Trade and Conflict in Myanmar: A Reverse China Shock[1]

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Abstract

I study the effect of trade in mining goods on conflict events in the border region of Myanmar. Using a shift-share measure, I disaggregate national exports to the township level. Imports from other low and middle-income countries are used to construct an instrumental variable to rule out reverse causality. I use a two-way fixed effects model for estimation. Export exposure to mining goods is associated with an increase in violent conflict. This increase predominantly affects townships inhabited by ethnic minorities. A placebo test confirms that the production of mining goods drives the effect. Night lights close to the mines are brighter in years with high export exposure, but surrounding areas do not seem to benefit.

JEL Classification: Q34, D74, F63, F14
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1 Introduction

Do increased exports of natural resources fuel conflict? This paper looks at Myanmar's[1] exports of mining goods to China over the period 2012 to 2020. It asks whether they can help to explain the high level of conflict in Kachin and Shan, the two states of Myanmar that share a border with China. I use a Bartik (1991) style shift-share measure to quantify a township's export exposure to mining goods. First, I disaggregate nationwide export values in different metals to the townships hosting construction sites that exploit these metals. Second, I construct an instrumental variable (IV) to deal with endogeneity concerns, using Chinese imports from other low and middle-income countries as an input. Effects are assessed using a two-way fixed effects model. Export exposure in mining goods increases the number of conflict events, with an elasticity of 0.46 for the OLS specification. This estimate is likely biased towards zero due to reverse causality, as higher levels of local conflict hamper exports. The elasticity increases to around 0.54 when using the IV approach. Ethnicity seems to matter, as most of the increase in conflict events is due to townships not inhabited by the nationwide ethnic majority. A placebo test further validates the results, replacing trade flows in mining goods with those in other goods of comparable importance for the export sector, typically produced elsewhere. As expected, the effect disappears when using this counterfactual measure of export exposure in placebo goods. Furthermore, I analyze the effect of export exposure on night lights as a proxy of economic development. In the immediate neighborhood of mines, pixels are brighter in years with higher export exposure. However, the effect does not spill over to nearby areas. Areas inhabited by ethnic minorities experience a lower increase in night lights when export exposure is higher, with the effect disappearing even quicker with distance.

When it comes to the effect of trade on civil conflict, the evidence is quite limited. Martin et al. (2008) find that international trade decreases the risk of severe civil wars, as the potential halt of this trade constitutes an additional cost. However, it might make low-scale conflict more likely, as trade within countries is less crucial if international alternatives exist. Brülhart et al. (2019) look at cross-border trade and find that for Africa an increase in cross-border trade is associated with a reduction in conflict. Candau et al. (2022) find that trade decreases the probability of ethnic wars in Africa, although this effect is driven mainly by agricultural products, while mining goods show no significant effect. The research by Calì and Miaari (2015) is probably closest to my work. They use a shift-share set up to assess the effect of Palestinian exports (mainly to Israel) on violence during the Second Palestinian Intifada. They argue that the Palestinian economy does not feature any extractive industries and that the state capacity channel is negligible, leading them to estimate an isolated opportunity cost channel (p.4). Consequently, they find a pacifying effect of export exposure. In contrast, in the case of Myanmar, the opportunity cost channel (better outside options in the formal sector), the rapacity channel (bigger prize that can be obtained by fighting), and the state capacity channel (higher income allows more funding of government forces) all play a role, which implies that the direction of the result is a priori not evident. Moreover, Calì and Miaari (2015) only consider a cross-section, while my data allows me to exploit a panel structure, controlling for constant factors across townships or

[1] No deliberate stance is implied by the usage of the word Myanmar instead of Burma in this article.

years. There are also studies considering the effect of war on trade. Glick and Taylor (2010) quantify a large negative impact of war on trade, while Qureshi (2013) shows that war has spillover effects, decreasing trade for neighboring countries, even if they do not participate in the conflict. The fact that there are papers highlighting both directions of causality calls for a thorough identification strategy.

While the evidence regarding the effect of trade on conflict is not unambiguous, it generally points towards a pacifying effect of trade. At the same time, there is a substantial literature relating world market prices of mining goods to conflict. This literature typically reports higher levels of conflict when the value of minerals rises (see, for example, Berman et al., 2017). As argued by Dube and Vargas (2013) and Dal Bó and Dal Bó (2011), a plausible explanation for this finding is that mining goods are less labor intensive than other goods, dampening the effect of the opportunity cost channel that causes workers to participate in the formal sector when prices are high. At the same time, mining goods are often spatially concentrated and more easily lootable than other goods (Ferraz et al., 2021).

There are good reasons to assume that the effect of trade goes beyond a mere price effect. The actual occurrence of trade implies that trade links have been established, contracts have been signed, workers have been employed, and the metals have been extracted and transported to the border. All of these steps require the cooperation of many different people from potentially different ethnic backgrounds, but they might also give rise to grievances. Candau et al. (2022, p.532) argue that "[i]n analysing global exogenous price shocks, many papers focus on the short-run effects of international trade." At the same time, focusing on actual trade faces the problem of reverse causality. In this regard, Myanmar provides an ideal laboratory, as most trade occurs with China, a trading partner which is far bigger and whose demand for natural resources is arguably independent of events within Myanmar. Despite the focus on trade, I confirm the positive effect of mining on conflict often reported in the literature.

My work contributes to the class of within-country studies on natural resources and conflict that is still limited but growing in recent years (see, for example, Aragón and Rud, 2016; Crost and Felter, 2020). These studies have the advantage that the institutional environment is relatively similar across the study area. Furthermore, the panel structure enables me to control for factors that are specific to a given township or year but invariant over the other dimension. Novel data allow me to work on the township level, the lowest level covered by the conflict dataset. Myanmar is a multi-ethnicity state, with the ethnic majority being clustered predominantly in the center of the country and controlling the government. This setting is not unusual in the literature, and ethnic composition has been used to explain the differential effects of natural resource wealth on conflicts (Janus and Riera-Crichton 2015, Morelli and Rohner 2015, Giménez-Gómez and Zergawu 2018). However, Myanmar differs from other settings because of the strength of the military and the level of repression it can exert. Arezki and Brueckner (2021) find that countries with high military expenditures do not exhibit a positive relation between rents from natural resources and civil conflict. In this context, the state capacity channel could explain why townships populated by, among others, the ethnic majority do not experience an export exposure effect on conflict.

