find that the negative relationship between trade and conflict holds mostly among countries that are member of trade agreements. Mansfield and Pollins (2003) bring together a number of studies showing that this relationship is contingent on both domestic and international factors. Dorussen (2006) shows that the relationship between trade and conflict should vary across industry sectors.

While trade generally reduces the likelihood of conflict, the relationship is weaker for commodities that are more easily appropriable by force, and stronger for manufactured goods (with the notable exceptions of chemical and metal industries and the high-technology sector). This result is in line with the idea that the characteristics of the economic activity is a crucial determinant of its effect on conflict. McDonald (2004) notes that the effect of opening to free trade may also depend on its distributional effects: by shaping the internal domestic policy decision process and changing the incentives of different group of interest, free trade may increase interstate war.

Finally, there is a limited but growing literature looking at the effects of trade liberalization on non economic outcomes such as crime (Dix-Carneiro et al., 2016) and mental distress (Crino et al., 2015). We contribute by providing robust evidence of an additional possible side-effect of the increase in trade exposure for developing countries, namely an increase in political violence.

3 Conceptual Framework

Two conflicting effects link trade liberalization to political violence. First, trade tariffs introduce a wedge between the price paid by consumers in importing countries and the unit price paid to producers in exporting countries. Removing tariffs on imports from country A to country B increases the equilibrium level of exports from A to B. In particular, removing tariffs on agricultural goods increases agricultural output and the unit price paid to producers in agriculture. The demand for farm labor increases, together

[3] See Schneider et al. 2003, Bussmann et al. 2006, and Schneider 2014 for a discussion of the main issues and a review of the literature.

with agricultural wages.[4] This increase in agricultural employment opportunities and wages increases the opportunity cost of engaging in political violence and decrease its supply (Becker 1968, Grossman 1991, Dube and Vargas 2013). If the *opportunity cost effect* holds, we expect reductions in agricultural tariffs to be associated with (i) higher levels of economic output and (ii) lower levels of political violence.

Second, a competing mechanism to the opportunity cost effect is the *rapacity effect* (Becker 1968, Grossman 1999, Dube and Vargas 2013). Lets assume that armed groups fight with the goal of appropriating resources. By raising prices, trade liberalization may also increase gains from appropriation and, in turn, it may raise the supply of labor in the conflict sector. If the *rapacity effect* holds, we expect reductions in agricultural tariffs to be associated with (i) higher levels of economic output and (ii) higher levels of political violence. Ultimately, whether the rapacity effect is larger than the opportunity cost effect depends on the relationship between return to appropriation and wages as well as on the nature of the conflict. If the return to appropriation raises relatively more than wages, trade liberalization should increase political violence.

Regardless of which effect is at play (i.e. opportunity cost or rapacity), reductions in agricultural tariffs does not affect all areas within the country in the same way. Agricultural output and employment increase differentially more in those areas that are more suitable to produce liberalized crops. At the same time, the positive impact on agricultural employment depends on the production technology used to produce each crop and its labor intensity.

Three elements needs to be taken into account when using PTAs to assess the effect of trade liberalization on political violence. First, in our conceptualization of the impact of agricultural tariff reduction, it is important to mention that, if agricultural producers sell both on the external and the internal market, internal prices also be affected by tariff reductions. In particular, prices of agricultural goods on the internal market can increase, possibly offsetting the real agricultural wage gains from tariff reduction. This issue is a problem if and only if consumers of agricultural products are concentrated more heavily in cells with high crop suitability compare to cell with low crop suitability, which appears unlikely.

Second, PTAs are bilateral or plurilateral agreements. They do not only reduce tariffs

[4] We assume that agricultural goods are produced using a Cobb-Douglas production technology with constant returns to scale, that agricultural farms are price takers, and that wages are equal to their marginal revenue product. Wages would still increase if we assume increasing returns to scale. In the presence of decreasing returns to scale, however, the output to labor ratio decreases with the scale of operations, but the marginal revenue product of labor and thus wages still increase if the positive change in prices more than offsets the negative change in output to labor ratio

on South countries' imports to the North countries, but it also decrease tariffs on North countries' imports to South countries. As a result, and despite the asymmetry in the timing of tariff cuts, the impact of agricultural tariff reduction for South countries is potentially mitigated by a reduction on import tariffs from North country on the same crops. The larger the latter effect, the less likely is that PTA has a positive impact on economic activity in South countries.

Third, PTAs did reduce tariffs for both agricultural and manufacturing products. Thus the same arguments apply for the latter: manufacturing tariff reductions increase output, labor demand and wages in the manufacturing sector. Therefore, PTAs may have increased the opportunity cost of engaging in political violence not through an increase in employment opportunities and wages in agriculture, but rather in manufacturing. However, our empirical strategy allows us to only focus on the impact of agricultural tariff reductions. Yet, it should be noted that manufacturing tariff reductions would confound our estimates if and only if those cells that are more suitable to produce liberalized crops are also those that benefit more from manufacturing trade liberalization. That is, those manufacturing sectors for which tariffs decreased more should be overrepresented in those cells that are particularly suitable to produce liberalized crops. This is far from being the case, as most of manufacturing activity is concentrated in metropolitan areas.

4 Data

In our empirical analysis, we plan to combine data from different sources. Our geographical unit of analysis is a 9km$\times$9km cell. There are 255,813 cells in our dataset for a given year (perfectly balanced panel). We first describe our sample and present our main independent variables.

Sample. Our sample covers 27 South countries between 1995 and 2014. We define a country as South country if it is *not* a high-income economy according to the World Bank categorization.[5] Our sample includes all the PTAs formed by these 27 countries with all major North trading entities: Australia, Canada, the European Union, Japan, South Korea, and the United States. Table A1 in the appendix provides the list of

[5] For details see here: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

countries included in the sample and the PTAs that these countries sign with North countries.

Our sample of countries has several appealing features. First, with few exception, the South countries in our sample show on average relatively low levels of violence. Many of them are quite stable democratic regimes. Notably, our sample excludes almost entirely Sub-Saharan Africa (except for South Africa), which experienced more than half of worldwide conflict incidents, despite having only about 16 percent of the world population (Cilliers 2015). In short, our sample sets a lower bound to find any relationship between trade and conflict. Second, North-South PTAs are more likely to be enforced due to power asymmetry (Baccini and Urpelainen 2014) and less likely to produce trade diversion compare to South-South PTAs (Magee 2008). Third, a scope condition of our theory is that South countries have a comparative advantage in agricultural products with respect to North countries. This scope condition is likely not to hold in many South-South trade relations.

Tariff Reductions. The second piece of information pertains to the details of PTAs and its implementation. We use the information in the Design of Trade Agreements (DESTA) database (Dür, Baccini and Elsig 2014). These data provide information on various types of preferential trade agreements for the time period between 1947 and 2014. For each agreement, the data include sector coverage, depth of commitments, trade integration and compliance tools.

Importantly for this project, DESTA provides information on baseline tariffs and reductions through the implementation period for each product at the 6-digit Foreign Trade Harmonized (HS) code.[6] At this level, we find tariffs for specific goods, such as "cacao" or "coffee", and we observe large differences in tariff reduction across products, which is crucial for our empirical strategy. There are two tariff schedules, one for North countries vis-á-vis South countries, and one for South countries vis-á-vis North countries. Tariff data are highly disaggregated, namely at the Harmonized Commodity Description and Coding System (HS) 6-digit level.

Tariff schedules are extracted from the officially negotiated tariff schedules listed in the appendices of the PTAs. Thus, our tariff cuts are *de jure* and not *de facto*, i.e. countries can set applied tariffs that are different from the ones negotiated. As such, *de jure* tariffs should be more exogenous than *de facto* tariffs. To assess the effect of PTAs on South countries' cells, we rely on the year of the signature of the agreement.

