Trade liberalization and political violence

SUMMARY

This paper investigates the impact of agricultural trade liberalization on economic activity and political violence in emerging countries. We use data on all preferential trade agreements (PTAs) signed between 25 low- and middle-income countries and their high-income trade partners between 1995 and 2013. We exploit the implied reduction in agricultural tariffs over time combined with variation within countries in their suitability to produce liberalized crops to find that economic activity increases differentially in affected areas. We also find strong positive effects on political violence, and present evidence consistent with both producer- and consumer-side mechanisms: violence increases differentially in more urbanized areas that are suitable to produce less labour-intensive crops as well as crops that are consumed locally. Our estimates imply that economic activity and political violence would have been around 2% and 7% lower, respectively, across countries in our sample had the PTAs not been signed.

JEL codes: D22, D24, F51, N45, O12

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Trade liberalization, economic activity and political violence in the Global South: evidence from PTAs

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1. INTRODUCTION

Trade liberalization creates winners and losers (Autor et al., 2013; Atkin, 2016). Recent papers show that the resulting distributional tensions increase political polarization and instability in high-income countries (Colantone and Stanig, 2017; Autor et al., 2020; Baccini and Weymouth, 2021; Dippel et al., 2022). Little is known, however, about

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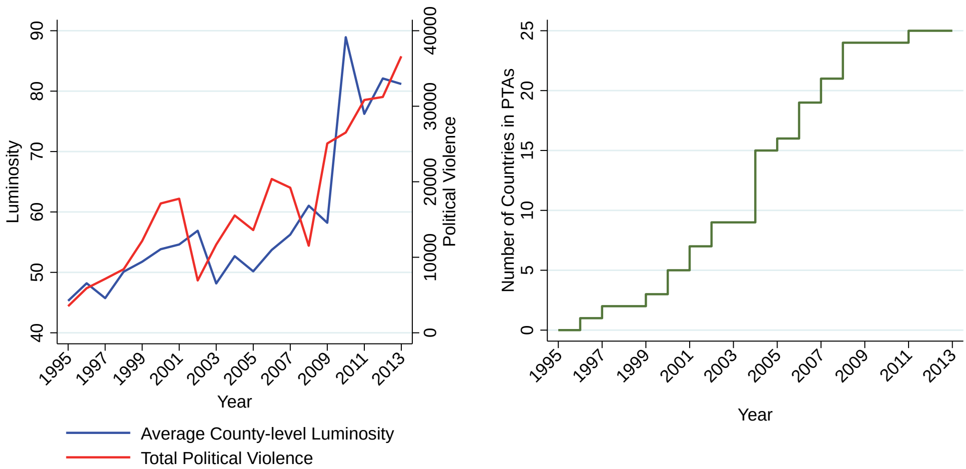

Figure 1. Economic activity, political violence and PTAs across countries

Notes: The left figure shows the evolution of the average county-level night-time luminosity and of the total count of politically violent episodes across the 25 countries in our sample over the period of the analysis, i.e. 1995–2013. The right figure shows the cumulative number of countries in the sample in any PTA at each point in time over the same period. Luminosity data are from the Defence Meteorological Satellite Programme's Operational Linescan System (DMSP-OLS), which we average across cells within counties (i.e., level 2 sub-national administrative units), then across counties within countries and then across countries each year. Data on politically violent episodes are from the ICEWS dataset. Data on PTAs come from the Design of Trade Agreements (DESTA) database. See Section 3 for additional information on each data source.

these issues in low- and middle-income countries. Contrary to the prediction of standard trade models, globalization has not reduced inequality in emerging economies (Goldberg and Pavcnik, 2007; Dix-Carneiro and Kovak, 2023), where political institutions are typically fragile and the state is weak. In these contexts, the uneven gains from trade and the distributional conflict for their appropriation can trigger political violence.

This paper investigates the effects of trade liberalization on economic activity and political violence in emerging countries. We use data on all preferential trade agreements (PTAs) signed between 1995 and 2013 involving 25 low- and middle-income countries and their high-income trade partners. Figure 1 provides the empirical motivation for this study. The left figure shows the evolution of economic activity (measured as night-time luminosity) across countries in our sample. It also shows the total count of politically violent episodes across countries, revealing a positive trend for both outcomes. The right figure shows that this happened as these low- and middle-income countries progressively entered in PTAs with high-income trade partners.

Through our empirical analysis, we examine whether these aggregate trends are causally interconnected. We focus on agricultural goods, and combine variation in the size and timing of tariff cuts with variation within and across countries in their suitability to produce liberalized crops. We find that economic activity increases differentially in those areas within countries that are more suitable to produce liberalized crops. We also find a positive, strong and robust differential effect on political violence.

To measure exposure to the agricultural tariff cuts mandated by PTAs, we use estimates of potential crop yields elaborated by the Food and Agriculture Organization's

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Global Agro-Ecological Zones (FAO-GAEZ) project. Those are derived solely on the basis of local soil and weather characteristics, and therefore independent from actual agricultural production and its trend. The very fine spatial resolution of these data, combined with the exogeneity of the measure, make them an ideal source to capture differences both within and across countries in their suitability to produce liberalized crops. The difference in the identity of partners, timing and tariff reduction schedules across the different PTAs in our sample further contributes to the variation that we exploit for identification.

We present three sets of results. First, we show that, following the PTA signature, economic activity increases differentially in those areas within countries that are more suitable to produce liberalized crops. A one standard deviation increase in export exposure at the county level yields a 7% increase in economic activity, as measured by night-time luminosity. Second, we show that political violence increases differentially in affected areas by about 4%, with the effect being differentially larger in more urbanized counties. Third, we show that this effect materializes through both producer- and consumer-side mechanisms. It is driven by crops whose production process is less labour-intensive, and by crops that are also consumed locally. We interpret these findings as revealing a struggle for redistribution of the gains from trade between land and capital owners on the one hand, and the rest of the population – agricultural workers and consumers of liberalized crops – on the other hand. Our estimates imply that overall economic activity and political violence would have been around 2% and 7% lower, respectively, across countries in our sample had the PTAs not been signed.

These findings stand up to a battery of robustness checks. We control for possible time-varying confounders by augmenting the baseline specification for all outcomes with the full set of country × year fixed effects, thus exploiting variation in export exposure across spatial units within countries in the same year. We also allow for differential trends within countries between ever-exposed and never-exposed areas, and further evaluate the robustness of results when controlling for future exposure.

Our study demonstrates how (agricultural) trade liberalization is both a boon and a curse for low- and middle-income countries: it brings about economic growth, but the uneven distribution of the gains from trade can increase political instability and violence. This is particularly important in contexts where inequality is high and the state lacks the capacity to put in place effective redistribution mechanisms. As such, our analysis highlights the importance for policymakers of taking into account and anticipating the distributional effects of trade liberalization and complementing it with other policies that can address potentially destabilizing imbalances (Atkin and Donaldson, 2015; Dix-Carneiro and Kovak, 2017, 2023; Autor et al., 2020). Our findings suggest that these policies should target areas in which agricultural production is less labour-intensive and the share of the urban population is sizeable. Indeed, these are locations in which, on the one hand, the positive effects on agricultural economic activity are less likely to be accompanied by an increase in employment and, on the other hand, real income is likely to fall because of the positive effect of trade liberalization on crop prices.

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Related literature and contributions Our paper is most related to the literature that studies the effect of trade liberalization on internal conflict and political violence.[1] The key contribution of Martin et al. (2008a) shows 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), especially if conflict puts those gains at risk. On the other hand, international trade may act as a substitute for internal trade during civil conflicts, reducing its opportunity cost and acting as an insurance mechanism. They conclude that trade openness may deter the most severe civil conflicts – those that destroy the largest amount of trade – but may increase the risk of lower-scale conflicts. The empirical evidence on trade-induced internal conflict is extremely limited. Focusing on Eastern African Countries only, Mayer and Thoenig (2016) find that, while decreasing the risk of inter-state conflict, regional trade agreements increase intra-state conflict. Amodio et al. (2021) provide microfounded evidence of how trade disruption increases political violence in the West Bank.

A richer body of economics and political science research investigates the association between economic conditions and political violence.[2] A large literature exploits changes in global commodity prices as a source of exogenous variation. Cross-country studies provide mixed evidence (see e.g., Fearon, 2005; Besley and Persson, 2008; Bruckner and Ciccone, 2010; Bazzi and Blattman, 2014). Other studies exploit variation at the sub-national level. Dube and Vargas (2013) show that the effect of export price variations on conflict intensity depends on the type of commodity. In Colombia, a reduction in the export price of coffee (a labour-intensive good) lowers wages and increases violence by reducing its opportunity cost, while the increase in the price of oil (a capital-intensive good) increases its value and thus violence through a rapacity effect.[3] Conducting a meta-analysis on 46 natural experiments, Blair et al. (2021) find that while

1 A related, complementary strand of the literature focuses on the effect of trade agreements on interstate wars. 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 (Schneider et al., 2003; Bussmann et al., 2006; Schneider, 2014). However, the empirical evidence is mixed (see for instance Barbieri, 1996; Beck et al. 1998; Vicard, 2012). 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 while countries more open to global trade have a higher probability of war.

2 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). 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 strong support for the opportunity cost theory of violence (Hidalgo et al., 2010; Bohlken and Sergenti, 2010).

3 Consistent with the rapacity effect, Berman et al. (2017) show that higher mineral prices increase conflict in mining areas and Crost and Felter (2020) find that the increase in the price of export crops in the Philippines leads to an increase in conflict, yet this happens only in areas not controlled by insurgents. Consistent with opportunity cost and state capacity mechanisms, Berman and Couttenier (2015) and Fjelde (2015) find that, in Africa, declining export revenues from agriculture increase the incidence of conflict battles.

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on average commodity price changes have no effect on civil conflict, price increases for labour-intensive agricultural commodities reduce conflict, while increases in the price of oil, a capital-intensive commodity, provoke conflict. McGuirk and Burke (2020) distinguish between producer- and consumer-side effects and between types of conflict, documenting a high degree of heterogeneity depending on the actors involved, commodities and forms of conflict. Finally, a few studies look at the link between (positive) agricultural shocks and conflict from a historical perspective. Iyigun et al. (2019) show that the introduction of the white potato from the Americas reduced conflict for two centuries in Europe. Dincecco et al. (2022) also study the introduction of New World crops after 1,500 and the consequent productivity shock, but find that greater caloric suitability due to the Columbian Exchange significantly increased conflict in Asia, consistent with a rapacity effect.

This paper contributes to the literature on trade liberalization, economic conditions and political violence in several ways. First, we combine data on tariff cuts with information on crop suitability at a fine geographical scale to provide direct evidence that PTAs that involve agricultural commodities increase economic activity in those areas within countries that are more suitable to produce liberalized crops. We do this for 25 low and middle-income countries at the same time, which in and of itself addresses possible concerns over the findings' external validity. Second, we show that political violence increases in these same areas. Third, building on the existing literature (Dube and Vargas, 2013; McGuirk and Burke, 2020), we exploit variation across crops in their characteristics to provide direct evidence that these political violence effects materialize through both producer- and consumer-side mechanisms. Fourth, differently from international commodity prices – which are determined by the interaction of demand and supply at the global level – trade agreements are policy tools on which governments have direct control. Therefore, our analysis provides clear policy implications that are useful to governments implementing trade liberalization.