Moreover, the paper sheds light on an effect of China's unprecedented rise over the last decades. By the sheer size of the development, it significantly affects many other parts of the global economy. Some of these consequences are well researched. Autor et al. (2013) find that local labor markets in the United States that experienced higher import exposure to Chinese manufacturing goods faced increased unemployment and reduced wages. Their seminal work inspired many other papers examining various plausible consequences, such as on worker health (McManus and Schaur, 2016) and voting behavior (Colantone and Stanig 2018, Autor et al. 2020). Dauth et al. (2017) also look at export exposure to China rather than just import exposure from China, finding that export exposure to China has slowed the decline of the German manufacturing sector. However, to my knowledge, most of the literature using this identification strategy to document the consequences of the rapid trade growth with China is concerned with effects on high-income countries. This focus is surprising, as trade with low and middle-income countries has also proliferated. Standard trade theory would suggest that the implications of this increase will be different for low and middle-income countries. Rather than looking at imports of manufactured goods from China, this paper considers exports of primary sector mining goods to China, driven by China's increasing demand for natural resources. In doing so, it mirrors the estimation strategy of Autor et al. (2013). While they use imports of other high-income countries from China to construct their instrument, this work considers Chinese imports from other low and middle-income countries.

This paper proceeds as follows: Section 2 explains the context in Myanmar and presents the data. Section 3 outlines the estimation method. Section 4 describes the results and explores their robustness. It also includes an analysis of local spillover effects using night lights. Section 5 provides a discussion and concludes.

2 Empirical Setting

This paper combines data from multiple sources, all of which are publicly available. The study period is defined by the availability of these data. The trade data used for this paper are currently available until 2020, while the night light data start in 2012.[2] This nine-year period was an eventful one in the history of Myanmar. It contains a slow process of democratic opening, with the National League for Democracy winning large majorities in general elections in 2015 and 2020. At the same time, the military still held considerable power, both in the democratic process and in the economy. The study period ends shortly before the coup d'état in February 2021.

The geographic focus of this paper is on Kachin and Shan, the two states within Myanmar that share a border with China (see Figure 2a). Nationwide, the largest ethnic group are the Bamar, who constitute about two-thirds of the population of Myanmar. They speak Burmese as their mother tongue, are predominantly Theravada Buddhist, and hold most of the positions

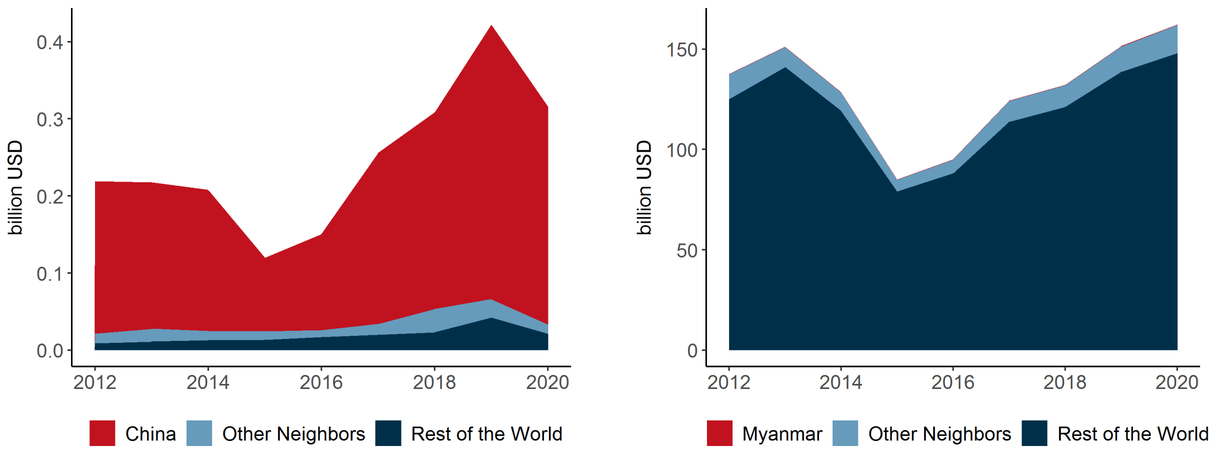
[2] Night light data also exist for the years before 2012. However, there was a discontinuity due to a change of satellites in 2012. There is no agreed on way to reconcile the data from the two different satellite systems (Chen and Nordhaus, 2015). Elvidge et al. (2013) provide a discussion on the many advantages the VIIRS system offers relative to the old DMSP-OLS system.

in the central government. Their settlement area also covers parts of Kachin and Shan (see Figure A2). However, these states are populated to a large extent by other ethnic groups like the Kachin, Shan, Wa, or Kayin. Both states host rebel groups. These groups often represent an ethnic minority and are referred to as ethnic armed organizations in these cases, a prominent example being the Kachin Independent Army. The military of Myanmar, the Tatmadaw, only partially asserts control over Kachin and Shan. In some places they do not fully control, they collaborate with paramilitary organizations, some of which are former rebel groups, that involve rent-sharing of the region's many natural resources. This situation regularly results in violent conflict between the different armed groups. Moreover, there are frequent cases involving violence against civilians, predominantly but not exclusively, committed by government forces (source: ACLED). For a detailed account of the situation and the different parties, see, e.g., Woods (2018).

2.1 Trade

The *Centre d'Études Prospectives et d'Informations Internationales* (CEPII) provides yearly trade data in the form of the *Base pour l'Analyse du Commerce International* (BACI).[3] Over the study period, trade between Myanmar and China increased sharply. Trade volume from and to China more than doubled from 7.5 billion USD in 2012 to almost 17 billion USD in 2020. As of 2020, China is by far the biggest trading partner for Myanmar, ahead of Thailand (6.6 billion USD), Singapore (2.8), and Japan (2.1) (BACI).

Figure 1: Development of trade in primary sector metals between 2012 and 2020.



(a) Value of metals exported from Myanmar by destination.

(b) Value of metals imported by China by origin.