[6]For further information on tariff data, see Baccini, Dür, and Elsig 2017.

Indeed, at the time of the signature relevant actors know that preferential tariff cuts kick in and so they are likely to change their behaviour before the actual implementation of the agreements. In other words, relying on the year of ratification is likely to generate anticipatory effects.

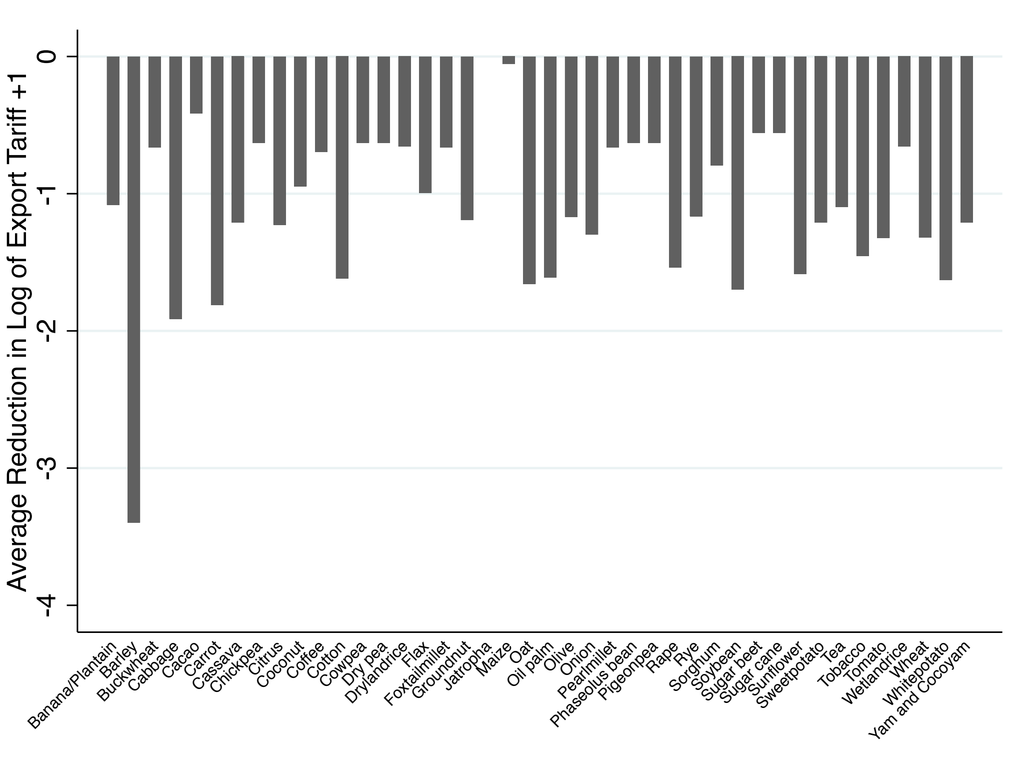
Crop Suitability and Potential Yields. We combine the information on tariff reductions with heterogeneity in crop suitability and potential yields across South African local municipalities. For this purpose, we use information from the Global Aero-ecological Zones (GAEZ Version 3) project (IIASA/FAO 2012, Fischer, van Nelthuizen, Shah and Nachtergaele 2002). Pursued jointly by the Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied System Analysis (IIASA), the paper produces detailed agronomic-based knowledge to assess land suitability and potential attainable yields. The corresponding data are freely available online, and have already been used in economic studies (Adamopoulos and Restuccia 2015, Bustos, Caprettini and Ponticelli 2016).

For each 9km$\times$9km cell in which the planet is divided into, and for each of the main crops, the data carry information on suitability and potential yield. In particular, we use the information on total production capacity per hectare under rain-fed agriculture and using low or intermediate level of inputs. These estimates of production capacity are solely based on agro-climatic conditions in the years 1961-1990, and are therefore exogenous to any change in the technology of agricultural production that might have occurred with the implementation of TDCA. As a result, GAEZ data allows us to derive an exogenous, agro-climatic-based measure of total production capacity for different crops for each South African local municipality. Figure 1 show tariff change by crop for the entire sample of trade agreements used in the analysis.

Let's now describe our left hand-side variables. Our chain of causation goes as follows: trade liberalization affects economic outcome through crop suitability, and in turn, lower tariffs reduce (*opportunity cost effect*) or increase (*rapacity effect*) the supply of violence. Therefore, we use two main outcome variables.

Economic Outcome. We use luminosity as a proxy of GDP (Henderson et al 2012, Michalopoulos and Papaioannou 2013). Data come from from the Defense Meteorological Satellite Programs Operational Linescan System (DMSP-OLS) that reports time-stable images of the earth at night captured between 8pm and 9:30pm. The main advantage of luminosity data is that they can be aggregated at the cell level, i.e. they

FIGURE 1: TARIFF CHANGE BY CROP



Notes. (Initial - Final) tariff by crop (average across HS4 digit related crops across all the agreements). Source: Desta (Baccini et al 2017).

have the same level of aggregation as our independent variables.

Table 1 shows the summary statistics of luminosity by country. It is evident that the variable luminosity has few outliers with large values. Thus, following previous studies (Henderson et al 2012, Michalopoulos and Papaioannou 2013, Pinkovskiy, and Sala-i-Martin 2016), we use the log of the raw value of luminosity, adding one not to lose observations with zero luminosity. We do so to avoid that few observations drive the results.

Political Violence. In order to derive a comprehensive measure of political instability at the cell level, we rely on the Integrated Crisis Early Warning System (ICEWS) dataset (Shilliday and Lautenschlager 2012). Prepared by the Lockheed Martin Advanced Technology Laboratories, these data have been recently made available online. The dataset covers the period from 1995 and 2015. It records any interaction between socio-political actors (i.e., cooperative or hostile actions between individuals, groups, sectors and nation states). Therefore, differently from other dataset such as Armed Con-

Table 1: Descriptive statistics of Luminosity by country

Country	**Mean**	**St. Dev.**	**Min**	**Max**
Algeria	0.63	3.73	0	63
Cambodia	0.15	1.81	0	63
Colombia	0.99	4.60	0	63
Costa Rica	3.39	7.18	0	63
Dominican Republic	3.42	8.36	0	63
Egypt	2.13	8.64	0	63
El Salvador	4.63	7.86	0	63
Guatemala	1.84	5.63	0	63
Honduras	1.27	4.71	0	63
India	3.54	6.56	0	63
Indonesia	0.92	4.12	0	63
Jordan	2.63	8.41	0	63
Laos	0.12	1.68	0	63
Lebanon	17.42	16.24	0	63
Malaysia	2.86	8.68	0	63
Mexico	2.23	7.09	0	63
Morocco	1.23	5.11	0	63
Myanmar	0.21	1.95	0	63
Nicaragua	0.50	3.24	0	63
Panama	1.18	5.17	0	63
Peru	0.38	2.93	0	63
Philippines	1.21	4.92	0	63
South Africa	1.42	6.06	0	63
Thailand	3.15	8.08	0	63
Tunisia	2.86	7.66	0	63
Turkey	2.63	6.71	0	63
Vietnam	2.04	6.02	0	63
Total	1.79	5.92	0	63

flict Location and Event Dataset, the ICEWS dataset does not only focus on episodes of political violence, but also codes and classifies any interaction that is political in nature. For instance, ICEWS events also include political statements, accusations of crime or corruption or human right abuses. Each entry provides information on the source and target of each interaction, together with the level of hostility involved using a scale from -10 to 10. Events are automatically identified and extracted from news articles, and geo-referenced and time-stamped accordingly.