There is also a limited but growing literature looking at the effects of trade liberalization on non-economic outcomes such as crime (Dix-Carneiro et al., 2018; Dell et al., 2019), education (Atkin, 2016), mental distress (Crino et al., 2019) and the environment (Tanaka et al., 2022). We contribute by providing robust evidence of an additional possible side effect of trade liberalization in developing countries, namely an increase in political violence.

The remainder of the paper is organized as follows. Section 2 presents the conceptual framework for the empirical analysis. Section 3 introduces the data, while the empirical strategy is presented in Section 4. Section 5 presents the main results, while Section 6 investigates the underlying mechanisms. Section 7 concludes.

2. CONCEPTUAL FRAMEWORK

Tariffs introduce a wedge between the price paid by consumers in importing countries and the price paid to producers in exporting countries. Removing tariffs on imports

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from country A to country B increases the equilibrium level of exports from A to B. The unit price paid to producers increases, as do marginal revenue productivity and agricultural output. This gives us a first prediction to take to the data: agricultural trade liberalization increases agricultural output and its value.

Does this matter for political violence and instability? The literature identifies several possible channels. On the one hand, increased economic activity in agriculture increases the demand for farm labour and thus wages in that sector. This decreases the opportunity cost of engaging in political violence, thereby reducing its supply (Becker, 1968; Grossman, 1991; Dube and Vargas, 2013). Hence, political violence should decrease in light of this *opportunity cost* channel. Yet, on the other hand, the increase in the value of agricultural output increases the gains from appropriation which can, in turn, increase the supply of violence. This *rapacity* effect generates a positive relationship between agricultural trade liberalization and political violence.[4]

Building on Dal Bo and Dal Bo (2011), we can qualify this reasoning further by taking into account the importance of the labour input in production. Labour intensity is tightly linked to the labour share of income and thus the extent to which the gains from trade benefits workers as opposed to land and capital owners. It therefore shapes the distributional effect of trade and the scope for the rapacity versus opportunity cost channel, as the former (latter) should prevail when liberalization interests mostly less (more) labour-intensive crops. This is the second prediction that we take to the data: trade liberalization of less labour-intensive crops should increase political violence differentially compared to trade liberalization of more labour-intensive crops.

The above considerations focus on the producer side. Yet, consumers are also likely to be affected. To understand how, we build on McGuirk and Burke (2020) and their analysis of how shocks to different kinds of crop prices differentially affect conflict depending on their production and consumption patterns. We expect the same increase in price that favours producers to be harmful to consumers as it decreases wages and income in real terms. This effect decreases the opportunity cost of fighting and increases political violence. But, the extent to which this consumer-side mechanism confounds the producer-side mechanisms identified above crucially depends on whether production and consumption of the same crop are spatially concentrated. This leads to our third and last prediction: trade liberalization of crops that are not only produced but also consumed locally should increase political violence differentially compared to trade liberalization of crops that are produced locally but consumed elsewhere.

To summarize, our conceptual framework predicts that, first, agricultural trade liberalization increases agricultural economic activity. Second, trade liberalization of less

4 The salience of the rapacity effect can increase through other mechanism such as migration: the positive boost in agricultural output and its value could act as a pull factor, and the resulting migrant influx and fight for appropriation can escalate into political violence. Although the lack of yearly data on migration flows and population count at the sub-national level limits our ability to study the role of migration, the evidence we present in Section 5.3 suggests that this is not the key mechanism behind our findings.

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labour-intensive crops increases political violence differentially compared to trade liberalization of more labour-intensive crops. Third, trade liberalization of crops that are not only produced but also consumed locally increases political violence differentially compared to trade liberalization of crops that are produced locally but consumed elsewhere.

In the empirical analysis that follows, we take these predictions to the data. To do so, we derive a plausibly exogenous measure of exposure to agricultural trade liberalization at the sub-national level for a number of countries and PTAs, and relate them to economic activity and political violence exploiting within-country variation over time at a fine geographical scale.

In using PTAs to assess the effect of trade liberalization on political violence, two caveats apply. First, PTAs are bilateral or plurilateral agreements. They reduce tariffs in a reciprocal way for all countries involved. As a result, and despite possible asymmetries in the timing of tariff cuts, the impact of cutting agricultural tariffs on imports from low-income countries is potentially mitigated by a similar reduction of tariffs on imports from the high-income partner country. This means that the effects that we identify are likely a lower bound for the impact of unilateral trade liberalizations.

Second, PTAs typically reduce tariffs for both agricultural and manufacturing products. Trade liberalization of manufacturing goods can map into political violence through the same opportunity cost, rapacity and consumption channels that we discussed above, a possibility we will discuss again in the conclusions. Yet, this would threaten the validity of our analysis 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, economic activity in the manufacturing sectors for which tariffs decreased more should overlap spatially with economic activity and production of liberalized crops. We believe that this is far from being the case as most of manufacturing activity is concentrated far from where agricultural activity takes place.

3. DATA

In our empirical analysis, we combine different data sources to derive a panel of sub-national geographical units for the period from 1995 to 2013.

3.1. Sample To build our sample, we start by considering all the 27 low- and middle-income countries that signed a PTA agreement with one major high-income country during the period 1995–2013.[5] The high-income PTA partners that we consider are Australia, Canada, the European Union, Japan, South Korea and the USA. Appendix Table A.1 provides the list of the 25 countries and PTAs that we consider in our sample.

5 To define low- and middle-income countries, we refer to the World Bank categorization, see https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups. As explained below, the last year we could consider is 2013 as that is the last year for which the night-time luminosity data we use are available.

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Out of the initial 27, we exclude Tunisia and Turkey as they both sign only one PTA (with the EU) in the first year of the data so we do not have information prior to the signature.

The sample of countries we consider has some interesting features. First, with few exceptions, the countries in our sample experience on average relatively low levels of violence, many of them being stable democratic regimes. Notably, our sample excludes almost entirely Sub-Saharan Africa (except for South Africa), which has experienced more than half of worldwide conflict incidents since the 1960s, despite having only about 16% of the world population (Cilliers, 2015). For this reason, we frame our analysis as a tough test as it is probably harder to find a relationship between trade and political violence in these countries. Second, because they involve a high-income and a low- and middle-income trade partner, the PTAs we consider are more likely to be enforced due to power asymmetry (Baccini and Urpelainen, 2014) and less likely to produce trade diversion compared to PTAs signed between lower-income countries (Magee, 2008).

3.2. Tariff cuts The second piece of information pertains to the details of these PTAs and their implementation. We use the information in the Design of Trade Agreements (DESTA) database (Dür et al., 2014). These data provide information on various types of PTAs 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 our purposes, DESTA provides information on the baseline level of tariffs and tariffs cuts for each year through the implementation period. It does so at the Harmonized Commodity Description and Coding System (HS) 6-digit level.[6] That is, information on tariff cuts is available for specific commodities, such as 'cacao' or 'coffee', and – crucially for our empirical strategy – large differences exist in the size of tariff cut across products within each PTA.

Tariff reduction schedules are extracted from the officially negotiated ones listed in the appendices of the PTAs. Thus, the tariff cuts that we consider are *de jure* and not *de facto* because countries can set applied tariffs that are different from the ones mandated by the PTA. For this reason, we regard *de jure* tariff cuts as more exogenous than *de facto* tariffs and independent from the evolution of output and trade flows after the PTA signature. For the same reason, and in order to rule out as much as possible any anticipatory effects, we take the year of the signature of the agreement – as opposed to the year of implementation – as the relevant year after which we aim to identify the economic and political impact of the PTAs.

3.3. Crop suitability, output and production value We combine the information on tariff cuts across crops and PTAs with data on crop suitability and potential yields at the sub-

6 For further information on tariff data, see Dür et al. (2014).

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national level, which we obtain from the Global Aero-Ecological Zones (GAEZ version 3) project (IIASA/FAO 2012; Fischer et al., 2002). Pursued jointly by the Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied System Analysis (IIASA), this source uses detailed agronomic-based knowledge to assess land suitability and potential attainable yields at a very fine geographical level. The corresponding data are freely available online, and have already been used in the economics literature and trade studies in particular (Costinot and Donaldson, 2012, 2016; Costinot et al., 2016). For each 9 km × 9 km cell into which the planet is divided into, and for each of 42 main crops, the data provide information on suitability and potential yield. We use the information on total production capacity per hectare under rain-fed agriculture and using low or intermediate levels of inputs. These estimates of production capacity are solely based on agro-climatic conditions (soil and weather characteristics) 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 the PTA. As a result, FAO-GAEZ data allow us to derive an exogenous, agro-climatic-based measure of total production capacity for different crops at the sub-national level for each country in our sample.

To validate these measures of agricultural suitability as well as the main measure of economic activity (see below), we also use data on actual production volumes and their value, which FAO-GAEZ makes available for the years 2000 and 2010 only. The data on actual yields are available for each crop while those on production value are available for each cell by aggregating all main crops.[7]

We map all HS 6-digit agricultural product codes into FAO-GAEZ crop categories to merge tariffs and agricultural suitability data. Figure 2 shows the average size of tariff cut across crops, averaged across all PTAs in our sample.

3.4. Crop features In the exploration of the mechanisms at play, we use additional information on the nature of each crop and its production process. First, we consider the relative importance of the labour input, which we take from Talhelm and English (2020). We classify the crops in the analysis accordingly and split them into a low and a high labour intensity group. The former includes barley, buckwheat, foxtail millet, maize, oat, pearl millet, rye, sorghum and wheat, while the latter includes (wetland and dryland) rice. Second, we build on McGuirk and Burke (2020) and their classification of crops into those that are likely produced and consumed in the same location, called ‘food’ crops, and those that are instead produced in a given cell but consumed elsewhere, named ‘cash’ crops. Among those in our sample, the former group includes maize, oil palm, dryland rice and wetland rice, sorghum, soybean, sugar beet and sugar cane, wheat and buckwheat, while the latter includes cocoa, coffee, tea and tobacco. Both

7 Crop production value is expressed in Geary Kharmis dollars (GK$), an international price weight (year 2000) used by UN to compare different commodities across countries in value terms.