This dominance is even more striking considering the trade of primary sector mining goods, which is the focus of this paper.[4] Figure 1a shows the evolution of exports from Myanmar for this set of goods. From 2012 to 2020, almost 86% of the value obtained by exporting mining

[3] Downloaded on 01.12.2022 from `http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=37`.

[4] Table A1 in the Appendix shows how different goods are mapped to the metals of interest for this analysis. Mining goods are included if i) they are part of the primary sector as defined by the Broad Economic Categories Rev 4., ii) they can be linked to a mine in Kachin or Shan state, and iii) BACI reports exports from Myanmar to China for at least one year in the study period. Figures 1a and 1b refer to this subset of mining goods.

goods was due to trade with China. During this period, there is an unmistakable resemblance between exports from Myanmar and the development of Chinese imports, which are depicted in Figure 1b. However, Myanmar only accounted for a tiny share of Chinese imports in mining goods, about 0.2%, from 2012 to 2020. Therefore, it seems safe to assume that variations in Chinese demand have a substantial impact on the mining sector of Myanmar while Chinese demand for mining goods is at most marginally affected by supply shocks within Myanmar.

2.2 Mining

The mining data used here are based on the 6th Extractive Industries Transparency Initiative (EITI) report, covering the fiscal year 2018 (MEITI, 2020).[5] The data have been processed and geocoded by the Myanmar Centre for Responsible Business (MCRB). Apart from mine coordinates, the dataset also includes information about mine size, type, and the material exploited (MCRB, 2022) To my knowledge, these data have not yet been used in an academic context.

There were 1,218 active mining licenses in the fiscal year 2018 in Myanmar, 399 (32.8%) of which were located in Kachin and Shan states. Figure 2c shows the spatial distribution of these mines. The most frequent mine types are lead & zinc (110 mines), followed by coal (62), antimony (41), and tin & tungsten (29).[6]

The EITI report also includes data about jade and gems. Jade is significant for the economy of Myanmar, accounting for anywhere between 2% (MEITI, 2015) and 48% (Global Witness, 2015) of GDP (Oak, 2018). The sector is notoriously intransparent as the range of these estimates demonstrates. Moreover, jade production is heavily clustered. Five townships account for all production in jade and gemstones, three of which are in Kachin and Shan.[7] Finally, Myanmar is the biggest jade producer globally. As a consequence, developments in Myanmar inevitably influence jade trade worldwide. There is no straightforward way to use variation that is exogenous to Myanmar to construct a credible instrumental variable. Export exposure in jade and gems will therefore only be included as a control variable.

2.3 Conflict

Data about conflict events come from the Armed Conflict Location & Event Data Project (ACLED, Raleigh et al. 2010).[8] Figure 2a depicts the number of conflict events during this period, aggregated by state. With the exemption of Rakhine state, home of the Rohingya,

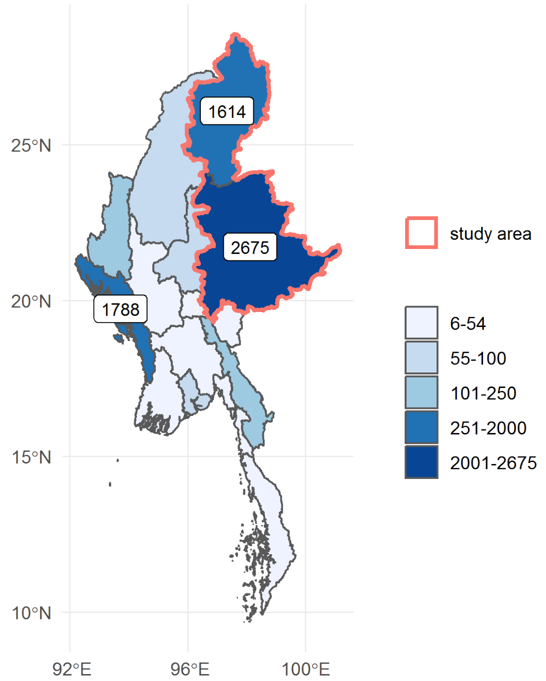
[5] In 2014, Myanmar became a member of the EITI, a global standard through which countries commit to publicly disclosing information about the extraction of their natural resources. Its membership is currently suspended as a consequence of the military coup (`https://eiti.org/countries/myanmar`, last accessed: 20.09.2022).

[6] The complete list of mines in Kachin and Shan by the material (mainly) extracted there includes: lead & zinc (110 mines), coal (62), antimony (41), tin & tungsten (29), iron (17), manganese dioxide (14), gypsum (11), marble (11), limestone (7), copper (6), baryte (4), quartzite (4), chromium (2), and dolomite (1). Moreover there are mines extracting gold (79) and bauxite (1). As there are no reported exports to China for the latter two metals, they are excluded from the study and not depicted on the map.

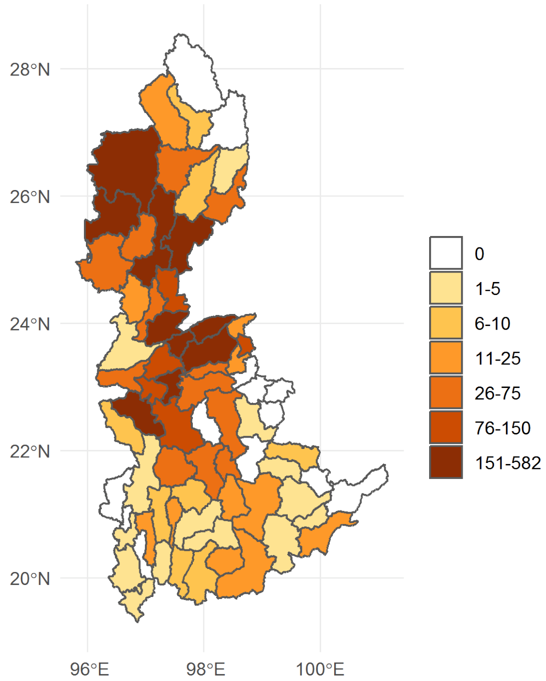
[7] In the trade data, it is not possible to distinguish jade from other gemstones. Global Witness (2015) argues that almost all of the export value is due to jade (p.101 f.). In the rest of the paper, I will just refer to this category as jade, implicitly including other types of gemstones.