We build our panel dataset of political violence at the cell level as follows. We keep all events geo-referenced between 1995 and 2014 in the 27 South countries and classified as *hostile*, meaning having intensity value from -10 to -1 (inclusive). We

Table 2: Descriptive statistics of Political Violence by country

Country	Mean	St. Dev.	Min	Max
Algeria	0.01	1.09	0	312
Cambodia	0.09	3.33	0	274
Colombia	0.07	5.05	0	1031
Costa Rica	0.09	1.71	0	88
Dominican Republic	0.05	0.95	0	42
Egypt	0.09	11.73	0	3835
El Salvador	0.17	2.76	0	104
Guatemala	0.08	2.26	0	149
Honduras	0.06	2.20	0	303
India	0.20	8.20	0	2179
Indonesia	0.05	4.16	0	1181
Jordan	0.11	3.48	0	215
Laos	0.00	0.29	0	44
Lebanon	5.55	58.97	0	2479
Malaysia	0.09	3.64	0	417
Mexico	0.05	2.75	0	775
Morocco	0.02	0.79	0	121
Myanmar	0.02	1.15	0	200
Nicaragua	0.03	1.09	0	106
Panama	0.03	0.85	0	58
Peru	0.02	1.67	0	643
Philippines	0.35	8.87	0	857
South Africa	0.07	2.26	0	417
Thailand	0.19	13.41	0	3182
Tunisia	0.07	4.82	0	689
Turkey	0.10	4.73	0	836
Vietnam	0.03	1.42	0	145
Total	0.09	6.05	0	3835

then classify each category as violent or non-violent.[7] We capture all events of political violence in which civilians, the government, and related entities (such as the police) are identified as the source. We also keep all the events regardless of the target. Our final dataset counts 472,980 events of political violence between 1999 and 2014 in the 27 South countries. The most frequent event types are: use of unconventional violence, fighting with small arms and light weapons, and use of conventional military force. We geographically match each event to the closest location , and sum them at the cell and year level. This allows us to track the evolution of political violence in each cell over time.

[7] See Table A.2 in the Appendix for the details of our classification.

Table 2 shows the summary statistics of the count variable *Politcal Violence* by country. Two features stand out. First, and not surprisingly, there is a large heterogeneity across countries. Second, the number of violent episodes is quite low, since we work at the cell level. Thus, in our main analysis we use the log of the count of violent episodes in cell i in time t (adding one not to lose observations with no violence) to mitigate the impact of outliers. In the robustness checks, we show that our results are not sensitive to this choice.

5 Empirical Strategy

We expect the implementation of PTAs to affect political violence through its positive impact on agricultural production, employment, and wages. We expect these effects to be larger in those cells that are more suitable to produce the more liberalized crops. For example, if PTAs decreased tariffs on maize more than for coffee, we would expect a larger increase in agricultural employment and wages in those cells that are highly suitable to produce maize, and less of an effect in those that are suitable for coffee. That is, the extent to which we expect each cell to be affected by PTAs is determined by the interaction between the size of tariff reductions and crop suitability.

We derive such measure of exposure to PTAs as follows. Let τ_{ct} be the proportional change in tariffs applied to South countries' imports to North countries of crop c between the baseline and year t. That is, if baseline tariffs applied to maize were 10 percent, and decreased to 5 percent in year t, then τ_{ct} would be equal to 0.5, i.e. $\frac{(10-5)}{10}$. Let then S_{ic} be the suitability of cell i to produce crop c, as measured by the agro-climatic-based total production capacity from GAEZ data. Our measure E_{it} of export exposure for cell i at time t is given by

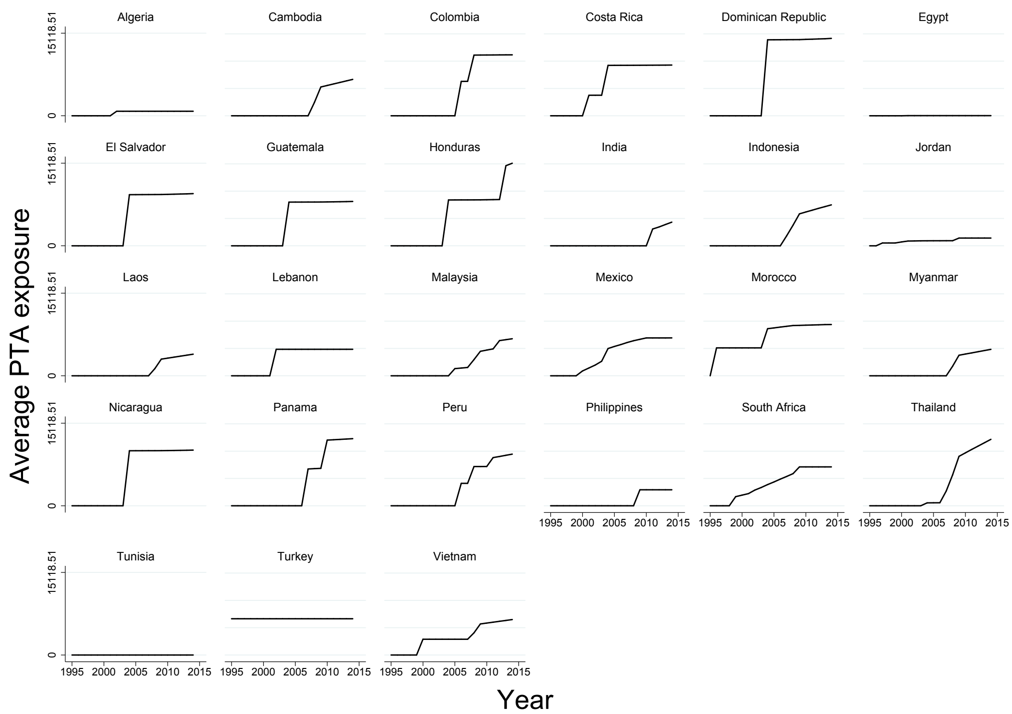
$$E_{it} = \sum_{c} \tau_{ct} S_{ic} \tag{1}$$

This is our variable of interest. Notice that, by definition, in the construction of our export exposure variable, we only consider those crops that are both affected by PTAs ($\tau_{ct} > 0$) and that at least one cell is suitable to produce ($S_{ic} > 0$).[8] Moreover, τ_{ct} is time-specific and common to all cells, while S_{ic} is not. Variation in S_{ic} across

[8] The interested crops are: Banana/Plantain, Cabbage, Cacao, Carrot, Chickpea, Citrus, Coffee, Cotton, Dry pea, Flax, Groundnut, Maize, Oil palm, Olive, Onion, Phaseolus bean, Rape, Sorghum, Soybean, Sunflower, Sweet potato, Tea, Tobacco, Wetlandrice, Wheat, White potato.

cells is given by heterogeneity in their suitability in producing different crops. This is derived using GAEZ estimates of production capacity that are informed by agro-climatic conditions only. Therefore, our source of cross-cell heterogeneity in export exposure is determined a priori and does not respond itself to the implementation of PTAs. Figure 2 shows the variation of export exposure by country.[9]

Figure 2: Panel-data line plot of export exposure



Regression Specification. Our goal is to find evidence of a systematic relationship between export exposure E_{it} and our outcome of interest Y_{it}. This variable measures both economic output by looking at luminosity and political violence by counting the number of ICEWS events that took place in local municipality *i* in year *t*. We use all observations of cells from the year 1999 to 2014 and implement the following baseline regression specification

$$Y_{it} = \gamma_i + \delta_t + \beta E_{it} + u_{it} \tag{2}$$

[9] We are unable to obtain estimates for Tunisia and Turkey since they both sign only one PTA (with the EU) throughout our time span, i.e. e does not vary over time.