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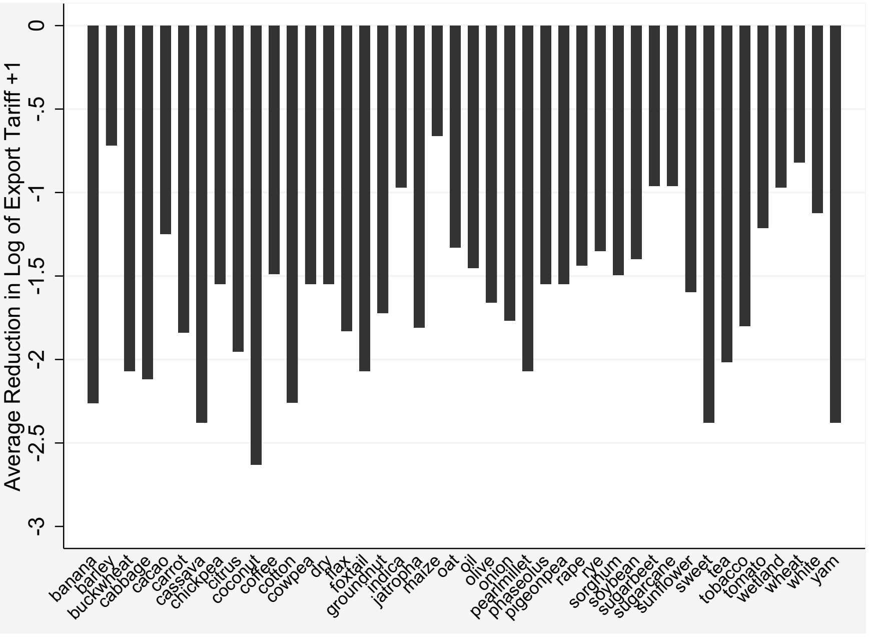

Figure 2. Average size of tariff cut by crop

Notes: For each FAO-GAEZ crop category, the figure shows the size of the tariff cut in % and averaged across all PTAs in our sample. That is, if baseline tariffs were 10%, and decreased to 5% as a result of the PTA, then the % tariff cut would be equal to 0.5 since (10−5)/10.

these classifications are not exhaustive, meaning that some crops cannot be classified into either category. For this reason, apart from using them in the corresponding heterogeneity exercises, we show the robustness of the main results using only the subset of crops that we can classify in either way.

3.5. Economic activity We measure economic activity at the sub-national level using data on luminosity at night (Henderson et al., 2012; Michalopoulos and Papaioannou 2013a,b). Commonly used as proxy for GDP in the absence of other reliable sources, the data come from the Defence Meteorological Satellite Programme's Operational Linescan System (DMSP-OLS). It reports time-stable images of the earth at night captured between 8 pm and 9:30 pm. We use Version 4 which spans the years from 1992 to 2013 included. The main advantage of luminosity data is that they can be aggregated at various geographical levels. Appendix Table A.2 shows the summary statistics of luminosity by country, averaged across the FAO-GAEZ 9 km × 9 km cell units. It is evident that the variable luminosity has few outliers with large values. We thus follow the literature and use the log of the raw value of luminosity, adding one not to lose observations with zero luminosity (Henderson et al., 2012; Michalopoulos and Papaioannou, 2013a,b; Pinkovskiy and Sala-i-Martin, 2016). For robustness, we also use a dummy equal to one if luminosity has positive values, i.e. if the cell or spatial unit is lit.

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The ability of these data to proxy for agricultural economic activity is an empirical question. As mentioned above, FAO-GAEZ provides data on actual production volumes and their value only for 2000 and 2010, preventing us from using those directly as measures of economic activity in agriculture. Still, as we show later, we can use this data to investigate the correlation between agricultural output and luminosity both across and within 9 km × 9 km cells (the FAO-GAEZ unit of observation), corroborating the use of night-time lights as proxy.

3.6. Political violence To measure political violence, we rely on the Integrated Crisis Early Warning System (ICEWS) dataset (Shilliday and Lautenschlager, 2012). Prepared by Lockheed Martin Advanced Technology Laboratories, these data cover the period from 1995 to 2022. The dataset records any interaction between socio-political actors (i.e., cooperative or hostile actions between individuals, groups, sectors and nation-states). Therefore, unlike other datasets such as Armed Conflict Location and Event Dataset (ACLED), the ICEWS dataset focuses on not only episodes of political violence but also codes and classifies any political interaction. For instance, ICEWS events also include political statements, accusations of crime or corruption or human rights abuses. Each entry provides information on the source and target of each interaction, together with the level of hostility or cooperation 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 as follows. We keep all events geo-referenced between 1995 and 2013 in the sample countries and classified as *hostile*, meaning having intensity value from −10 (high intensity) to −1 (low intensity). We then classify each category as violent or non-violent.[8] The final dataset counts 472,980 events of political violence between 1995 and 2013 in the 25 sample countries. The most frequent events are: use of unconventional violence, fighting with small arms and light weapons and use of conventional military force. Events can be aggregated at a given geographical level, allowing us to track the evolution of political violence over time at sub-national scale.

Appendix Table A.3 shows the summary statistics of political violence by country, averaged across the FAO-GAEZ 9 km × 9 km cells. Two features stand out. First, and not surprisingly, there is large variation across countries. Second, the number of violent episodes is quite low, as many cells do not record any violence. In the main analysis, and similarly to what we do with luminosity, we use the log of the count of violent episodes in a given spatial unit (adding one not to lose observations with no violence) to mitigate the impact of outliers, and assess robustness using a dummy equal to one if any violence is recorded. We also show that the results hold true when measuring political violence using the information from the Social Conflict Analysis Database (SCAD), which has

8 See Supplementary Appendix Table B.1 for the details of the classification.

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been used extensively in the conflict literature (e.g., see Berlanda et al., 2022). SCAD represents a complete and extensive measure of social violence of different forms (protests, demonstrations, riots, strikes and other forms of social disturbances) and comprises a classification of different event types, including organized events, spontaneous events and events related to elections, economic grievances or human rights. As such, it focuses on social violence defined as social and political unrest, as opposed to large-scale organized armed conflicts as it is the case for UCDP/PRIO data (Sundberg and Melander, 2013).[9]

3.7. Country institutions We categorize the type of government in each country by using the Polity V database (Center for Systemic Peace, 2021). This database compiles data on several components of governing institutions in 167 countries. These components are then merged into an overall scale ranging from −10 to +10 scale which can be used to split regimes in three categories: autocracies (−10 to −6), anocracies (−5 to +5) and democracies (+6 to +10). For the Polity V Project, and in line with our conceptual framework, democracy has three key dimensions: (i) the presence of institutions and procedures through which citizens can express effective preferences about alternative policies and leaders; (ii) institutionalized constraints on the exercise of power by the executive; and (iii) the guarantee of civil liberties to all citizens in their daily lives and in acts of political participation.[10] As of 1995 (our baseline year), about 40% of our sample is represented by democracies (10 out of 25 countries).

3.8. Urbanization, geographical characteristics, ethnic diversity and population We retrieve information on the level of urbanization of sub-national units within countries from MODIS (Schneider et al., 2010). The data are available for all years from 2001 to 2012 at the level of 250 m × 250 m cells. We calculate the share of area classified by MODIS as 'urban' in its first available year. We define a dummy equal to one if the geographical unit under consideration has a share of urban land that is above the country-level median. We do the same with other characteristics that, as we explain in Section 5.4, the literature has identified as salient. These include: presence of natural resource such as diamond or oil, distance from the border, distance from the coast, ruggedness and ethnic diversity. We report the data sources for all these variables in Appendix B.2. We source population data at the sub-national level from the Gridded Population of the World version 4 dataset (CIESIN, 2016) which provides estimates of population count at fine spatial resolution every 5 years starting from 1990.[11] In our

9 We cannot explore robustness to using ACLED data because coverage begins in 1997 and data for all years since then exist only for African countries.

10 Besides these three dimensions, other aspects of pluralistic democracy include the rule of law, systems of checks and balances and freedom of the press.

11 Harmonized, yearly data on migration flows and population count at the sub-national level are not available for the countries in our sample and over the period of our analysis.

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analysis, we assign the 1990 population value to all observations from 1990 to 1994, the 1995 value to observations from 1995 to 1999, and so on.

3.9. Other controls We also construct several additional sub-national controls. To account for elevation, we construct the average altitude in each spatial unit by averaging out the 1 km × 1 km raster dataset from the National Oceanic and Atmospheric Administration (NOAA). To capture climatic features, we construct average precipitation and temperatures measures from 1960 to 1991 from the Climatic Research Unit version 2.0. We retrieve data on average temperature from 1960 and 1991 from FAO-GAEZ. We also use information on area covered by water using water bodies in the Digital Chart of the World. We report the data sources for these variables in Appendix B.2

4. EMPIRICAL STRATEGY

We expect the economic and political effects of PTAs to be differential within countries, and larger in those areas that are more suitable to produce crops that experience a larger tariff cut. As such, the interaction between the size of tariff cut and crop suitability determines each area's exposure to the PTA and its consequences. For example, if a given PTA cut tariffs on maize more than for coffee, we would expect a larger increase in economic activity in those areas that are highly suitable to produce maize relative to those that are suitable for coffee.

We build on this intuition and derive a measure of PTA exposure as follows. Let τ_{ct} be the proportional change in tariffs applied by the high-income partner country to the country's imports of crop c between baseline and year t. That is, if baseline tariffs applied to maize were 10%, and decreased to 5% 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 area i to produce crop c.

We compute the $Export\ Exposure_{it}$ for each area i at time t as

$$Export\ Exposure_{it} = \sum_c \tau_{ct} S_{ic} \tag{1}$$

This is our main explanatory variable. It combines variation over time in the size of tariff cuts with geographical variation in the suitability to produce different crops. It differs from zero if the area is suitable to produce crops ($S_{ic} > 0$) for which the PTA mandates a tariff cut ($\tau_{ct} > 0$). By construction, τ_{ct} is equal to zero for all crops and so is $Export\ Exposure_{it}$ for all years prior to the PTA signature. Notice also that τ_{ct} is specific to each year and PTA (and thus country) while S_{ic} is time-invariant but different across crops and geography. The latter is informed by agro-climatic conditions only, so that the variation within country and year in export exposure is determined a priori and does not respond itself to the implementation of PTAs. Figure A.1 shows the variation in export exposure by country averaged across 9 km × 9 km cells.

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4.1. Regression specification For a given geographical unit i and outcome of interest Y_{it}, we identify the impact of $Export\ Exposure_{it}$ by implementing the following baseline regression specification

$$Y_{it} = \gamma_i + \delta_t + \beta\, Export\ Exposure_{it} + u_{it} \tag{2}$$

where the fixed effects γ_i control for and net out all time-invariant characteristics at the level of the geographical unit, while δ_t nets out year-specific trends. The residuals u_{it}, which we cluster at the level of the unit i, capture any time-variant unobserved determinant of Y_{it}. Our coefficient of interest is β. It captures any systematic relationship between PTA-driven export exposure and the outcome of interest. To ease the interpretation of the coefficient, we rescale the $Export\ Exposure_{it}$ variable and divide it by its standard deviation so that β directly captures the effect of a one standard deviation increase in export exposure.