[8] There exists also the Uppsala Conflict Data Program Georeferenced Event Dataset, which serves a similar purpose. However, for the case of Myanmar, ACLED has more than 9 times as many entries over the study period. For that reason, I prefer to work with ACLED for this analysis.

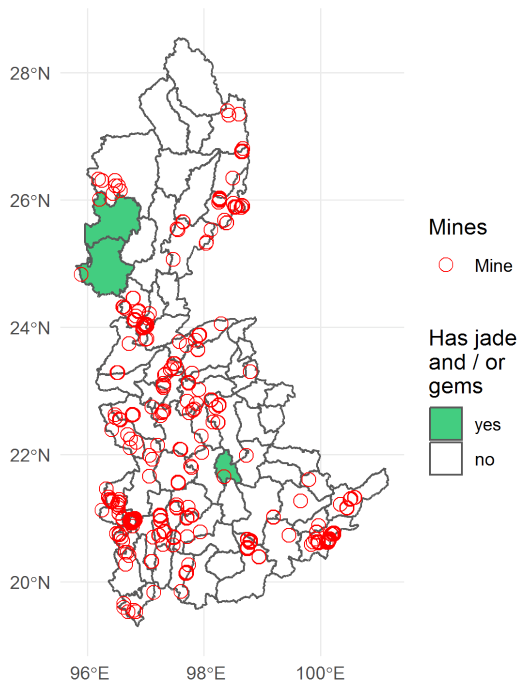
Figure 2: Geography of Myanmar (Panel a), with a particular focus on Kachin and Shan states (Panels b, c, and d).



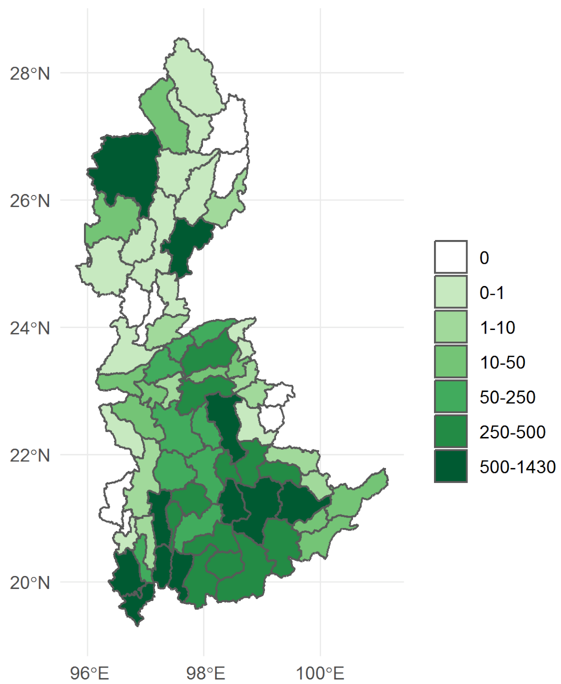
(a) Number of violent conflict events between 2012 and 2020 by state.



(b) Number of violent conflict events between 2012 and 2020 by township in Kachin and Shan.



(c) Active mining licenses in the fiscal year 2017/18 in Kachin and Shan states.



(d) Area of opium cultivation in hectares by township in Kachin and Shan states.

Kachin and Shan are by far the most conflict-ridden states in Myanmar. Figure 2b shows the spatial distribution of conflict events within Kachin and Shan by township. Figure A1 provides corresponding maps with conflict fatalities.

2.4 Opium

Myanmar is estimated to be the second largest opium producer in the world, behind Afghanistan (Kramer, 2017). Over 96% of the opium cultivated in Myanmar is grown in Kachin and Shan states (UNODC, 2021, p. 8). Moreover, the value of the produced opium has varied widely over the years. It seems, therefore, imperative to include a measure of the value of opium produced in a township in any given year. However, given the illegality of the sector, data are scarce and inevitably imprecise. This paper makes use of information provided by the United Nations Office on Drugs and Crime (UNODC), which produces yearly reports about opium cultivation in Myanmar. Appendix B describes the steps I take to convert this information into a variable measuring export exposure in opium by township and year.

2.5 Night lights

Night light data are a good proxy for economic activity and development levels, especially in countries where geographically disaggregated statistics about these factors are unreliable (Henderson et al., 2012). Data are collected by the "Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB)" (Elvidge et al., 2021) and made available by the Earth Observation Group of the Payne Institute for Public Policy.[9]

2.6 Other data

Township and state boundaries are taken from the Myanmar Information Management Unit. Data on the presence of different ethnic groups come from the Ethnic Power Relations data sets (Vogt et al., 2015). Figure A2 depicts the settlement area of the ethnic majority (the Bamar) according to these data.[10] The correspondence table used to determine which goods belong to the primary sector is provided by the United Nations Statistics Division. Finally, the classification of low and middle-income countries is taken from the World Bank.

3 Estimation

To estimate the effect of trade exposure on conflict, I use a two-way fixed effects model, controlling for township and year fixed effects. To control for potential endogeneity, I employ a Bartik-style shift-share instrument.

I construct a measure for the exposure of a township to mining exports to China, which will be my variable of interest. For each metal m, the nationwide export value for this metal in year t is disaggregated to all townships i in which the metal is mined. However, mineral sources vary considerably in size. In my main specification, I do the disaggregation with regard to the

[9] More precisely, average values from the "Annual VNL V2" are used.
[10] Parts of this area overlap with the settlement areas of other ethnic groups.

share a township has in the nationwide mining area of the metal m. If, for instance, a township possesses 5% of the nationwide mining area of iron, I attribute 5% of the export value of iron for each year to this township. As a township can be endowed with several different metals, I then aggregate these exposures.

$$\text{Export Exposure}_{it} = \sum_{m} \text{Share}_{im} \times \text{Exports}_{mt}^{\text{MMR}\rightarrow\text{CHN}} \tag{1}$$