In this specification, cell fixed effects γ_i control for time-invariant characteristics at the cell level, while δ_t nets out year-specific trends that are common to all cells. u_{it} captures instead any residual determinant of political violence in a cell *i* in year *t*. If the *opportunity cost effect* is at play, $\beta < 0$. If the *rapacity effect* is at play, $\beta > 0$.

We enrich our baseline specification with country- and grid-specific linear time trends (including flexible trends). We also include country-year fixed effects, which account for time-varying country specific characteristics, e.g. type of regime or level of development. Moreover, we include spatial lags to control for spillover effects of economic output and violence.

6 Results

In line with our conceptual framework, we first present the results related to the effect of export exposure on economic output and then explore the effect of export exposure on political violence.

6.1 Economic Output

Results of the effect of export exposure on the economic output is reported in Table 3. The sign of e is positive and statistically significant in every model except in Models 7 and 8. More specifically, Model 1 reports the results of our baseline estimates with cell and year fixed effects. Model 2 includes country-specific trends as a first check of the parallel trend assumption. Model 3 includes grid-specific trends, where a grid is a 550km$\times$550km area. This second set of trends allows a more accurate test of the parallel trend assumption. Model 4 includes spatial lags to account for spillover effects, which would violate the Stable Unit Treatment Value Assumption (SUTVA). In short, spatial lags are 110km$\times$110km grids that capture the sum of export exposure in the other FAO cells falling within the same bigger grid.[10] Model 5 is a model that include country-year fixed effects. For computational reasons, we are unable to run this model on the entire sample and so we run it on a random sub-sample that includes ten percent of the total observations.

To further defend the parallel trend assumption, we include country-specific flexible trends. That is, every country has its own trend in the years prior to signature, a jump

[10]Each of these smaller grids include 24 FAO cells.

in year of signature, and another linear trend in the years after. This should account for any confounding factors varying together export exposure at the country level. Model 6 shows that our results hold even in this case. Moreover, we include flexible trends which are different within country between treated (export exposure>0 at any point) and non-treated cells. These trends are similar to the previous ones, but they vary between the two groups, i.e. treated and controls. Model 7 shows that the results hold even with this model specification.[11]

Furthermore, Model 8 includes a rich set of geographic and location controls. To account for elevation, we construct the average altitude in the cell by averaging out the 1km×1km raster dataset from the National Oceanic and Atmospheric Administration (NOAA). To further account on differences on geographic characteristics, we use a measure of ruggedness of terrain derived by Nunn and Puga (2010).[12] To capture climatic features, we construct the cell level average precipitation in millilitres from 1960 to 1991 from the Climatic Research Unit 2.0.[13] We retrieve cell-level data on averages temperature from 1960 and 1991 from FAO GAEZ. We then calculate the total area, the area covered by water (using water bodies in the Digital Chart of the World) and the absolute latitude for each cell. We compute distances from cell centroids to the country border and to the coast.[14] Finally, we calculate the number of ethnic groups in the cell from the Geo-referencing of ethnic groups (GREG) dataset (Weidmann, Ketil Rd, and Cederman 2010).[15]

Note that all these cell-specific characteristics are time invariant and so they cannot be included alone since they are perfectly correlated with cell fixed effects. By interacting them with linear trends, we account for cell-specific characteristics that may vary together with export exposure with the risk of violating the parallel trend assumption. There is no evidence of that: our results remain the same as in the previous model specifications.[16]

[11] We run these two models on a random subsample that includes ten percent of the total observations.

[12] The original dataset is constructed at the 1km×1km resolution (30 arc-second grid). As for the elevation data, we calculate the average ruggedness in the cell. Further information about the Terrain Ruggedness Index can be found at http://diegopuga.org/data/rugged/.

[13] Original data can be accessed at https://crudata.uea.ac.uk/~timm/grid/CRU_TS_2_0.html.

[14] We perform distance calculation using the WGS84 Equal Area Scalable Earth (EASE) projection.

[15] This is the digital version of the paper Soviet Narodov Mira atlas created in 1964. In 2010 the GREG project digitized all maps depicting the spatial distribution of ethnic groups contained in this Atlas. Data is available at https://icr.ethz.ch/data/greg/.

[16] We run this model on a random subsample that includes ten percent of the total observations.

TABLE 3: ECONOMIC OUTPUT AFTER PTAS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Luminosity (Ln+1)				
E [export exposure]	0.016***	0.029***	0.028***	0.024***	0.030***	0.027***	0.026***	0.0025***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.006)	(0.005)	(0.005)
Constant	0.329***	0.322***	0.333***	0.329***	0.331***	0.461***	0.328***	0.459***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific trends	No	Yes	No	No	No	No	No	No
Grid-specific trends	No	No	Yes	No	No	No	No	No
Spatial lags	No	No	No	Yes	No	No	No	No
Country-year FE	No	No	No	No	Yes	No	No	No
Country-specific flex trends	No	No	No	Yes	No	Yes	No	No
Country-spec. trends (tr/non-tr)	No	No	No	Yes	No	No	Yes	Yes
Cell-specific char.×linear trends	No	No	No	Yes	No	No	No	Yes
No. of obs.	4,445,620	4,445,620	4,445,620	4,445,620	444,562	444,562	444,562	444,562
R^2	0.039	0.043	0.057	0.039	0.073	0.039	0.039	0.039

Notes. (* p-value< 0.1; ** p-value<0.05; *** p-value<0.01) Standard errors in parenthesis. Unit of observation is the cell level. E is the export exposure in cell i in time t. The dependent variable is the log of luminosity. Sources: Desta, GAEZ Version 3, and DMSP-OLS.

TABLE 4: ECONOMIC OUTPUT AND PTA EXPOSURE (EXPORT AND IMPORT)

	Luminosity (Ln+1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
E [export exposure]	0.012	0.024***	0.022***	0.022***	0.017**	0.014*	0.016*
	(0.009)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
I [import exposure]	0.002	0.001	0.005	0.005	0.011	0.012	0.008
	(0.013)	(0.010)	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific trends	No	Yes	No	No	No	No	No
Country-specific flex trends	No	No	Yes	No	No	No	No
Country-year FE	No	No	No	Yes	No	No	No
Country-specific trends (tr/non-tr)	No	No	No	No	Yes	Yes	Yes
Cell-specific char.*linear trends	No	No	No	No	No	Yes	Yes
Spatial lag	No	No	No	No	No	No	Yes
Number of observations	444,562	444,562	444,562	444,562	444,562	444,562	444,562
R^2	0.040	0.055	0.057	0.069	0.059	0.062	0.063

Notes. (***, **, * p-value$<$0.001, 0.005, 0.01, respectively) Standard errors in parenthesis. All regressions estimated using 10% of the sample stratified by country. Unit of observation is the cell level. E is the export exposure in cell i in time t. The dependent variable is the log of luminosity. Sources: Desta, GAEZ Version 3, and DMSP-OLS.