Identification requires changes over time in export exposure across units to be orthogonal to changes in the unobserved determinants of the outcome of interest. That is, we assume parallel trends: in the absence of the PTAs, the evolution of economic and political outcomes would not have been systematically different between areas with varying levels of export exposure. To validate this assumption and address possible violations, we augment the baseline specification for all outcomes with country-specific year fixed effects or linear and non-linear trends. We even allow for differential trends within countries between ever-exposed ($Export\ Exposure_{it} > 0$ at any point) and never-exposed areas. Finally, we evaluate the robustness of results when controlling for future exposure.

5. RESULTS

In what follows, we present three sets of results. First, we document the effect of export exposure on economic activity at the finest geographical resolution for which we can consistently retrieve data. Second, we show the same results hold when aggregating data at the county level, i.e. level 2 sub-national administrative units. Third, we investigate the effect of export exposure on political violence.

5.1. Economic activity

5.1.1. Cell-level analysis. Table 1 reports the estimates of the main coefficient from Equation (2) that we obtain using OLS. It does so having as unit of analysis the 9 km × 9 km cells for which crop suitability data are available. The dependent variable is the (log of) night-time luminosity in the cell. In column 1, we implement the regression specification in Equation (2) as such, with only cell and year fixed effects as additional regressors. Starting with column 2, we control for possible time-varying confounders. In column 2, we include the full set of country × year fixed effects, thus

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Table 1. Export exposure and economic activity at cell level

	Economic activity						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Export exposure	0.016***	0.025***	0.023***	0.025***	0.024***	0.023***	0.018***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No	No	No
Country-specific trends	No	No	Yes	No	No	No	No
Country-specific flex. trends	No	No	No	Yes	No	No	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes	Yes	Yes
Spatial lags	No	No	No	No	No	Yes	No
Cell specific char. × linear trends	No	No	No	No	No	No	Yes
Observations	4,356,871	4,356,871	4,356,871	4,356,871	4,356,871	4,356,871	4,178,252
R-squared	0.895	0.898	0.896	0.897	0.897	0.897	0.898

Notes: *p-value< 0.1; **p-value< 0.05; ***p-value< 0.01. The unit of observation is the FAO-GAEZ cell. Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of night-time luminosity. Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature, and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units. In column 6, we include spatial lags to account for spillover effects within larger 110 km×110 km cells. In column 7, we include a rich set of (time-invariant) geographic and other controls that include elevation, ruggedness of terrain, share of area covered by water, precipitation, temperature, distance from the border and the coast and the number of ethnic groups, and interact them with linear trends.

exploiting variation in export exposure across cells within countries in the same year. In column 3, we include country-specific linear trends. In column 4, we include country-specific flexible trends. That is, we allow every country to have its own trend in the years prior to signature, a jump in the year of signature, and another linear trend in the years after. Column 5 considers flexible trends which are further different within countries between ever-exposed ($Export\ Exposure_{it} > 0$ at any point) and never-exposed cells. These trends are similar to the previous ones, but they vary between the two groups, that is, treated and controls. In column 6, we include spatial lags to account for spillover effects within 110 km. More precisely, we control for the sum of export exposure in the other cells falling within the same 110 km × 110 km larger grid. Finally, in column 7, we saturate the specification with a rich set of geographic and other controls that include elevation, ruggedness of terrain, share of area covered by water, precipitation, temperature, distance from the border and the coast and the number of ethnic groups. We interact all these time-invariant controls with linear trends in order to account for cell-specific characteristics that could possibly vary together with export exposure.

Across all these specifications, the estimate is remarkably stable. Export exposure increases economic activity. One standard deviation increase in export exposure is

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associated with an increase in economic activity of about 2%. With these estimates in hand, we can calculate the percentage change in aggregate economic activity that is attributable to the PTAs in our sample. Setting the value of the coefficient of export exposure equal to zero, we predict the value of output in each cell that we would have observed in absence of the PTA.[12] We find that economic activity would have been around 2% lower in sample countries had the PTAs not been signed.

The magnitude of this effect is comparable to the one found in the literature. Anderson et al. (2006) estimate that full trade liberalization would increase agricultural output by 2.2% in developing countries, while van der Mensbrugghe and Beghin (2005) estimate an increase of 2.6%. Other studies focusing on Middle East and North African countries find that liberalization is expected to increase real GDP by 1–3% (IPFRI, 2007). Other studies looking at the impact of bilateral free trade agreements between the EU and other countries on agricultural output also report estimates in this range (Beranger et al., 2016; Norman-López, 2016).

5.1.2. Validation. A first, immediate concern with these results pertains to the validity of night-time lights as proxy for economic activity. Although several studies provide evidence in this direction (see for instance Michalopoulos and Papaioannou 2013a,b), our analysis focuses on agricultural economic activity, and its relation with night-time luminosity is not straightforward. To address this concern, we use data on the value of agricultural production at the cell level and correlate them with luminosity at night. We can do this exercise separately for the two years for which both data are available, i.e. 2000 and 2010, but also look at variation over time by means of a fixed effects (or first-difference, since we have only two time periods) specification that nets out all time-invariant characteristics at the cell level that may yield a spurious correlation. Appendix Table A.4 shows the corresponding results, whose strength validates night-time lights as proxy of agricultural economic activity.

A similar concern pertains to our main explanatory variable and the use of suitability and potential yields – as opposed to actual production – as a way to capture the differential exposure to the economic and political effects of tariff cuts within countries. As discussed in Section 3, we do this to address from the start any concerns of endogeneity of the exposure measure to the PTA itself. Nonetheless, we correlate the suitability data with actual production by crop for the years 2000 and 2010. We can pool together all crops, and explore this correlation conditional on crop fixed effects as well as country

12 We quantify the percentage increase in aggregate economic activity as follows. We use the coefficient estimates in column 1 of Table 1 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 $\beta = 0$, that is, $\tilde{y}_{it} = \hat{y}_{it} - \hat{\beta} \times$ *Export Exposure*$_{it}$. We then aggregate both values across cells and years for the post-treatment period to get $\hat{Y} = \sum_{t=0}^{10} \sum_s \hat{y}_{it}$ and $\tilde{Y} = \sum_{t=0}^{10} \sum_s \tilde{y}_{it}$. The estimated increase in aggregate economic activity due to the policy is given by $(\tilde{Y} - \hat{Y})/\hat{Y}$.

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and even cell fixed effects. Appendix Table A.5 reports the results, showing that potential yields strongly correlate with actual yields.

5.1.3. County-level analysis. We estimate the effect of export exposure on economic activity at the county level, i.e. level 2 sub-national administrative units. We do this for several reasons. First, using 9 km $\times$ 9 km cells as units of analysis can be problematic if the effects of export exposure are not extremely localized, because of violations of SUTVA. Second, the administrative unit is a more natural unit of analysis to analyse economic but especially political effects, as these are politically relevant units. Third, using administrative units is less arbitrary or controversial than using cells as we can take the former as given and not driven by data availability.

We thus compute our measure of export exposure and night-time lights at the county level, and implement the regression specification in Equation (2). Table 2 shows the corresponding OLS coefficient estimates. The specifications in columns 1–5 map exactly from those in Table 1. The number of observations falls to about 200,000 because we are now aggregating data at a lower spatial resolution. Yet, the positive effect of export exposure is strong and precisely estimated. The results are robust and stable across the various specification that, as in Table 1, take into account and net out unobserved trends in various ways. One standard deviation increase in export exposure at the county level is associated with a 1.7% increase in economic activity.

5.2. Political violence

Evidence shows that PTAs increase economic activity, differentially more so in those areas that are suitable to produce liberalized crops. We now ask whether this has any consequences for political violence.

Figure 3 illustrates the relationship between the change in export exposure between the first and the last year in our sample, i.e. between 1995 and 2013, and the change in economic activity and political violence across all counties in our sample. Specifically, it reports the average change in each of the two variables by bins of the change in export exposure, together with the linear fit. Both lines are positively sloped, indicating that economic activity and political violence increase differentially in those counties that experience larger export exposure.

To investigate the effect on political violence in a systematic way, we implement the same regression specification in Equation (2) having the county as unit of analysis and replacing as dependent variable the (log of) political violence. Table 3 reports the corresponding coefficient estimates, ordered as in Table 2. Export exposure increases political violence. The estimated effect is comparable across specifications, particularly when country-level trends are accounted for, and highly significant. The estimates in columns 3–5 indicate that a one standard deviation increase in export exposure increases political violence in the county by about 1%.

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Table 2. Export exposure and economic activity at county level

	Economic activity				
	(1)	(2)	(3)	(4)	(5)
Export exposure	0.014***	0.013**	0.017***	0.017***	0.017***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.931	0.938	0.934	0.934	0.934

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of night-time luminosity. Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units.

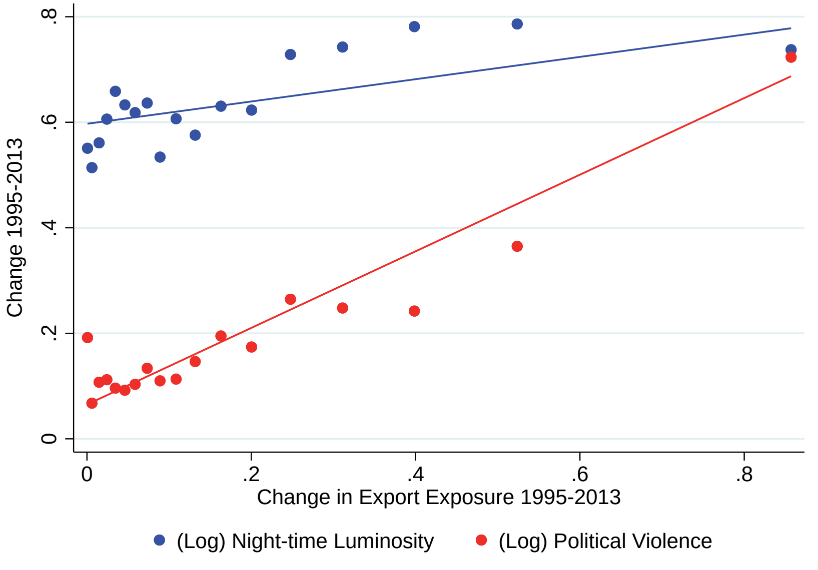

Figure 3. Change in export exposure, economic activity and political violence

Notes: The Figure shows the relationship between the change in export exposure between the first and the last year in our sample, i.e. between 1995 and 2013, and the change in economic activity and political violence across all counties in our sample. It reports the average change in each of the two variables by bins (ventiles) of the change in export exposure, together with the linear fit.

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Table 3. Export exposure and political violence at county level

	Political violence				
	(1)	(2)	(3)	(4)	(5)
Export exposure	0.026***	0.008***	0.010***	0.010***	0.010***
	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.663	0.716	0.701	0.701	0.701

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS). Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units.

Assuming export exposure only affects violence through its impact on economic activity, we can combine the estimates in Tables 2 and 3 to derive the implied elasticity of political violence to economic activity. For example, the coefficient in column 2 of Table 3 divided by the corresponding one in Table 2 implies an elasticity of about 0.6.