Regressing a measure of conflict intensity, for example the number of conflict events, on this measure of export exposure is the basis of what can be seen as the ordinary least squares (OLS) version of the analysis. Townships vary from one another in their proneness to conflict due to many different factors not related to trade. All regressions include township fixed effects λ_i to control for all such time-invariant factors. Moreover, they include year fixed effects μ_t to account for the fact that the overall situation in Kachin and Shan was more fragile in some years and more stable in others. I estimate the following OLS specification in which X_{it} consists of control variables for export exposure in jade and opium.

$$\text{Conflict Events}_{it} = \alpha + \beta \times \text{Export Exposure}_{it} + \gamma X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{2}$$

The two fixed effects attenuate the worry that the regression will be biased due to omitted variables. However, the analysis might also suffer from reverse causality as we might expect conflict to obstruct trade. As exports of a township are inferred by allocating a fraction of overall exports on a national scale even the OLS specification has a certain level of robustness against this problem. To go one step further, I use Chinese mining imports from other low and middle-income countries (LMIC) to construct a shift-share instrument of the following form.

$$\text{Export Exposure}_{it}^{\text{IV}} = \sum_{m} \text{Share}_{im} \times \text{Exports}_{mt}^{\text{LMIC}\rightarrow\text{CHN}} \tag{3}$$

Doing this yields a measure of counterfactual export exposure in mining goods for each township. It captures the part of the increase in trade driven by China's rising demand for natural resources. As Myanmar only accounts for a small share of overall Chinese imports, this measure should not be influenced by conflict within Myanmar. The IV version of the analysis can be expressed as

$$\text{Export Exposure}_{it} = a + b \times \text{Export Exposure}_{it}^{\text{IV}} + cX_{it} + l_i + m_t + e_{it} \tag{4}$$

$$\text{Conflict Events}_{it} = \alpha + \beta \times \widehat{\text{Export Exposure}}_{it} + \gamma X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{5}$$

4 Results

4.1 Main specification

Table 1 shows the regression results of the baseline specifications. All regressions are estimated with two-way fixed effects (73 townships and 9 years) and with two-way clustered standard errors (at the township and year level). I take logs off all variables so the coefficients can be interpreted as elasticities. There is a positive relationship between export exposure in metals and the number of conflict events. Columns (1) and (3), as well as (2) and (4), show very similar coefficients of interest. This implies that controlling for export exposure in jade and opium does not make a big difference. The OLS specifications show an elasticity of around 0.44. The elasticity increases to around 0.54 with the IV specification. This difference is consistent with (some degree of) reverse causality, causing us to underestimate the true effect when using simple OLS.

Table 1: Main specification

Dependent Variable:	ln(conflict events)					
Model:	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
ln(export exposure metals)	0.42**	0.52*	0.46**	0.56*	0.72**	1.07***
	(0.17)	(0.25)	(0.17)	(0.26)	(0.22)	(0.30)
Bamar × ln(export exposure metals)					-0.75**	-1.55**
					(0.27)	(0.60)
ln(export exposure jade)			0.15	0.14	0.14	0.12
			(0.20)	(0.21)	(0.20)	(0.20)
ln(export exposure opium)			-0.43	-0.44	-0.31	-0.18
			(0.26)	(0.26)	(0.28)	(0.32)
Cragg-Donald Wald F statistic		206.74		203.16		98.49

Note: The table shows regressions of violent conflict events on export exposure in primary sector mining goods. The balanced panel consists of 73 townships in Kachin and Shan and 9 years (657 observations). All specifications include township fixed effects and year fixed effects. The parentheses show standard errors, which are two-way clustered by township and by year. I obtain export exposure by disaggregating nationwide exports to the townships where the goods are produced, using the townships' share of the national production area. The export exposure in jade and in opium is computed in the same way. Specifications five and six consider heterogeneous effects by including an interaction term, with Bamar being an indicator variable for the presence of the ethnic majority in a township. For the IV specifications, I construct a shift-share instrument using Chinese imports from other low and middle-income countries, multiplied by the same shares of national production area as above. I take logs for all export exposures and conflict events to interpret the coefficients as elasticities. To keep observations with zero values, I add 0.1 to all variables before taking logs. The levels of significance are * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

In columns (5) and (6), export exposure in metals is interacted with an indicator variable for the presence of the Bamar ethnic majority. The positive effect of export exposure in mining goods on conflict seems to be driven entirely by townships that are completely populated by ethnic minorities. For townships in which the ethnic majority is present, the effect becomes very small in the OLS specification and negative in the IV specification.

I construct the export exposure in jade and opium in a similar way to the export exposure in metals. In all cases, exports on a national level are disaggregated to individual townships according to a township's share of national production.[11] Jade exposure also shows a consistently positive relation with conflict events, while export exposure in opium is negatively associated with conflict in most specifications. However, for both control variables, the coefficients are far from being statistically significant. The data on jade and opium seem to be particularly imprecise. For example, MEITI reports individual licenses for other metals, but only township aggregates for jade. Measurement error might therefore explain part of the insignificance when it comes to the control variables.

4.2 Robustness

Control variables

Table A2 shows that the specific set of control variables is not critical for the results. Even if the inclusion of jade exposure does not considerably alter the results, townships involved in the jade sector could greatly influence them. To attenuate this worry, Panel A excludes the three townships for which MEITI reports the presence of mines extracting jade. Panel B only controls for export exposure in jade, but not opium.

Allocating exports to townships

Table A3 explores the robustness to the allocation of nationwide exports to townships. In the main specification, for each material, exports are disaggregated by the share of a township's mining area relative to the whole country. Before this disaggregation is done, the area is winsorized to the 0.01 and the 0.99 percentiles as there are a few entries reporting unrealistically large values, mostly linked to exploration. Panel A of Table A3 shows the results without winsorizing.

Panel B proposes a disaggregation method that is more robust to outliers and erroneous information about the size of a mining area. MEITI categorizes mines into four categories: large-scale production, small-scale production, subsistence, and exploration. For each combination of these four categories and the metal to be extracted, I compute the average area and assign it to the mine. In other words, a subsistence marble mine is weighted by the whole country's average area of all subsistence marble mines. Finally, Panel C allocates national exports of mining goods by the number of mines a township has of that good. In that specification, jade exposure is also allocated by the number of jade mines in a township, while it is done by area for all other specifications.