The magnitude of the effect is not trivial. Indeed, with our estimates in hand, we can calculate the percentage gain in aggregate economic output attributable to the policy. Setting the value of the coefficient of interest equal to zero, we predict the value of output in each cell that we would have observed in absence of the PTA. We find that, in South countries, the economic output value would have been 2.2 percent lower in absence of the trade agreement with major North trading entities.[17]

Finally, we re-run some of our main models including a proxy for import exposure.[18] Indeed, PTAs are symmetric agreements in which both parties are required to cut tariffs. Import exposure is built in a similar way as export exposure. The only difference is that we use tariff reductions implemented by South countries with North countries in interaction with crop suitability.[19] Results are shown in Table 4. Export exposure remains positive and significant in every model, except Model 1, whereas import exposure is never significant.[20]

Robustness Checks. We implement several robustness checks to corroborate our results. First, we re-run all models in Table 3 using the raw data of luminosity to check if our results are sensitive to the log transformation. Results are virtually the same as showed in Table A.3 in the appendix. Second, our results hold if we drop these cells with zero luminosity (see Table A.4 in the appendix).[21] Third, our results hold if we use wild-bootstrapped clustered standard errors at the level of the country or if we cluster standard errors at the level of the grid. Both tests produce more conservative standard errors.[22] Finally, Table A.5 reports the results of our baseline model for each country. Out of 25 countries, the coefficient of export exposure is positive and significant for 18 countries, whereas for only one country (Peru) the coefficient of e is negative and significant.[23]

[17]We quantify the percentage increase in aggregate economic output value as follows. We use the coefficient estimates in column (1) of Table 3 to predict the value of output $\hat{y}_{it}$ in each cell and year. We also predict the value of output $\tilde{y}_{it}$ that we would have observed if $\beta = 0$, i.e. $\tilde{y}_{it} = \hat{y}_{it} - \hat{\beta} E_{it} \times \mathsf{E}_{it}$. We then aggregate both values across cells and years for the post-treatment period to get $\widehat{Y} = \sum_{t=0}^{10} \sum_s \hat{y}_{it}$ and $\widetilde{Y} = \sum_{t=0}^{10} \sum_s \tilde{y}_{it}$. The estimated increase in aggregate economic output value due to the policy is given by $(\widetilde{Y} - \widehat{Y})/\widehat{Y}$.

[18]We run these model on a random subsample that includes ten percent of the total observations.

[19]Figure A.1 shows the scatter plot of the average reduction of export tariff versus the average reduction of import tariff.

[20]We run these models on a random sub-sample that includes ten percent of the total observations.

[21]Results hold if we first-difference luminosity to capture economic growth rather than level of economic output.

[22]The last two sets of checks are available upon request.

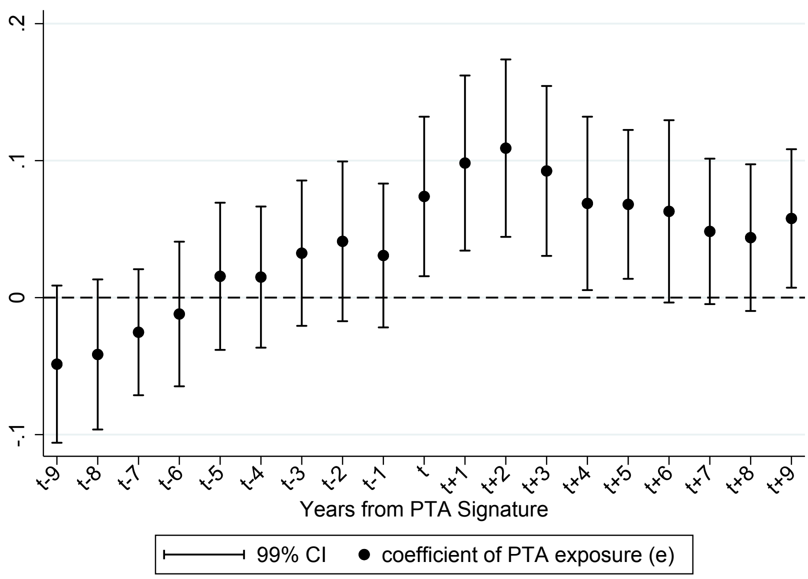
[23]We acknowledge that this test is biased in favor of big countries, which have a larger number of observations and so smaller standard errors.

In sum, North-South PTAs have a large positive long-lasting effect on the economic output of cells with high crop suitability in developing countries. This implies that both wages and gains from appropriation increase differentially more in cells with high crop suitability compare to cells with low crop suitability. The net effect of export exposure on violence depends on which of these two increases dominates the other, something that we explore in the next sub-section.

6.2 Political Violence

We now move to explore the second outcome: political violence. Figure 3 shows preliminary evidence of the impact of trade liberalization on political violence. We define a dummy equal to one if the cell is suitable to produce any of the liberalized crops. We also define a set of time dummies, one for each year before and after the PTA signature. We then regress the level of violence in the cell over the set of year dummies, cell fixed effects, and the interaction between the year dummies and the suitability dummy. The estimated coefficients of these interactions capture the difference in the level of violence between suitable and non-suitable cells in each year.

FIGURE 3: PTA EXPOSURE AND POLITICAL VIOLENCE OVER TIME



Notes. Dependent variable is the log of the count of violent episodes. The Figure plots the estimated coefficient of the interaction of export exposure variable e with the corresponding year dummy. The solid vertical lines show the 99% confidence interval of each estimate, while the dash horizontal line indicates zero. Sources: Desta, GAEZ Version 3, and ICEWS.

Figure 3 plots these estimated coefficients together with their 99% confidence interval. We do not find any evidence of a systematic difference in the level of violence between suitable and non-suitable cells in the years prior to the PTA signature. This indicates that, once cell time-invariant characteristics and time trends are controlled for in a flexible way, suitable and non-suitable cells are no different in their level of violence prior to the PTA signature. A significant difference emerges instead in the years following the PTA signature. Violence increases differentially in those cells that are suitable to produce liberalized crops, as we record a systematically higher level of violence in these cells with respect to non-suitable ones.

Table 5 shows the main results in a more systematic way. The export exposure variable E has always a positive sign, except in Model 7, and it is significant across all model specifications. The coefficient remains positive and significant even when we include country-specific and grid-specific trends (Models 2 and 3), which check the validity of the parallel trend assumption. Moreover, the results hold when we include spatial lags to account for spillover effects of violence (Model 4) as well as when we include country-year fixed effects, effects, which control for any time-varying heterogeneity across countries (Model 5).[24]

In line with luminosity, we also include country-specific flexible trends and flexible trends which are different within country between treated and non-treated cells (respectively Model 6 and 7). Results remain positive and significant. Moreover, we obtain similar results if we include time-invariant cell-specific characteristics in interaction with linear trends (Model 8). All in all, the fact that our results are robust to saturate the models with different types of trends reassure us against the risk of violating the parallel trend assumptions and validate our identification strategy.

Finally, Table 6 includes import exposure in some of our main models. Our results hold in every model, except Model 7. Interestingly, import exposure is negative and significant in all the model but Model 7. This finding is in line with the rapacity effect. Since import exposure reduces the rents available in these cells that face the competition of North countries, gains from appropriation are smaller, reducing incentives to engage in political violence.

[24]We run this and subsequent models on a random subsample that includes ten percent of the total observations.

TABLE 5: POLITICAL VIOLENCE AFTER PTAS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Violence (Ln+1)				
E [export exposure]	0.001***	0.003***	0.003***	0.002***	0.003***	0.003***	0.002***	0.002***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.003***	0.004***	0.004***	0.003***	0.003***	0.018***	0.003***	0.021***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0008)	(0.0003)	(0.0002)	(0.0003)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific trends	No	Yes	No	No	No	No	No	No
Grid-specific trends	No	No	Yes	No	No	No	No	No
Spatial lags	No	No	No	Yes	No	No	No	No
Country-year FE	No	No	No	No	Yes	No	No	No
Country-specific flex trends	No	No	No	yes	No	Yes	No	No
Country-spec. trends (tr/non-tr)	No	No	No	yes	No	No	Yes	Yes
Cell-specific char.×linear trends	No	No	No	Yes	No	No	No	Yes
No. of obs.	4,445,620	4,445,620	4,445,620	4,445,620	444,562	444,562	444,562	444,562
R^2	0.003	0.008	0.011	0.003	0.014	0.003	0.003	0.003

Notes. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01) Standard errors in parenthesis. Unit of observation is the cell level. e is the export exposure in cell i in time t. The dependent variable is the log of the count of violent episodes. Sources: Desta, GAEZ Version 3, and DMSP-OLS.