In Appendix Table A.6, we report the estimates obtained considering the 9 km × 9 km cell as unit of analysis, thus mirroring Table 1. Similar to what we did for luminosity, we can take the estimate in column 1 of Appendix Table A.6 and predict the level of political violence that we would have observed in the absence of the PTAs. We find that they account for about 7% of the total number of violent events in the sample countries in the period of analysis. Also in this case, the two effects align closely, with export exposure increasing simultaneously economic activity and political violence at such small geographical scale. The implied elasticity of political violence to economic activity is lower in this case, equal to about 0.12. This is likely due to the fact that the effects of export exposure on political outcomes are not as localized as the economic ones, underscoring the importance of taking the county as baseline unit of analysis, as we do in Table 3.

5.3. Robustness

The estimated positive effect of export exposure on both economic activity and political violence at the county level stands up to a battery of robustness checks, which we report in Tables A.7–A.18.

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First, we replace the continuous log night-time luminosity variable with the dummy variable *lit* which is equal to one if the area has luminosity greater than zero. We also replace the continuous log political violence variable with a dummy equal to one if any violence is recorded in the county. We report the results in Appendix Tables A.7 and A.8. Export exposure is a strong and significant determinant of whether a county is *lit* after the implementation of the PTA. We find equally strong effects for political violence measured at the extensive margin.

Second, we implement the Conley (2009) procedure to correct our estimates for spatial and serial correlation errors within a radius of 500 km (McGuirk and Burke 2020). As shown in Appendix Table A.9, this does not affect the results.

Third, and most importantly, we consider the possibility that counties with differentially higher exposure to the PTA were already on a different trend prior to its signature and implementation. Allowing for differential trends within each country between ever-exposed ($Export\ Exposure_{it} > 0$ at any point) and never-exposed counties, as we do in column 5 of Tables 2 and 3, already assuages this concern. We take one step forward and include as additional regressors export exposure as measured at several points in time in the near future, with and without controlling for past exposure as well. Appendix Table A.10 shows the results. Although some of the coefficients capturing future exposure are statistically significant, many of them are negative, and the estimated effect of contemporaneous export exposure on both economic activity and violence is even larger than the baseline. This diminishes further the concerns over possible violations of the parallel trend assumption.

Fourth, we check whether the effect of export exposure on political violence still stands when using alternative sources and definitions for political violence. We implement two exercises in this direction. First, we use SCAD data to measure political violence. These include protests, riots, strikes, inter-communal conflict, government violence against civilians and other forms of social conflict. Appendix Table A.11 shows the corresponding results, which, with the exception of column 1, are highly comparable to the baseline ones in both magnitude and significance.[13] Second, we dissect the ICEWS data further to derive alternative measures of hostility and violence. We consider: (i) all (violent and non-violent) events classified as hostile, meaning with intensity lower than or equal to -1; (ii) we count only high hostility events, i.e. with intensity lower than or equal to -5; (iii) we consider only very high hostility events, meaning those with intensity equal to -10. We report the results in Appendix Tables A.12. They are mostly comparable to baseline when considering hostile and high hostility events, but smaller in magnitude and insignificant when considering only very high hostility. While intriguing, interpreting this last result is challenging because very high hostility events are

13 The SCAN dataset covers only 13 of the 25 countries in our analysis. This makes our sample size drop by more than 50%, from around 200,000 to about 85,000 observations.

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much rarer to begin with, and power issues may affect the ability to capture significant effects within our framework.

Fifth, we investigate whether our results are driven by a single country. We implement our main specification excluding one country at the time from the estimating sample. The results in Appendix Tables A.13 and A.14 show that no individual country is driving the findings, both for economic activity and political violence.

Sixth, to check whether our results are driven by who is the partner country, we include North partner country FEs and we also allow for trends in economic activity and political violence to be specific to each partner country and different in the years prior versus after the signature. Appendix Table A.15 shows that this does not change the main results in any meaningful way.

Seventh, the results hold true when we control for population at the county level. Appendix Table A.16 shows that the coefficient for *Export Exposure* in both the economic activity and political violence regressions do not change, suggesting that migration and population changes are not the main determinants of our findings.

To conclude, we return on the discussion in Section 2 on how PTAs typically reduce tariffs in a reciprocal way for both parties, and how this could mitigate the effect of export exposure that we estimate in reduced form. To shed light on this issue, we compute a measure of *Import Exposure* that mirrors the *Export Exposure* measure by replacing τ_{ct} in Equation (1) with the proportional change in tariffs applied by South country to the import of crop c from high-income partner between baseline and year t. We include both measures as explanatory variables in our main regression specification. Appendix Tables A.17 and A.18 report the corresponding coefficient estimates. The results show that, first, compared to baseline, the effect of export exposure is much bigger in magnitude when controlling for import exposure, and that, relatedly, the effect of import exposure *per se* on economic activity and political violence is negative and significant.

5.4. Heterogeneity

Export exposure positively impacts economic activity and political violence in those areas within countries that are suitable to produce liberalized crops. In exploring the determinants of political violence and conflict, the literature has unveiled a number of empirical regularities. We now bring those results into the analysis to investigate whether those play any role in mediating the impact of export exposure on political violence.

5.4.1. Country institutions. We begin by exploring the possibility that country-level institutional characteristics may mediate the effect of export exposure on economic activity and political violence. A possible key distinction is between democracies and non-democracies, with theoretically ambiguous predictions. On the one hand, democratic institutions incorporate multiple redistribution mechanisms while also conducting free and fair elections. These both contribute to mitigating the societal tensions caused by

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Table 4. Differential effect of export exposure in democracies

	Economic activity			Political violence		
	(1)	(2)	(3)	(4)	(5)	(6)
Export exposure	0.018***	0.008	0.012**	−0.001	0.004*	0.003*
	(0.006)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)
× Democratic	−0.014	0.019	0.020	0.087***	0.016**	0.027***
	(0.010)	(0.013)	(0.013)	(0.013)	(0.007)	(0.008)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	Yes	No
Country-specific trends	No	No	Yes	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676	197,676
R-squared	0.931	0.938	0.934	0.666	0.716	0.701

Notes: *$p < 0.1$. **$p < 0.05$. ***$p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit *inyear* that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of luminosity for the first three columns and the log of political violence (i.e., the number of hostile and violent events in ICEWS) for 4–6 columns. Democratic is a dummy that equals 1 if there is democracy in the respective country for 1995 based on Polity V. A state is democratic if the *polity2* score is higher than or equal to 6.

the uneven gains from trade. More generally, democracies allow for the possibility to publicly express discontent towards the effect of a given policy, a condition that is not always given in non-democratic countries. On the other hand, democratic systems, by giving people the opportunity to voice their grievances and mobilize, may also foster instances of protests and riots, possibly leading to political violence. In fact, in non-democratic countries, political violence may be less likely to occur simply because police control is much stricter to begin with.

Results in Table 4 columns 1–3 indicate that the effect of export exposure on economic activity is not differential between democratic and non-democratic countries. But, this is not the case for political violence. As shown in columns 4–6, the effect on political violence is significantly differentially larger in democratic countries. These results suggest that freedom of mobilization and protest is more salient than institutional redistribution mechanisms in shaping the impact of export exposure on political violence.[14]

5.4.2. County characteristics. Next, we consider a number of local-level characteristics that may mediate the impact of export exposure on political violence. The first dimension we consider is the level of urbanization. Poverty and marginalization of the

14 Other possibly important heterogeneities to be considered in terms of country-level institution characteristics are: i) existence and extent of taxation system (Besley and Persson, 2009); ii) existence and extent of welfare system (Fetzer, 2020); iii) revenue sharing mechanisms (Fetzer and Kyburz, 2022); contestability of rents (Fetzer and Marden, 2017). Unfortunately, cross-country data to test these hypotheses are only available for a small number of countries in our sample and only for selected years throughout the period of analysis.

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periphery are at the core of some of the most prominent explanations of armed conflict (Herbst, 2000; Blattman and Miguel, 2010). Agricultural activity takes place predominantly in rural areas, and if agricultural trade liberalization improves living standards, we should expect less or even a reduction of political violence in more rural counties. At the same time, while producers in rural areas should benefit from higher food prices, consumers will be harmed. Because the relative numerosity of the latter is higher in urban areas, higher food prices could both reduce rural rebellions and increase urban-based unrest (McGuirk and Burke, 2020). We investigate whether this is the case by defining a dummy equal to one if the urbanization level of the county is above the country median, which we interact with the main measure of export exposure. We also consider alternative measures of remoteness such as distance from the border, distance from the coast and ruggedness. Similar to what we do for urbanization, we operationalize them by defining a dummy above the country median.

We also consider the presence of natural resources as a mediating factor. Agricultural trade liberalization may decrease violence in areas that are rich in natural resources as the gains from trade may dilute pre-existing societal tension and distributional conflict. Specifically, we consider whether the county is rich in diamonds (Guidolin and La Ferrara, 2007; Rigterink, 2020) or oil (Collier and Hoeffler, 2004; Dube and Vargas, 2013), and define dummy variables accordingly.

The last key determinant of conflict that we consider is ethnic diversity (Montalvo and Reynal-Querol, 2005). Conflict over the appropriation of the gains from trade is more likely to escalate and become violent where the number of ethnic groups is larger. Also in this case, we consider the median number of ethnic groups across counties in each country, and define accordingly a dummy equal to one for more ethnically diverse counties.

Table 5 reports the results that we obtain when considering all these dimensions of heterogeneity altogether by including all interactions of each dummy with export exposure in the same regression specification. Urbanization stands out as being the most relevant feature and thus key in shaping the impact of agricultural trade liberalization on political violence. The coefficient of the interaction between export exposure and the urban dummy is significant at the 1% level across all specifications.[15] The effect of export exposure is also differentially lower for counties located further away from the coast, but since coastal areas are typically denser, we interpret this as another manifestation of the rural-urban gradient. As for the other interaction variable coefficients, in most cases, their sign is consistent with the reasoning outlined above. It is negative for diamond and oil-rich counties, and positive for more ethnically diverse counties. However, the estimates are not statistically significant at standard levels.

We take the strong urban heterogeneity result as an indication that consumer-side mechanisms are at play. In the next section, we provide an in-depth investigation of the channels, focusing on both producer- and consumer-side mechanisms.

15 The results are robust to using SCAD to measure political violence, see Appendix Table A.19.

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Table 5. Export exposure and political violence – heterogeneity

	Political violence				
	(1)	(2)	(3)	(4)	(5)
Export exposure	0.121***	0.065***	0.076***	0.076***	0.076***
	(0.016)	(0.012)	(0.012)	(0.012)	(0.012)
× Urban	0.101***	0.065***	0.073***	0.073***	0.073***
	(0.025)	(0.017)	(0.019)	(0.019)	(0.019)
× Far from border	0.010	0.004	0.005	0.005	0.005
	(0.008)	(0.005)	(0.006)	(0.006)	(0.006)
× Far from coast	−0.119***	−0.069***	−0.078***	−0.078***	−0.078***
	(0.016)	(0.012)	(0.012)	(0.012)	(0.012)
× Rugged	0.000	−0.014*	−0.012	−0.012	−0.012
	(0.011)	(0.008)	(0.008)	(0.008)	(0.008)
× High in diamonds	0.035**	−0.006	−0.004	−0.004	−0.004
	(0.017)	(0.012)	(0.013)	(0.013)	(0.013)
× High in petrol	−0.015*	−0.004	−0.006	−0.006	−0.006
	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
× Ethnically diverse	0.000	0.007	0.004	0.004	0.004
	(0.011)	(0.007)	(0.008)	(0.008)	(0.008)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.668	0.717	0.703	0.703	0.703

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS). All interaction variables are dummies equal to one if the value for the county is above the median at the country level. Through fspecific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units.