When choosing how to conduct this disaggregation, there is a trade-off between using all information available (area) and having a more robust specification to outliers and potential misreporting (projected area, number of mines). I choose the winsorized area in the main specification as a

[11] As for metals, most jade and gems exports from Myanmar go to China. Over the study period, China accounted for over 93% of the corresponding export value. I use exports to China to construct the control variable for export exposure in jade and gems. Unfortunately, the export data for opium are not broken down by destination. I, therefore, use estimates for opium exports to all destinations to construct the control for export exposure in opium (see Appendix B).

middle ground between these two options. Table A3 shows that the estimation results are fairly robust to this crucial modeling choice. The coefficients of interest are of similar magnitude in all specifications, showing a positive relationship between export exposure in metals and conflict events, which is statistically significant in almost all specifications.

Set of countries for the IV

For the instrumental variable strategy, I construct a measure of counterfactual export exposure using Chinese imports from low and middle-income countries (LMIC)[12] instead of Chinese imports from Myanmar (see Section 3).[13] The set of countries used to construct the instrument mirrors the one chosen by Autor et al. (2013), who use Chinese exports to other high-income countries. However, using another set of countries for the instrument is imaginable. Table A4 recomputes the instrumental variable regressions using three different sets of countries. The first two columns use imports from all other countries, including high-income countries. Columns (3) and (4) only use neighboring countries of China for the instrument. Finally, columns (5) and (6) consider all LMIC that are not neighbors of China. While some coefficients fail to reach statistical significance, they are all similar in size. If anything, using other sets of trading partners for the IV yields somewhat larger point estimates than the main specification..

Different conflict measures

This paper focuses on the number of violent conflict events in a township within a given year. The main specifications include all events in ACLED, except for those categorized as peaceful protests and strategic developments. Table A5 considers alternative conflict measures. Panel A is concerned with fatalities, while Panel B looks at fatal events, which means all events resulting in at least one fatality. Generally speaking, the direction of the effect is confirmed in all specifications with the baseline OLS effects being somewhat smaller, but statistically significant in all but one regression. However, the IV estimates are mostly insignificant and substantially smaller, compared with the main specification. This difference suggests that mining triggers violent conflict, but not always of the most deadly type. This is in line with the findings of Martin et al. (2008). They provide the intuition that increased international trade can substitute internal trade and therefore reduce the cost of conflict, but only if the scale of the conflict is limited such that trade can continue. Panel C considers the extensive margin of conflict. In this case, the dependent variable is a binary indicator of whether at least one reported conflict event exists for a township-year pair. A linear probability model confirms the main findings above: Export exposure is positively associated with conflict, especially in townships inhabited by ethnic minorities. Moreover, the IV specifications show larger coefficients, consistent with the OLS results being biased downwards due to reverse causality.

Government participation

Finally, Table A6 focuses on differential effects by the type of conflict parties. Panel A only includes events with the government forces as one of the conflict parties, while Panel B looks at

[12] All sets of countries exclude Myanmar.

[13] As reconciled trade data from BACI are used, exports from Myanmar to China and Chinese imports from Myanmar are equivalent.

conflicts in which none of the parties belongs to the government forces. It is unclear which type of conflict drives the main effect more. The OLS estimates are higher and statistically significant for events without government participation, while the IV estimates report higher coefficients for events with government participation. Nevertheless, this table contains interesting insights: First, the interaction effect seems stronger for conflict involving government forces. For this type of conflict, townships at least partially inhabited by the ethnic majority experienced a negative correlation between export exposure in mining goods and conflict. One plausible explanation for this finding is that the rebels struggle to find support to challenge the government's repression in these townships and increasingly so when the export business is booming. Another could be that increased revenues from mining exports enable the government to take increasingly repressive measures in these townships, shifting the balance of power to a point where challenging it is very costly. Second, the effect of export exposure in opium becomes substantially negative and highly significant for conflicts without government participation. While these results have to be taken with a grain of salt (see Section 2.4), they are in line with findings in the literature. Dal Bó and Dal Bó (2011) argue that one would expect a negative effect of prices on conflict for labor-intensive goods as the opportunity cost channel prevails over the rapacity channel. Dube and Vargas (2013) confirm this finding for coffee in Colombia. Opium production also requires a decent amount of manual labor. However, unlike coffee, it comes with the issue of the illegality of the sector. Basic intuition suggests that this illegality will mainly influence government actions, thereby potentially lessening the pacifying effect of the opportunity cost channel. For conflict between non-government actors, on the other hand, we would expect the economic trade-off between the rapacity and the opportunity channel to play more freely.

4.3 Placebo test

The OLS results in Section 4.1 show a positive correlation between export exposure in mining goods and conflict events. The instrumental variable strategy used above is the first way to validate these findings. However, exports from Myanmar increased in many different sectors during the 2010s. For example, Tanaka (2020) documents the positive effects of an increase in apparel exports on working conditions in the respective firms around Yangoon and Mandalay, the two biggest cities in the center of the country. To explore whether the effect on conflict is indeed plausibly driven by metals mined in Kachin and Shan states and not just an artifact of the general trade liberalization, I construct a placebo test.

Each metal used in this study is replaced by another good unrelated to metals. In order to represent the importance of the export sector of Myanmar in general and for trade with China in particular, I choose "placebo" goods to match the value of exports to China in the last pre-study year of 2011 as close as possible. For example, I replace copper with natural rubber, iron with tropical wood, and marble with dried fish. Table A7 describes the complete mapping.

These placebo trade flows are then used as if they would represent the actual trade flows of the metal to which they are mapped. For instance, I disaggregate exports (and Chinese imports) in tropical wood to townships according to their share of the national iron mining area using the same procedure as for the non-placebo specifications. Then, for each township, I sum up disaggregated placebo trade flows over all metals existing there, producing a measure of counterfactual export exposure.

While the placebo goods are similarly important for exports to China in 2011, their evolution over time differs from their non-placebo counterparts. For some pairs, the export value grew faster in the placebo good. For others this value grew slower and peak export values occurred in different years. In particular, conflict around the mines should not impact export value development as the placebo goods are generally not produced there.