TABLE 6: POLITICAL VIOLENCE AND PTA EXPOSURE (EXPORT AND IMPORT)

	Violence (Ln+1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
E [export exposure]	0.005**	0.006***	0.006***	0.006***	0.006**	0.006**	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
I [import exposure]	-0.005***	-0.004***	-0.004**	-0.004**	-0.004**	-0.004**	-0.003
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific trends	No	Yes	No	No	No	No	No
Country-specific flex trends	No	No	Yes	No	No	No	No
Country-year FE	No	No	No	Yes	No	No	No
Country-spec.trends (tr/non-tr)	No	No	No	No	Yes	Yes	Yes
Cell-specific char.*linear trends	No	No	No	No	No	Yes	Yes
Spatial lag	No	No	No	No	No	No	Yes
Number of observations	467,960	467,960	467,960	467,960	467,960	467,960	467,960
R^2	0.003	0.009	0.010	0.013	0.010	0.011	0.011

Notes. (***, **, * p-value<0.001, 0.005, 0.01, respectively) Standard errors in parenthesis. All regressions estimated using 10% of the sample stratified by country. Unit of observation is the cell level. E is the export exposure in cell i in time t. The dependent variable is the log of luminosity. Sources: Desta, GAEZ Version 3, and DMSP-OLS.

Even with respect to this outcome, the magnitude of the effect is not trivial. Again, we can use our estimates to calculate the total fraction of events of political violence that can be attributed to the PTAs. Setting the value of the interaction term equal to zero, we can predict the number of events per cell in each year that we would have observed if the trend in political violence had never diverged across cells after the PTA signature. According to the estimates in Model 1 of Table 5, the effects of PTAs that we investigate account for an increase of 10 percent of the total number of violent events in South countries in the period under investigation.[25]

Robustness Checks. We implement several robustness checks to corroborate our results. First, we show that results are similar if we use a dummy for political violence (Table A.6). Second, results are substantively unchanged if we use the raw value of political violence, i.e. count outcome without log transformation (Table A.7).[26] Third, our results hold if we use wild-bootstrapped clustered standard errors at the level of the country or if we cluster standard errors at the level of the grid. Both tests produce more conservative standard errors.[27] Finally, Table A.8 reports the results of our baseline model for each country. Out of 25 countries, the coefficient of export exposure is positive and significant for 14 countries, whereas for only two countries (Algeria and Peru) the coefficient of e is negative and significant.

All in all, our results support the *rapacity effect* hypothesis. PTAs exposure increases the economic output and in turn, raises gains from appropriation. As a result of that, a larger number of people are dragged into the conflict and/or existing fighting groups engage more frequently with conflict than it happened before the formation of PTAs. This leads to an increase of the occurrence of violent episodes differentially more in cells with high crop suitability than in cells with low crop suitability.

Beyond North-South Cooperation. To check how generalizable our results are, we re-run our main models with all trade agreements formed by China with South coun-

[25] We quantify the percentage reduction in political violence as follows. We use the coefficient estimates in Model 1 of Table 5 to predict the value of political violence $\hat{y}_{it}$ in each cell and year. We also predict the value of political violence $\tilde{y}_{it}$ that we would have observed if $\beta = 0$, i.e. $\tilde{y}_{it} = \hat{y}_{it} - \hat{\beta} e_{it} \times \mathsf{e}_{it}$. We then aggregate both values across cells for the post-treatment period to get $\widehat{Y} = \sum_{t=0}^{10} \sum_s \hat{y}_{it}$ and $\widetilde{Y} = \sum_{t=0}^{10} \sum_s \tilde{y}_{it}$. The estimated increase in political violence due to the policy is given by $\widetilde{Y} - \widehat{Y})/\widehat{Y}$.

[26] If we drop the cells that never experience violent episodes throughout the time span, results are similar, though weaker. Results are also similar if we use negative binomial regressions and zero-inflated negative binomial regressions, which are particularly suitable with count outcomes, though they struggle often to converge. This set of results is available upon request.

[27] The last two sets of checks are available upon request.

tries. In doing so, we are able to explore what is the effect of South-South PTAs on economic output and violence and to see if results differ from North-South PTAs. China formed PTAs with ASEAN countries (2004), Pakistan (2006), and Peru (2009).[28] Pakistan is the only country that was not included in our previous analysis.

Tables A.9 and A.10 report the results for the Chinese PTAs. Findings are in line with the North-South PTAs. Export exposure increases economic output and political violence. In addition to improve the external validity of our analysis, these results help also elucidate why we find evidence of anticipatory effect. Take ASEAN-China , for instance: this free trade area, which was signed in 2004, is likely to create anticipatory effects in ASEAN countries for the PTAs formed by Australia and Japan with the same countries in subsequent years.

7 Conclusion

Our paper explores the micro-foundations of this trade-conflict nexus. Our preliminary results are two-fold. First, North-South PTAs increase substantively the economic output of areas with high crop suitability compare to areas with low crop suitability. To our knowledge, we are the first study to estimate the effect of PTAs on agricultural output with micro-level data. Second, we find strong support for the *rapacity effect*. After the formation of North-South PTAs political violence increases differentially more in areas with high crop suitability than in areas with low crop suitability. This finding implies that gains from appropriation increases proportionally more than wages and that positive economic shocks triggered by trade liberalization fuel intra-state conflict in developing countries.

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[28] China formed PTAs with New Zealand and Singapore, which are however high-income countries.

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Appendix: Tables and Figures

Figure A.1: Sample of countries and trade agreements (year of signature in brackets)

Notes. Average reduction in log of export tariff versus average reduction in log of import tariff by crop (average across HS4 digit related crops across all the agreements). Source: Desta (Baccini et al 2017).

Figure A.2: Sample of countries and trade agreements (year of signature in brackets)

No.	South Country	PTA	No.	South Country	PTA
1	Algeria	Algeria-EU (2002)	17	Mexico	Mexico EU (2000)
2	Cambodia	ASEAN Japan (2008)			Mexico Japan (2004)
		ASEAN Australia New Zealand (2009)	18	Morocco	Morocco EU (1996)
3	Colombia	Colombia USA (2006)			Morocco US (2004)
		Colombia Canada (2008)	19	Myanmar	ASEAN Japan (2008)
4	Costa Rica	Costa Rica Canada (2001)			ASEAN Australia New Zealand (2009)
		CAFTA DR USA (2004)	20	Panama	Panama US (2007)
5	Dominican Republic	CAFTA DR USA (2004)			Panama Canada (2010)
6	Egypt	Egypt-EU (2001)	21	Peru	Peru US (2006)
7	El Salvador	CAFTA DR USA (2004)			Peru Canada (2008)
8	Guatemala	CAFTA DR USA (2004)			Peru Japan (2011)
9	Honduras	CAFTA DR USA (2004)	22	Philippines	Philippines Japan (2006)
		Honduras Canada (2013)			ASEAN Japan (2008)
10	Nicaragua	CAFTA DR USA (2004)			ASEAN Australia New Zealand (2009)
11	India	India Japan (2011)	23	South Africa	South Africa EU (1999)
12	Indonesia	Indonesia Japan (2007)	24	Thailand	Thailand Australia (2004)
		ASEAN Japan (2008)			Thailand Japan (2007)
		ASEAN Australia New Zealand (2009)			ASEAN Japan (2008)
13	Jordan	Jordan US (2000)			ASEAN Australia New Zealand (2009)
		Jordan EU (1997)	25	Tunisia	Tunisia EU (1995)
		Jordan Canada (2009)	26	Turkey	Turkey EU (1995)
14	Laos	ASEAN Japan (2008)	27	Vietnam	Vietnam US (2000)
		ASEAN Australia New Zealand (2009)			Vietnam Japan (2008)
15	Lebanon	Lebanon EU (2002)			ASEAN Japan (2008)
16	Malaysia	Malaysia Japan (2005)			ASEAN Australia New Zealand (2009)
		ASEAN Japan (2008)			
		ASEAN Australia New Zealand (2009)			
		Malaysia Australia (2012)			