6. MECHANISMS

Evidence shows that export exposure positively impacts economic activity and political violence in those areas within countries that are suitable to produce liberalized crops, and that it does so differentially in more urbanized areas. In the following, we explore the possible mechanisms behind these results. We build on the conceptual framework in Section 2, and take its implications to the data exploiting heterogeneity across crops and their characteristics.

6.1. Crop labour intensity

Based on existing evidence, our conceptual framework predicts that the effect of agricultural trade liberalization on political violence depends on the importance of labour

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input in production. Labour intensity is tightly linked to the labour share of income and thus the extent to which the gains from trade benefit workers as opposed to land and capital owners. It therefore shapes the distributional effect of trade and the scope for the rapacity versus opportunity cost channels. Drawing on the theoretical insights of Dal Bo and Dal Bo (2011), we expect that the trade liberalization of less labour-intensive crops should increase political violence differentially compared to trade liberalization of more labour-intensive crops.

In testing this prediction, a challenge lies in is the possibility to categorize crops according to their labour content. We adopt the classification proposed by Talhelm and English (2020) for which (wetland and dryland) rice is a high labour intensity crop while barley, buckwheat, foxtail millet, maize, oat, pearl millet, rye, sorghum and wheat are low labour intensity crops. We use this information to construct two different versions of our $\textit{Export Exposure}_{it}$ variable computed considering only low and only high labour intensity crops.[16]

Table 6 shows the results that we obtain when implementing a version of regression Equation (2) which includes both variables as main regressors, having political violence as an outcome. It shows that the main average effect is driven exclusively by less labour-intensive crops. We interpret this evidence as showing that asymmetry in the gains from trade between workers versus land and capital owners is a key mechanism through which export exposure increases political violence.

Following the heterogeneous analysis in Section 5.4, we look at the possibility that the crop-specific effect on political violence varies depending on the county's level of urbanization. Table 7 shows that the increase in violence is largest in more urbanized counties that are suitable to produce less labour-intensive crops, and lower in rural ones. Violence increases differentially also in urbanized counties that are suitable to produce more labour-intensive crops, but to a lower extent, and absent in rural ones. Evidence supports the hypothesis that the distributional conflict arising from trade liberalization of less labour-intensive crops manifests itself in more urbanized areas, where a lower share of the population is employed in agriculture and thus reaps the (already small, in the case of low intensive crops) benefits from trade.

6.2. Crop production and consumption

We further explore the mechanisms behind the trade-induced increase in political violence and its differential effects that we document by looking at the distinction between

16 This categorization does not allow us to classify all the crops considered in the baseline analysis, but it is comprehensive enough to generate meaningful variation across counties. Appendix Table A.20 shows that our baseline result (i.e., that trade liberalization increases political violence) holds also if we consider only this subset of classifiable crops to compute overall export exposure.

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Table 6. Crop labour intensity, export exposure and political violence

	Political violence				
	(1)	(2)	(3)	(4)	(5)
EE – Low labour intensity crops	0.083***	0.026***	0.035***	0.035***	0.035***
	(0.013)	(0.008)	(0.008)	(0.008)	(0.008)
EE – High labour intensity crops	−0.003	0.002	0.002	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.669	0.716	0.702	0.702	0.702

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). This is calculated separately for low and high labour intensity crops (Talhelm and English, 2020). The former include barley, buckwheat, foxtail millet, maize, oat, pearl millet, rye, sorghum and wheat, while the latter includes (wetland and dryland) rice. The dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS). Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units.

types of crops introduced by McGuirk and Burke (2020).[17] They distinguish between 'food crops' (i.e., crops that are consumed locally) and 'cash crops' (i.e., non-food crops or crops that are more likely to be consumed elsewhere). We expect the impact of trade agreements on political violence to be different across counties producing the two types of crops. Because trade liberalizations increase local crop prices and their volatility, they could harm consumers and, if produced crops are also consumed locally, reduce real income. It follows that we expect the effect of trade liberalization on political violence to be larger in counties producing more food crops.

Similarly to what we have done for labour intensity, we construct two alternative export exposure measures computed considering only cash (cocoa, coffee, tea and tobacco) and only food crops (maize, oil palm, dryland rice and wetland rice, sorghum, soybean, sugar beet and sugar cane, wheat and buckwheat). Table 8 shows the main results obtained when the two are included as regressors.[18] Evidence shows that trade liberalization has opposite effects on political violence depending on whether the county

17 Note that our ICEWS-based measure of political violence is close in spirit to the one adopted by McGuirk and Burke (2020) when they measure output conflict, that is, violence over the appropriation of surplus. They select events that are likely to be more transitory and less organized than large-scale factor conflict battles. To this end, they use the ACLED categories 'riots and protests' and 'violence against civilians'.

18 Appendix Table A.21 shows that our baseline result (i.e., that trade liberalization increases political violence) holds also if we consider only this subset of crops to build our variable Export Exposure.

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Table 7. Crop labour intensity, export exposure, urbanization and political violence

	Political violence				
	(1)	(2)	(3)	(4)	(5)
EE – Low labour intensity crops	0.044***	0.007	0.011**	0.011**	0.010**
	(0.012)	(0.005)	(0.005)	(0.005)	(0.005)
EE – Low labour intensity crops × Urban	0.109***	0.068***	0.075***	0.075***	0.075***
	(0.018)	(0.009)	(0.010)	(0.010)	(0.010)
EE – High labour intensity crops	−0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
EE – High labour intensity crops × Urban	−0.000	0.014*	0.014**	0.014**	0.014**
	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)
County FE					
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.672	0.717	0.703	0.703	0.703

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). This is calculated separately for low and high labour intensity crops (Talhelm and English, 2020). The former include barley, buckwheat, foxtail millet, maize, oat, pearl millet, rye, sorghum and wheat, while the latter includes (wetland and dryland) rice. The dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS). Urban is a dummy equal to one if the share or urban land in the county is above the median at the country level. Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units.

produces mainly crops that are consumed locally versus not. Political violence increases in counties that produce crops that are mostly consumed locally while it decreases in counties producing crops consumed elsewhere (thus also exported). We interpret these results as being fully consistent with an opportunity cost mechanism. In counties producing crops that are both produced and consumed locally, the price increase due to trade liberalization and the subsequent reduction in real income more than offsets the gains from trade. The opportunity cost of fighting decreases, and political violence increases as a result. On the contrary, in counties producing crops consumed elsewhere, the trade gain effect dominates, the marginal revenue product of labour increases, and the opportunity cost of fighting increases. The larger this latter effect, the more likely that the net effect of the trade liberalization is a reduction in political violence in counties producing cash crops.[19]

19 These results are in line with those in McGuirk and Burke (2020) showing that shocks to food crop prices have a greater impact on output conflict than shocks to cash crop prices.

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Table 8. Food and cash crops, export exposure and political violence

	Political violence				
	(1)	(2)	(3)	(4)	(5)
EE – Food crops	0.048***	0.018**	0.030***	0.030***	0.030***
	(0.015)	(0.007)	(0.008)	(0.008)	(0.008)
EE – Cash crops	−0.037***	−0.013**	−0.026***	−0.026***	−0.026***
	(0.011)	(0.006)	(0.006)	(0.006)	(0.006)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.663	0.716	0.701	0.701	0.701

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). This is calculated separately for food and cash crops (McGuirk and Burke, 2020). The former include maize, oil palm, dryland rice and wetland rice, sorghum, soybean, sugar beet and sugar cane, wheat and buckwheat, while the latter includes cocoa, coffee, tea and tobacco. The dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS). Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units.

This interpretation is also supported by the heterogeneity results shown in Table 9. In line with our reasoning, we find that the increase in political violence occurs only in more urbanized counties, where the agricultural share of employment is lower. We also find that the reduction in political violence in counties that produce cash crops is concentrated in rural counties, once again corroborating the hypothesis of a positive urban gradient in political violence.

7. CONCLUSION

This paper studies the effects of agricultural trade liberalization on economic activity and political violence in low- and middle-income countries. We use newly combined data on agricultural suitability by crop at very fine spatial resolution together with information on the tariff cuts mandated by a large number of PTAs signed between 25 low- and middle-income countries and their high-income trade partners between 1995 and 2013. We find that economic activity increases significantly in those areas within countries that are most suitable to produce liberalized crops. Yet, political violence also increases, and differentially so in more exposed urban counties.

Evidence shows that, when workers and consumers do not share the gains from trade, agricultural trade liberalization can exacerbate distributional conflict. Our

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Table 9. Food and cash crops, export exposure, urbanization and political violence

	Political violence				
	(1)	(2)	(3)	(4)	(5)
EE – Food crops	0.020**	0.012**	0.019***	0.019***	0.019***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
EE – Food crops × Urban	0.229***	0.086**	0.117***	0.117***	0.117***
	(0.062)	(0.036)	(0.037)	(0.037)	(0.037)
EE – Cash crops	−0.018**	−0.012**	−0.019***	−0.019***	−0.019***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
EE – Cash crops × Urban	−0.085**	−0.007	−0.029	−0.029	−0.029
	(0.033)	(0.016)	(0.018)	(0.018)	(0.018)
County FE					
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.666	0.717	0.702	0.702	0.702

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). This is calculated separately for food and cash crops (McGuirk and Burke, 2020). The former include maize, oil palm, dryland rice and wetland rice, sorghum, soybean, sugar beet and sugar cane, wheat and buckwheat, while the latter includes cocoa, coffee, tea and tobacco. The dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS). Urban is a dummy equal to one if the share or urban land in the county is above the median at the country level. Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units.

findings highlight the need for policymakers to address the imbalances between trade winners and losers so as to escape the trade-off between economic growth and political instability. At the same time, trade-induced political violence may not necessarily be negative if, for instance, it is instrumental to achieving redistribution and reallocation of the gains from trade, which can increase stability in the long term. Furthermore, the violence we observe can also be tightly linked with the triggering or deepening of democratization processes. Due to the limitations of our data and identification strategy, we are unable to collect evidence on these mechanisms, leaving their exploration for future research.

Finally, while focusing on agricultural trade liberalization, the mechanisms we uncover are not exclusive to the agricultural sector. When the labour input does not reap the benefit, manufacturing trade liberalization can also lead to increased societal and political tension. This is particularly relevant as many low-income countries are now experiencing a pattern of industrialization that is markedly different from the ones observed in the past. Assessing quantitatively the impact of manufacturing trade liberalization on political instability and violence in emerging countries presents its own challenges that future research will need to address.