Table 2 shows the results of regressing conflict events on export exposure in placebo goods. All estimates are statistically insignificant and close to zero. IV estimates are positive, but with large standard errors. Therefore, the null hypothesis that placebo export exposure does not affect conflict can not be rejected. Given the construction of the measure, this is the behavior we would have expected. The results in Section 4.1 do not seem to be driven by trends in nationwide trade with China that are unrelated to mining.

Table 2: Placebo test

Dependent Variable:	ln(conflict events)					
Model:	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
ln(export exposure metals)	0.12	-0.02	0.11	-0.07	0.14	-0.05
	(0.11)	(0.19)	(0.11)	(0.19)	(0.12)	(0.19)
Bamar × ln(export exposure metals)					-0.08	-0.20
					(0.12)	(0.75)
ln(export exposure jade)			0.18	0.18	0.18	0.19
			(0.22)	(0.22)	(0.22)	(0.23)
ln(export exposure opium)			-0.35	-0.37	-0.33	-0.32
			(0.26)	(0.26)	(0.27)	(0.29)
Cragg-Donald Wald F statistic		107.31		106.56		7.14

Note: The table shows regressions of violent conflict events on export exposure in placebo goods. Each primary sector mining good is replaced by another good that has an export value in the last pre-study year of 2011 that matches the one of the mining good as close as possible. I obtain export exposure by disaggregating nationwide exports in the placebo goods to the townships where the mining goods are produced, using the townships' share of the national production area in the mining goods. The balanced panel consists of 73 townships in Kachin and Shan and 9 years (657 observations). All specifications include township fixed effects and year fixed effects. The parentheses show standard errors, which are two-way clustered by township and by year. The export exposure in jade and in opium is computed as in Table 1. Specifications five and six consider heterogeneous effects by including an interaction term, with Bamar being an indicator variable for the presence of the ethnic majority in a township. For the IV specifications, I construct a shift-share instrument using Chinese imports in the placebo goods from other low and middle-income countries, multiplied by the same shares of national production area as above. I take logs for all export exposures and conflict events to interpret the coefficients as elasticities. To keep observations with zero values, I add 0.1 to all variables before taking logs. The levels of significance are * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

4.4 Night lights

In Kachin and Shan, from 2012 to 2020, export exposure in mining goods increased conflict in the townships where the mines are located. This finding is in line with the rapacity channel dominating the opportunity cost channel (while the military capacity channel can potentially explain the geographic differences in the magnitude of the effect). As a final exercise, I assess the opportunity cost channel. Following the literature, I use VIIRS night light data to approximate income levels on a geographic resolution that is more disaggregated than the available income data (see, for example, Henderson et al. 2012). Compared to the data used above, I can work at an even finer scale for the night light data, as these data are available at a resolution of 500 $\times$ 500 meters.[14]

To leverage this precision, I recompute export exposure in mining goods at the mine level. Again, I disaggregate national exports to an individual mine, using the mine area as a weight for the allocation.[15] Equivalently to the procedure above, (log-) night light values are then regressed on the (log-) export exposure, using pixels as the unit of observation. I focus on mines that are already producing output. For conflict, we can expect the sheer presence of precious materials to matter. To expect an effect on income, however, something needs to be sold (or at least exploited). Apart from year fixed effects, I include a fixed effect for every pixel in a panel regression. Standard errors are two-way clustered at the year and the pixel level.

I split the sample into seven parts, depending on the distance of a pixel to the closest mine: 0 to 1 km, 1 to 2 km, 2 to 3 km, 3 to 5 km, 5 to 10 km, 10 to 15km, and 15 to 20 km.[16] This allows me to assess whether the economic effects of higher export exposure only affect the mine and its immediate surroundings or if they also spread further into the regions that host the mines.

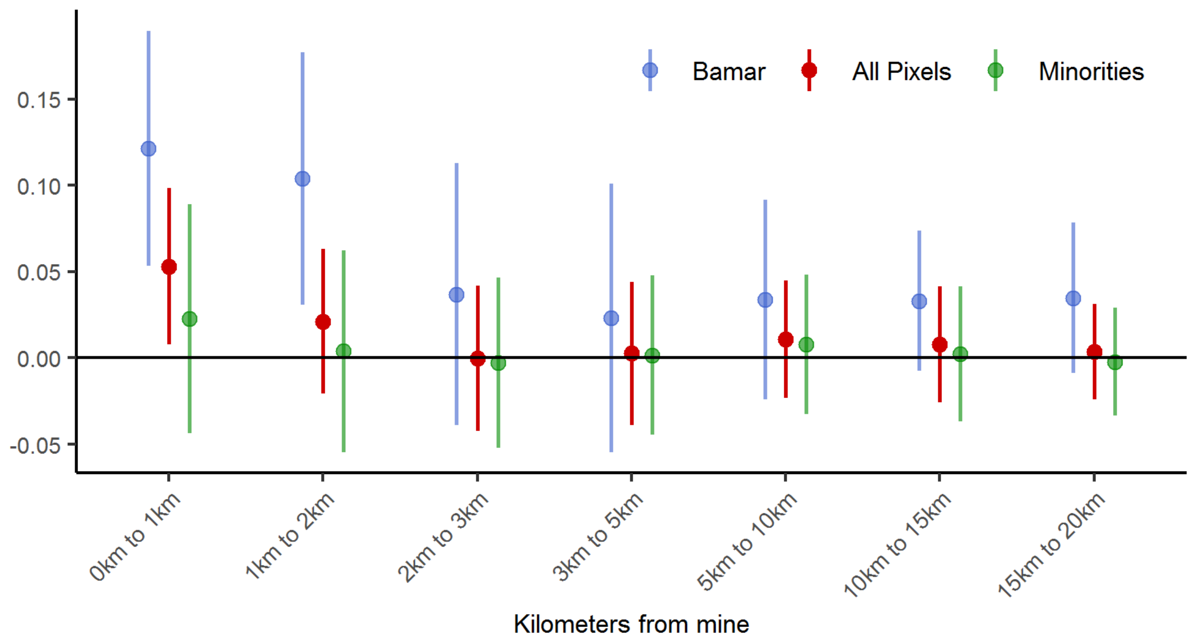
The red points in Figure 3 show the regression coefficients for all pixels in Kachin and Shan that are in the respective distance brackets. A statistically significant effect of export exposure on night light values can be found in the immediate neighborhood of the mines. For the first bracket, a 10 percent higher level of export exposure is associated with a 0.6 percent higher level of night lights. This effect might be due to the workers employed at the mines and local businesses directly involved.