TABLE A.2: CLASSIFICATION OF VIOLENT AND NON-VIOLENT EVENTS 1/4

Violent	CAMEO Event Category
1	Abduct, hijack, or take hostage
1	Arrest, detain, or charge with legal action
1	Assassinate
1	Attempt to assassinate
1	Carry out car bombing
1	Carry out roadside bombing
1	Carry out suicide bombing
1	Coerce
1	Conduct suicide, car, or other non-military bombing
1	Demonstrate military or police power
1	Destroy property
1	Employ aerial weapons
1	Engage in ethnic cleansing
1	Engage in mass expulsion
1	Engage in mass killings
1	Engage in violent protest for leadership change
1	Expel or deport individuals
1	Expel or withdraw
1	Expel or withdraw peacekeepers
1	Fight with artillery and tanks
1	Fight with small arms and light weapons
1	Kill by physical assault
1	Mobilize or increase armed forces
1	Mobilize or increase police power
1	Physically assault
1	Protest violently, riot
1	Seize or damage property
1	Sexually assault
1	Torture
1	Use chemical, biological, or radiological weapons
1	Use conventional military force
1	Use tactics of violent repression
1	Use unconventional violence

TABLE A.2: CLASSIFICATION OF VIOLENT AND NON-VIOLENT EVENTS 2/4

Violent	CAMEO Event Category
0	Accuse
0	Accuse of aggression
0	Accuse of crime, corruption
0	Accuse of espionage, treason
0	Accuse of human rights abuses
0	Accuse of war crimes
0	Appeal for change in institutions, regime
0	Appeal for change in leadership
0	Appeal for de-escalation of military engagement
0	Appeal for easing of administrative sanctions
0	Appeal for easing of economic sanctions, boycott, or embargo
0	Appeal for easing of political dissent
0	Appeal for policy change
0	Appeal for political reform
0	Appeal for release of persons or property
0	Appeal for rights
0	Appeal for target to allow international involvement (non-mediation)
0	Appeal to yield
0	Ban political parties or politicians
0	Bring lawsuit against
0	Complain officially
0	Conduct hunger strike
0	Conduct hunger strike for policy change
0	Conduct strike or boycott
0	Conduct strike or boycott for policy change
0	Confiscate property
0	Criticize or denounce
0	Decline comment
0	Defy norms, law
0	Demand
0	Demand change in institutions, regime
0	Demand change in leadership
0	Demand de-escalation of military engagement
0	Demand diplomatic cooperation (such as policy support)
0	Demand easing of administrative sanctions
0	Demand easing of economic sanctions, boycott, or embargo
0	Demand easing of political dissent
0	Demand economic aid
0	Demand humanitarian aid
0	Demand intelligence cooperation
0	Demand judicial cooperation

TABLE A.2: CLASSIFICATION OF VIOLENT AND NON-VIOLENT EVENTS 3/4

Violent	CAMEO Event Category
0	Demand material cooperation
0	Demand mediation
0	Demand meeting, negotiation
0	Demand military aid
0	Demand policy change
0	Demand political reform
0	Demand release of persons or property
0	Demand rights
0	Demand settling of dispute
0	Demand that target yields
0	Demonstrate for leadership change
0	Demonstrate for policy change
0	Demonstrate or rally
0	Deny responsibility
0	Give ultimatum
0	Halt mediation
0	Halt negotiations
0	Impose administrative sanctions
0	Impose blockade, restrict movement
0	Impose curfew
0	Impose embargo, boycott, or sanctions
0	Impose restrictions on political freedoms
0	Impose state of emergency or martial law
0	Increase military alert status
0	Increase police alert status
0	Investigate
0	Investigate crime, corruption
0	Investigate human rights abuses
0	Investigate military action
0	Investigate war crimes
0	Make pessimistic comment
0	Obstruct passage, block
0	Occupy territory
0	Rally opposition against
0	Reduce or break diplomatic relations
0	Reduce or stop economic assistance
0	Reduce or stop humanitarian assistance
0	Reduce or stop material aid
0	Reduce or stop military assistance
0	Reduce relations
0	Refuse to de-escalate military engagement

TABLE A.2: CLASSIFICATION OF VIOLENT AND NON-VIOLENT EVENTS 4/4

Violent	CAMEO Event Category
0	Refuse to ease administrative sanctions
0	Refuse to ease economic sanctions, boycott, or embargo
0	Refuse to ease popular dissent
0	Refuse to release persons or property
0	Refuse to yield
0	Reject
0	Reject economic cooperation
0	Reject judicial cooperation
0	Reject material cooperation
0	Reject mediation
0	Reject plan, agreement to settle dispute
0	Reject proposal to meet, discuss, or negotiate
0	Reject request for change in institutions, regime
0	Reject request for change in leadership
0	Reject request for economic aid
0	Reject request for military aid
0	Reject request for military protection or peacekeeping
0	Reject request for rights
0	Threaten
0	Threaten non-force
0	Threaten to halt negotiations
0	Threaten to impose curfew
0	Threaten to reduce or break relations
0	Threaten to reduce or stop aid
0	Threaten with administrative sanctions
0	Threaten with military force
0	Threaten with political dissent, protest
0	Threaten with repression
0	Threaten with restrictions on political freedoms
0	Threaten with sanctions, boycott, embargo
0	Use as human shield
0	Veto
0	Violate ceasefire

Notes. Sources: Integrated Crisis Early Warning System (ICEWS) dataset. Cases selected by the authors.

TABLE A.3: ECONOMIC OUTPUT AFTER PTAS

	(1)	(2)	(3)	(4)	(5)
			Luminosity		
E [export exposure]	0.08534***	0.24431***	0.24536***	0.17928***	0.22457***
	(0.00399)	(0.00404)	(0.00451)	(0.00702)	(0.01075)
Constant	1.41793***	1.18330***	1.22440***	1.42061***	1.43770***
	(0.00351)	(0.00395)	(0.00402)	(0.00349)	(0.01424)
Cell FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country-specific trends	No	Yes	No	No	No
Grid-specific trends	No	No	Yes	No	No
Spatial lags	No	No	No	Yes	No
Country-year FE	No	No	No	No	Yes
No. of obs.	4,445,620	4,445,620	4,445,620	4,445,620	444,562
R^2	0.06434	0.06858	0.09369	0.06494	0.10849

Notes. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01) Standard errors in parenthesis. Unit of observation is the cell level. e is the export exposure in municipality i in time t. The dependent variable is luminosity. Sources: Desta, GAEZ Version 3, and DMSP-OLS.

TABLE A.4: ECONOMIC OUTPUT AFTER PTAS

	(1)	(2)	(3)	(4)	(5)
			Luminosity (Ln+1)		
E [export exposure]	-0.00495***	0.04431***	0.04479***	0.00200	0.01304***
	(0.00074)	(0.00104)	(0.00112)	(0.00134)	(0.00265)
Constant	1.92186***	1.66960***	1.66907***	1.92223***	1.89731***
	(0.00122)	(0.00099)	(0.00096)	(0.00122)	(0.00453)
Cell FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country-specific trends	No	Yes	No	No	
Grid-specific trends	No	No	Yes	No	No
Spatial lags	No	No	No	Yes	No
Country-year FE	No	No	No	No	Yes
No. of obs.	951,315	951,315	939,207	951.315	95,329
R^2	0.50553	0.27362	0.28716	0.50564	0.53835

Notes. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01) Standard errors in parenthesis. Unit of observation is the cell level. e is the export exposure in municipality i in time t. The dependent variable is the log of luminosity (only strictly positive values). Sources: Desta, GAEZ Version 3, and DMSP-OLS).