APPENDIX 1: ADDITIONAL TABLES AND FIGURES

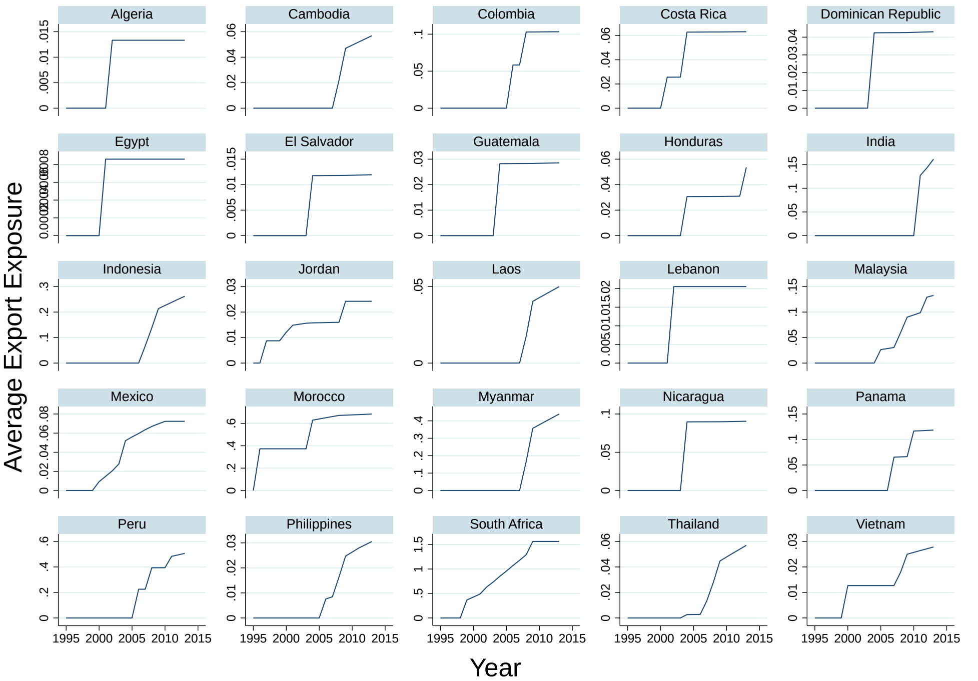

Figure A.1. Export exposure by country over time

Notes: The figure shows the average value of Export Exposure across FAO-GAEZ cells within countries over time. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). As such, the variable begins to take positive values at the time of PTA signature, and only if and only if any agricultural crop experiences any tariff cut and any cell in the country is suitable to produce it.

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Table A.1. List of Countries and PTAs

ID	Country	PTA
1	Algeria	Algeria-EU (2002)
2	Cambodia	ASEAN Japan (2008)
		ASEAN Australia New Zealand (2009)
3	Colombia	Colombia USA (2006)
		Colombia Canada (2008)
4	Costa Rica	Costa Rica Canada (2001)
		CAFTA DR USA (2004)
5	Dominican Republic	CAFTA DR USA (2004)
6	Egypt	Egypt-EU (2001)
7	El Salvador	CAFTA DR USA (2004)
8	Guatemala	CAFTA DR USA (2004)
9	Honduras	CAFTA DR USA (2004)
		Honduras Canada (2013)
10	Nicaragua	CAFTA DR USA (2004)
11	India	India Japan (2011)
12	Indonesia	Indonesia Japan (2007)
		ASEAN Japan (2008)
		ASEAN Australia New Zealand (2009)
13	Jordan	Jordan US (2000)
		Jordan EU (1997)
		Jordan Canada (2009)
14	Laos	ASEAN Japan (2008)
		ASEAN Australia New Zealand (2009)
15	Lebanon	Lebanon EU (2002)
16	Malaysia	Malaysia Japan (2005)
		ASEAN Japan (2008)
		ASEAN Australia New Zealand (2009)
		Malaysia Australia (2012)
17	Mexico	Mexico EU (2000)
		Mexico Japan (2004)
18	Morocco	Morocco EU (1996)
		Morocco US (2004)
19	Myanmar	ASEAN Japan (2008)
		ASEAN Australia New Zealand (2009)
20	Panama	Panama US (2007)
		Panama Canada (2010)
21	Peru	Peru US (2006)
		Peru Canada (2008)
		Peru Japan (2011)
22	Philippines	Philippines Japan (2006)
		ASEAN Japan (2008)
		ASEAN Australia New Zealand (2009)
23	South Africa	South Africa EU (1999)
24	Thailand	Thailand Australia (2004)
		Thailand Japan (2007)
		ASEAN Japan (2008)
		ASEAN Australia New Zealand (2009)
25	Vietnam	Vietnam US (2000)
		Vietnam Japan (2008)
		ASEAN Japan (2008)
		ASEAN Australia New Zealand (2009)

Notes: The table lists the 25 countries and PTAs that are part of our analysis.

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Table A.2. Descriptive statistics of night-time 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	1.85	5.63	0	63
Honduras	1.28	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	8.69	0	63
Mexico	2.23	7.09	0	63
Morocco	1.23	5.11	0	63
Myanmar	0.21	1.96	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	3.16	8.09	0	63
Vietnam	2.05	6.03	0	63

Notes: The table reports summary statistics of the night-time luminosity variable by country and across FAO-GAEZ cells.

Table A.3. Descriptive statistics of violence by country

Country	Mean	St. Dev.	Min	Max
Algeria	0.01	1.01	0	294
Cambodia	0.08	2.88	0	254
Colombia	0.07	4.98	0	987
Costa Rica	0.09	1.64	0	80
Dominican Republic	0.05	0.86	0	35
Egypt	0.07	10.14	0	3,502
El Salvador	0.15	2.50	0	99
Guatemala	0.07	2.11	0	126
Honduras	0.05	2.09	0	289
India	0.17	7.28	0	2,090
Indonesia	0.05	3.88	0	1,054
Jordan	0.10	3.27	0	213
Laos	0.00	0.29	0	44
Lebanon	4.65	52.90	0	2,262
Malaysia	0.09	3.46	0	395
Mexico	0.04	2.56	0	727
Morocco	0.02	0.75	0	111
Myanmar	0.02	1.12	0	194
Nicaragua	0.03	1.06	0	103

(*continued*)

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Table A.3. Continued

Country	Mean	St. Dev.	Min	Max
Panama	0.03	0.88	0	58
Peru	0.02	1.67	0	637
Philippines	0.29	7.96	0	816
South Africa	0.06	1.84	0	300
Thailand	0.16	11.68	0	2,947
Vietnam	0.03	1.39	0	142

Notes: The table reports summary statistics of the political violence variable (i.e., the number of hostile and violent events in ICEWS) by country and across FAO-GAEZ cells.

Table A.4. Night-time luminosity and value of agricultural production

	(Log) Night-time Luminosity				
	2000		2010		All
	(1)	(2)	(3)	(4)	(5)
(Log) Production Value	0.101***	0.109***	0.124***	0.131***	0.094***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Country FE	No	Yes	No	Yes	n.a.
Cell FE	No	No	No	No	Yes
Observations	229,309	229,309	229,309	229,309	458,618
R-squared	0.168	0.255	0.184	0.264	0.925

Notes: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. The unit of observation is the FAO-GAEZ cell. Standard errors in parenthesis, clustered at the same level. The dependent variable is the log of night-time luminosity. The main independent variable is the log of agricultural production value from FAO-GAEZ. Crop production value is expressed in Geary Kharmis dollars (GK), i.e. an international price weight (year 2000), used by UN, to compare different commodities in value terms.

Table A.5. Suitability and total agricultural production

	(Log) Total production				
	2000		2010		All
	(1)	(2)	(3)	(4)	(5)
(Log) Suitability	0.144***	0.130***	0.153***	0.135***	0.141***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Crop FE	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	n.a.
Cell FE	No	No	No	No	Yes
Observations	4,127,562	4,127,562	4,127,562	4,127,562	8,255,124
R-squared	0.391	0.443	0.399	0.455	0.523

Notes: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. The unit of observation is the FAO-GAEZ crop × cell. Standard errors in parenthesis, clustered at the cell level. The dependent variable is the log of produced yields (in tons) from FAO-GAEZ. The main independent variable is the log of suitability and thus potential yields estimated at the same level. Because we have multiple observations (one per crop) for each cell and year, in column 5, we can include both crop and cell fixed effects.

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Table A.6. Export exposure and political violence at cell level

	Political violence						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Export exposure	0.002**	0.003***	0.003***	0.003***	0.002***	0.003***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No	No	No
Country-specific trends	No	No	Yes	No	No	No	No
Country-specific flex. trends	No	No	No	Yes	No	No	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes	Yes	Yes
Spatial lags	No	No	No	No	No	Yes	No
Cell-specific char. × linear trends	No	No	No	No	No	No	Yes
Observations	4356871	4356871	4356871	4356871	4356871	4356871	4178252
R-squared	0.580	0.584	0.583	0.583	0.583	0.583	0.582

Notes: $*p < 0.1$. $**p < 0.05$. $***p < 0.01$. The unit of observation is the FAO-GAEZ cell. Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS). Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure $>$ 0 at any point) and never-exposed spatial units. In column 6, we include spatial lags to account for spillover effects within larger 110 km×110 km cells. In column 7, we include a rich set of (time-invariant) geographic and other controls that include elevation, ruggedness of terrain, share of area covered by water, precipitation, temperature, distance from the border and the coast and the number of ethnic groups and interact them with linear trends.

Table A.7. Export exposure and economic activity – lit versus not lit

	Economic Activity				
	(1)	(2)	(3)	(4)	(5)
Export Exposure	0.001	0.003*	0.004**	0.004**	0.004**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.750	0.761	0.753	0.753	0.753

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable a dummy equal to one if night-time luminosity is greater than zero, and zero otherwise. Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure $>$ 0 at any point) and never-exposed spatial units.

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Table A.8. Export exposure and political violence – any violence versus no violence

	Political violence				
	(1)	(2)	(3)	(4)	(5)
Export exposure	0.008***	0.004***	0.004***	0.004***	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.485	0.519	0.508	0.508	0.508

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable a dummy equal to one if political violence (i.e., the number of hostile and violent events in ICEWS) is greater than zero, and zero otherwise. Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units.

Table A.9. Export exposure, economic activity and violence: robustness using Conley standard errors

	Economic activity		Political violence	
	(1)	(2)	(3)	(4)
Export exposure	0.014***	0.013**	0.026***	0.008***
	(0.003)	(0.003)	(0.004)	(0.002)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	Yes
Observations	197,676	197,676	197,676	197,676
R-squared	0.931	0.938	0.663	0.716

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The unit of observation is the county (level 2 administrative unit). Conley standard errors in round brackets (500 km of distance as cut-off). Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). In columns 1 and 2, the dependent variable is the log of night-time luminosity. In columns 3 and 4, the dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS).

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Table A.10. Future and past export exposure, economic activity and violence

	Economic activity		Political violence	
	(1)	(2)	(3)	(4)
Export exposure	0.024***	0.021***	0.049***	0.015*
	(0.007)	(0.007)	(0.008)	(0.008)
Export exposure $t+1$	−0.012	−0.020*	−0.014	−0.037**
	(0.008)	(0.010)	(0.010)	(0.015)
Export exposure $t+2$	−0.015***	−0.016**	−0.031***	−0.011
	(0.006)	(0.007)	(0.009)	(0.009)
Export exposure $t+3$	0.002	0.008	−0.011	−0.006
	(0.005)	(0.006)	(0.008)	(0.010)
Export exposure $t+4$	0.017***	0.017***	−0.006	−0.011
	(0.006)	(0.005)	(0.007)	(0.007)
Export exposure $t+5$	−0.009	−0.013**	0.038***	0.035***
	(0.005)	(0.005)	(0.008)	(0.011)
Export exposure $t-1$		0.015*		0.048***
		(0.009)		(0.011)
Export exposure $t-2$		−0.013*		−0.013
		(0.008)		(0.008)
Export exposure $t-3$		−0.015		−0.173***
		(0.011)		(0.030)
Export exposure $t-4$		0.023		0.101***
		(0.014)		(0.022)
Export exposure $t-5$		0.015		0.147***
		(0.009)		(0.021)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	145,656	93,636	145,656	93,636
R-squared	0.948	0.964	0.676	0.737

Notes: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). We include leads and lags as additional regressors in columns 1 and 2, the dependent variable is the log of night-time luminosity. In columns 3 and 4, the dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS).

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Table A.11. Export exposure and political violence – SCAD data

	Political violence				
	(1)	(2)	(3)	(4)	(5)
Export exposure	−0.002 (0.003)	0.012** (0.005)	0.011** (0.005)	0.011** (0.005)	0.011** (0.005)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	84,664	84,664	84,664	84,664	84,664
R-squared	0.324	0.350	0.332	0.332	0.333

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of political violence, now measured as the number events in SCAD. Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units.

Table A.12. Export exposure and alternative measures of hostility and violence

	(1)	(2)	(3)	(4)	(5)
	All hostile events				
Export exposure	0.026*** (0.007)	0.009** (0.004)	0.011*** (0.004)	0.011*** (0.004)	0.011*** (0.004)
	Events of High Hostility				
Export exposure	0.025*** (0.007)	0.007** (0.003)	0.010*** (0.004)	0.010*** (0.004)	0.009** (0.004)
	Events of Very High Hostility				
Export exposure	0.009*** (0.003)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of political violence measured in different ways. In the top panel we consider all (violent and non-violent) events classified as hostile, meaning with intensity lower than or equal to −1. In the mid panel, we count only high hostility events,i.e. with intensity lower than or equal to −5. In the bottom panel, we consider only very high hostility events, meaning those with intensity equal to −10. Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (export exposure > 0 at any point) and never-exposed spatial units.

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Table A.13. Export exposure and economic activity – dropping individual countries

	Economic activity				
	(1)	(2)	(3)	(4)	(5)
	Algeria	Cambodia	Colombia	Costa Rica	Dominican R.
Export exposure	0.018***	0.013***	0.012***	0.014***	0.013***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
	Egypt	El Salvador	Guatemala	Honduras	India
Export exposure	0.014***	0.013***	0.014***	0.013***	0.013***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
	Indonesia	Jordan	Laos	Lebanon	Malaysia
Export exposure	0.012**	0.014***	0.013***	0.013***	0.014***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
	Mexico	Morocco	Myanmar	Nicaragua	Panama
Export exposure	0.012**	0.012***	0.011**	0.013***	0.014***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
	Peru	Philippines	South Africa	Thailand	Vietnam
Export exposure	0.022***	0.009**	0.017***	0.013***	0.016***
	(0.007)	(0.005)	(0.006)	(0.005)	(0.005)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of night-time luminosity. The coefficient is estimated dropping one country in our sample at a time. For example, the first value is the coefficient from the subsample dropping Algeria.

Table A.14. Export exposure and political violence – dropping individual countries

	Political violence				
	(1)	(2)	(3)	(4)	(5)
	Algeria	Cambodia	Colombia	Costa Rica	Dominican R.
Export exposure	0.023***	0.026***	0.031***	0.026***	0.026***
	(0.006)	(0.006)	(0.009)	(0.006)	(0.006)
	Egypt	El Salvador	Guatemala	Honduras	India
Export exposure	0.026***	0.025***	0.026***	0.026***	0.020***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
	Indonesia	Jordan	Laos	Lebanon	Malaysia
Export exposure	0.030***	0.026***	0.026***	0.026***	0.026***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)

(*continued*)

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Table A.14. Continued

	Political violence				
	(1)	(2)	(3)	(4)	(5)
	Mexico	Morocco	Myanmar	Nicaragua	Panama
Export exposure	0.025***	0.026***	0.026***	0.026***	0.026***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
	Peru	Philippines	South Africa	Thailand	Vietnam
Export exposure	0.053***	0.026***	0.013***	0.025***	0.025***
	(0.008)	(0.006)	(0.004)	(0.006)	(0.006)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS). The coefficient is estimated dropping one country in our sample at a time. For example, the first value is the coefficient from the subsample dropping Algeria.

Table A.15. Export exposure and robustness to partner-specific trends

	Economic activity			Political violence		
	(1)	(2)	(3)	(4)	(5)	(6)
Export exposure	0.017***	0.016***	0.016***	0.010***	0.010***	0.009***
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-spec. trends (tr/non-tr)	Yes	Yes	Yes	No	No	No
North partner post-sign. FE	No	Yes	Yes	No	Yes	Yes
North partner post-sign. flex. trends	No	No	Yes	No	Yes	Yes
Observations	197,676	197,676	197,676	197,676	197,676	197,676
R-squared	0.934	0.935	0.935	0.701	0.702	0.702

Notes: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of night-time luminosity in columns 1–3, and the log of political violence (i.e., the number of hostile and violent events in ICEWS) in columns 4–6. For each dependent variable, the first column replicates column 5 in Tables 2 and 3, respectively. In the second column, we include dummies for each high-income partner involved in the PTA interacted with a post-signature dummy. In the third column, we further interact the latter with linear time trends.

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Table A.16. Export exposure and robustness to population changes

	Economic activity			Political violence		
	(1)	(2)	(3)	(4)	(5)	(6)
Export exposure	0.017***	0.017***	0.017***	0.010***	0.010***	0.010***
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific flex. trends	Yes	No	No	Yes	No	No
Country-spec. trends (tr/non-tr)	No	Yes	Yes	No	Yes	Yes
County 5-year population	No	No	Yes	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676	197,676
R-squared	0.934	0.934	0.934	0.701	0.701	0.704

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of night-time luminosity in columns 1–3, and the log of political violence (i.e., the number of hostile and violent events in ICEWS) in columns 4–6. For each dependent variable, the first two columns replicate columns 4 and 5 in Tables 2 and 3, respectively. In the third column, we control for population by assigning the 1990 population value to all observations from 1990 to 1994, the 1995 value to observations from 1995 to 1999, etc., using data from Gridded Population of the World (CIESIN 2016).

Table A.17. Export and import exposure and economic activity

	Economic activity				
	(1)	(2)	(3)	(4)	(5)
Export exposure	0.028**	0.048***	0.071***	0.071***	0.070***
	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)
Import exposure	−0.014	−0.034**	−0.052***	−0.052***	−0.052***
	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.931	0.938	0.934	0.934	0.934

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export and Import Exposure are the PTA-driven export and import exposures of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of night-time luminosity. Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature, and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export and Import Exposure > 0 at any point) and never-exposed spatial units.

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Table A.18. Export and import exposure and political violence

	Political Violence				
	(1)	(2)	(3)	(4)	(5)
Export exposure	0.188***	0.056***	0.092***	0.092***	0.092***
	(0.019)	(0.013)	(0.013)	(0.013)	(0.013)
Import exposure	−0.164***	−0.047***	−0.079***	−0.079***	−0.079***
	(0.017)	(0.011)	(0.012)	(0.012)	(0.012)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.666	0.716	0.702	0.702	0.702

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export and Import Exposure are the PTA-driven export and import exposures of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS). Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export and Import Exposure > 0 at any point) and never-exposed spatial units.

Table A.19. Export exposure, urbanization and political violence – SCAD data

	Political violence				
	(1)	(2)	(3)	(4)	(5)
Export exposure	−0.007**	0.007	0.006	0.006	0.006
	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Export exposure × Urban county	0.015**	0.014**	0.014**	0.014**	0.014**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	84,664	84,664	84,664	84,664	84,664
R-squared	0.324	0.350	0.333	0.333	0.333

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). The dependent variable is the log of political violence, now measured as the number of events in SCAD. Urban is a dummy equal to one if the share or urban land in the county is above the median at the country level. Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units.

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Table A.20. Export exposure and political violence – only low/high labour int. crops

	Political violence				
	(1)	(2)	(3)	(4)	(5)
Export exposure	0.043***	0.013***	0.019***	0.019***	0.019***
	(0.010)	(0.004)	(0.005)	(0.005)	(0.005)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.665	0.716	0.701	0.701	0.702

Notes: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). This is calculated considering only those crops that we can classify into low and high labour intensity crops (Talhelm and English, 2020). The former include barley, buckwheat, foxtail millet, maize, oat, pearl millet, rye, sorghum and wheat, while the latter includes (wetland and dryland) rice. The dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS). Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units.

Table A.21. Export exposure and political violence – only food and cash crops

	Political violence				
	(1)	(2)	(3)	(4)	(5)
Export exposure	0.015***	0.006**	0.007**	0.007**	0.007**
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country–year FE	No	Yes	No	No	No
Country-specific trends	No	No	Yes	No	No
Country-specific flex. trends	No	No	No	Yes	No
Country-spec. trends (tr/non-tr)	No	No	No	No	Yes
Observations	197,676	197,676	197,676	197,676	197,676
R-squared	0.663	0.716	0.701	0.701	0.701

Notes: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. The unit of observation is the county (level 2 administrative unit). Standard errors in parenthesis, clustered at the same level. Export Exposure is the PTA-driven export exposure of spatial unit i in year t that we obtain combining time variation in tariffs with cross-sectional variation in crop suitability, as described in Equation (1). This is calculated considering only those crops that we can classify into food and cash crops (McGuirk and Burke, 2020). The former include maize, oil palm, dryland rice and wetland rice, sorghum, soybean, sugar beet and sugar cane, wheat and buckwheat, while the latter includes cocoa, coffee, tea and tobacco. The dependent variable is the log of political violence (i.e., the number of hostile and violent events in ICEWS). Through country-specific flexible trends in column 4, we allow each country to have its own linear trend in the years prior to signature, a jump in the year of signature and another linear trend in the years after. In column 5, we further allow these flexible trends to be different across ever-exposed (Export Exposure > 0 at any point) and never-exposed spatial units.

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