TABLE A.5: ECONOMIC OUTPUT AFTER PTAS BY COUNTRY

	ln(Luminosity)				
VARIABLES	Algeria	Cambodia	Colombia	Costa Rica	Dominican Rep.
e	0.09***	0.00	0.005***	0.02	-0.00
	(0.003)	(0.008)	(0.002)	(0.013)	(0.012)
	Egypt	El Salvador	Guatemala	Honduras	India
e	1.42***	0.00	-0.01	0.04***	0.08***
	(0.117)	(0.018)	(0.009)	(0.009)	(0.004)
	Indonesia	Jordan	Laos	Lebanon	Malaysia
e	0.02***	0.25***	0.06***	-0.01	0.09***
	(0.001)	(0.022)	(0.009)	(0.021)	(0.006)
	Mexico	Morocco	Myanmar	Nicaragua	Panama
e	0.02***	0.08***	0.03***	0.02***	0.05***
	(0.001)	(0.004)	(0.004)	(0.004)	(0.008)
	Peru	Philippines	South Africa	Thailand	Vietnam
e	-0.01***	0.09***	0.03***	0.11***	0.16***
	(0.001)	(0.013)	(0.002)	(0.005)	(0.010)
Cell FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Notes. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01) Standard errors in parenthesis. Unit of observation is the cell level. e is the export exposure in municipality i in time t. The dependent variable is the log of luminosity. Sources: Desta, GAEZ Version 3, and DMSP-OLS.

TABLE A.6: POLITICAL VIOLENCE AFTER PTAS

	(1)	(2)	(3)	(4)	(5)
	Violence (dummy)				
E [export exposure]	0.00053***	0.00199***	0.00191***	0.00131***	0.00179***
	(0.00009)	(0.00010)	(0.00011)	(0.00015)	(0.00036)
Constant	0.00236***	0.00315***	0.00319***	0.00238***	0.00225***
	(0.00012)	(0.00010)	(0.00011)	(0.00012)	(0.00055)
Cell FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country-specific trends	No	Yes	No	No	No
Grid-specific trends	No	No	Yes	No	No
Spatial lags	No	No	No	Yes	No
Country-year FE	No	No	No	No	Yes
No. of obs.	4,445,620	4,445,620	4,445,620	4,445,620	444,562
R^2	0.00278	0.00781	0.00989	0.00281	0.01174

Notes. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01) Standard errors in parenthesis. Unit of observation is the cell level. e is the export exposure in cell i in time t. The dependent variable is a dummy variable that scores one if a cell has positive values of violent episodes. Sources: Desta, GAEZ Version 3, and DMSP-OLS.

TABLE A.7: POLITICAL VIOLENCE AFTER PTAS

	(1)	(2)	(3)	(4)	(5)
			Violence		
E [export exposure]	0.00469	0.02382***	0.02753***	0.01327	0.03618*
	(0.00643)	(0.00712)	(0.00817)	(0.00952)	(0.02118)
Constant	0.01862***	0.02083**	0.02173**	0.01888***	0.00812
	(0.00708)	(0.00888)	(0.00923)	(0.00707)	(0.02347)
Cell FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country-specific trends	No	Yes	No	No	No
Grid-specific trends	No	No	Yes	No	No
Spatial lags	No	No	No	Yes	No
Country-year FE	No	No	No	No	Yes
No. of obs.	4,445,620	4,445,620	4,445,620	4,445,620	444,562
R^2	0.00013	0.00035	0.00063	0.00013	0.00985

Notes. (* p-value< 0.1; ** p-value<0.05; *** p-value<0.01) Standard errors in parenthesis. Unit of observation is the cell level. e is the export exposure in cell i in time t. The dependent variable is the count of violent episodes. Sources: Desta, GAEZ Version 3, and DMSP-OLS.

TABLE A.8: ECONOMIC OUTPUT AFTER PTAS BY COUNTRY

	ln(Violence)				
VARIABLES	Algeria	Cambodia	Colombia	Costa Rica	Dominican Rep.
e	-0.002***	0.00	0.001**	0.01**	0.00
	(0.001)	(0.001)	(0.000)	(0.006)	(0.002)
	Egypt	El Salvador	Guatemala	Honduras	India
e	0.14***	0.02**	0.005*	0.00	0.02***
	(0.051)	(0.010)	(0.003)	(0.001)	(0.002)
	Indonesia	Jordan	Laos	Lebanon	Malaysia
e	0.001**	0.03***	0.00	0.06	0.01***
	(0.000)	(0.010)	(0.001)	(0.050)	(0.002)
	Mexico	Morocco	Myanmar	Nicaragua	Panama
e	0.002***	0.001*	0.00	-0.00	0.002**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
	Peru	Philippines	South Africa	Thailand	Vietnam
e	-0.0003**	0.09***	0.01***	-0.00	-0.00
	(0.000)	(0.012)	(0.001)	(0.001)	(0.000)
Cell FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Notes. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01) Standard errors in parenthesis. Unit of observation is the cell level. e is the export exposure in municipality i in time t. The dependent variable is the log of political violence. Sources: Desta, GAEZ Version 3, and DMSP-OLS.

TABLE A.9: ECONOMIC OUTPUT AFTER PTAS – SOUTH-SOUTH COOPERATION

	(1)	(2)	(3)	(4)	(5)
			Luminosity (Ln+1)		
E [export exposure]	-0.00496***	0.00324***	0.00467***	0.00609***	0.00557***
	(0.00060)	(0.00059)	(0.00057)	(0.00116)	(0.00163)
Constant	0.21706***	0.21655***	0.22585***	0.21706***	0.21442***
	(0.00099)	(0.00079)	(0.00082)	(0.00099)	(0.00382)
Cell FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country-specific trends	No	Yes	No	No	No
Grid-specific trends	No	No	Yes	No	No
Spatial lags	No	No	No	Yes	No
Country-year FE	No	No	No	No	Yes
No. of obs.	1,661,740	1,661,740	1,560,945	1,661,740	165,858
R^2	0.03160	0.04079	0.04259	0.03194	

Notes. (* p-value< 0.1; ** p-value<0.05; *** p-value<0.01) Standard errors in parenthesis. Unit of observation is the cell level. e is the export exposure in cell i in time t. The dependent variable is the log of luminosity. Sources: Desta, GAEZ Version 3, and DMSP-OLS.

TABLE A.10: POLITICAL VIOLENCE AFTER PTAS – SOUTH-SOUTH COOPERATION

	(1)	(2)	(3)	(4)	(5)
			Violence (Ln+1)		
E [export exposure]	0.00442***	0.00453***	0.00338***	0.00579***	0.00434***
	(0.00046)	(0.00047)	(0.00043)	(0.00115)	(0.00107)
Constant	0.00364***	0.00461***	0.00438***	0.00364***	0.00399***
	(0.00027)	(0.00026)	(0.00029)	(0.00027)	(0.00137)
Cell FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country-specific trends	No	Yes	No	No	
Grid-specific trends	No	No	Yes	No	
Spatial lags	No	No	No	Yes	No
Country-year FE	No	No	No	No	Yes
No. of obs.	1,749,200	1,749,200	1,643,100	1,749,200	174,920
R^2	0.00355	0.00983	0.01325	0.00359	0.01358

Notes. (* p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01) Standard errors in parenthesis. Unit of observation is the cell level. e is the export exposure in cell i in time t. The dependent variable is the log of the count of violent episodes. Sources: Desta, GAEZ Version 3, and DMSP-OLS.