On the other hand, spillover effects are very small. The effect still seems to be positive for pixels between 1 and 2 kilometers from the mines but fails to meet significance at the 10% level. Furthermore, the estimates are statistically insignificant for all distance brackets above 2 kilometers, with point estimates close to zero. The weak spillover effects are consistent with reports that argue that the gains from metal exploitation rarely benefit the local population. Instead, they are often transferred to more central parts of Myanmar, benefiting political leaders, army officials, or investors abroad. Global Witness (2015) provides a vivid example for the case of jade.

I redo the same analysis taking the subset of pixels that are in parts of Kachin and Shan that are inhabited by Bamar (blue points in Figure 3) and in parts that are inhabited exclusively by minorities (green points). Minority areas seem to profit less from export exposure in mining than

[14] More precisely, cell size is 500 $\times$ 500 meters at the equator and somewhat larger in the case of Myanmar.
[15] I winsorize the mine area at the (0.01, 0.99) percentile, consistent with the main specification above.
[16] I measure the distance from the centroid of a pixel to the centroid of a mine. A pixel is exclusively assigned to the bracket that corresponds to the closest distance, even if other mines exist further away. In case multiple mines are situated within the same distance bracket, I sum up their respective export exposures.

Figure 3: Elasticity of night lights to export exposure in mining, by distance from the mine



Note: Each point represents the estimated coefficient of a regression of night lights on export exposure in primary sector mining goods. The units of observation are pixels (500m × 500m). The regressions differ by the distance between a pixel and its closest mine (7 categories) and by whether all pixels in Kachin and Shan are considered (red) or only the subset in areas inhabited by Bamar (blue) or exclusively by ethnic minorities (green). The panels consist of between 7,416 (0km to 1km, Bamar) and 982,973 (15km to 20km, all pixels) observations. All specifications include pixel fixed effects and year fixed effects. I obtain export exposure by disaggregating nationwide exports to the mines where the goods are produced, using the mines' share of the national production area. Mines categorized as exploration are excluded. If two mines are in the same distance bracket, I sum up their export exposures. I only include pixels in the regressions that correspond to their closest bracket. I take logs for export exposure and night light to interpret the coefficients as elasticities. To keep observations with zero values, I add 0.1 to all variables before taking logs. The lines represent confidence intervals at the 90% level, constructed from standard errors, which are two-way clustered by mine and by year.

areas with a presence of the ethnic majority. This finding affects both the direct surroundings of the mines and the areas in the regions around them. For the pixels in Bamar areas, the elasticity is large and statistically significant for the first two brackets and higher than the main specification for all brackets. The pixels in territories exclusively inhabited by minorities show no significant effect in any bracket, with a point estimate of essentially zero already from the second bracket.

5 Conclusion

I use a two-way panel data model on a township-year basis to estimate the effect of trade in natural resources on conflict. While the literature tends to find that trade attenuates conflict, various studies find that higher world-market prices for mining goods increase conflict. This group of goods is, therefore, an obvious candidate to test the limits of the pacifying effect of trade. Using novel data on mining licenses, I analyze the effect of a trade shock in the case of Myanmar. Most of the trade in mining goods happens with the neighboring country of China.

While mining companies in Myanmar depend on Chinese demand, Myanmar is only a minor trading partner of China.

As an identification strategy, I first disaggregate nationwide export values for different metals to the townships where these metals are exploited. Then, as a second step, I construct an instrument using trade flows of the same metals from other low and middle-income countries to China. This procedure essentially mirrors the identification strategy of Autor et al. (2013), who use Chinese exports to high-income countries other than the United States to construct their instrument.

I focus on Kachin and Shan, the two states within Myanmar that share a border with China. Both states are conflict-ridden, including many incidents between Myanmar's government and rebel groups; often made up of ethnic minorities. Both states are crucial for the mining sector of Myanmar. Moreover, they produce a considerable amount of opium and jade; two factors for which I control.

The results suggest that trade in primary sector mining goods is indeed associated with conflict. The elasticity between violent conflict events and export exposure in metals is about 0.46 for the OLS specification and about 0.56 for the IV specification that controls for reverse causality. There is heterogeneity in the results concerning the presence of the ethnic majority. The positive relation appears to be predominantly driven by townships where the ethnic majority is absent.

A possible explanation for this finding could be a higher level of military control over areas inhabited by the ethnic majority. Crost and Felter (2019) consider the case of bananas in the Philippines and find that increased export exposure is more likely to trigger conflict in townships that are not fully controlled by one conflict party. Arezki and Brueckner (2021) show that the positive relation between export exposure and conflict disappears for countries with high military expenditures. According to the World Development Indicators from the World Bank, Myanmar is 17th of 140 countries when it comes to military expenditure as a percentage of GDP,[17] so one would expect their findings to be relevant for this setting. Only at the fringes of the country might the military be weak enough to be seriously challenged by other actors.

Violent conflict has severe costs. Nevertheless, there is, of course, also an upside to an increased trade volume, at least in theory. First, it should create jobs, allowing people to become employed in lawful sectors. Second, profiting from the sale of natural resources via taxes or direct involvement would allow the government to inject funds into the public treasury that could be used for the benefit of the people. Unfortunately, only a tiny part of Myanmar's revenue from the sale of natural resources seems to be allocated to the local population in the regions where these resources are mined (Global Witness, 2015). This lack of local benefit can be validated using night light data as a proxy for economic activity. An increase in a mine's export exposure is indeed correlated with an increase in night light activity. However, this increase is very local around the mines. The data cannot confirm spillover effects on the surrounding areas. More-

[17] Military spending was on average 3.5% of GDP over the years 2012-2020. For this statistic, I only considered countries with non-missing values for all 9 years. Data downloaded 28.09.2022 from `https://databank.worldbank.org/source/world-development-indicators`.

over, the increase in night lights is smaller, and declines even quicker, in minority areas. In this regard, too, the recent developments around the military coup of February 2021 do not give rise to optimism.

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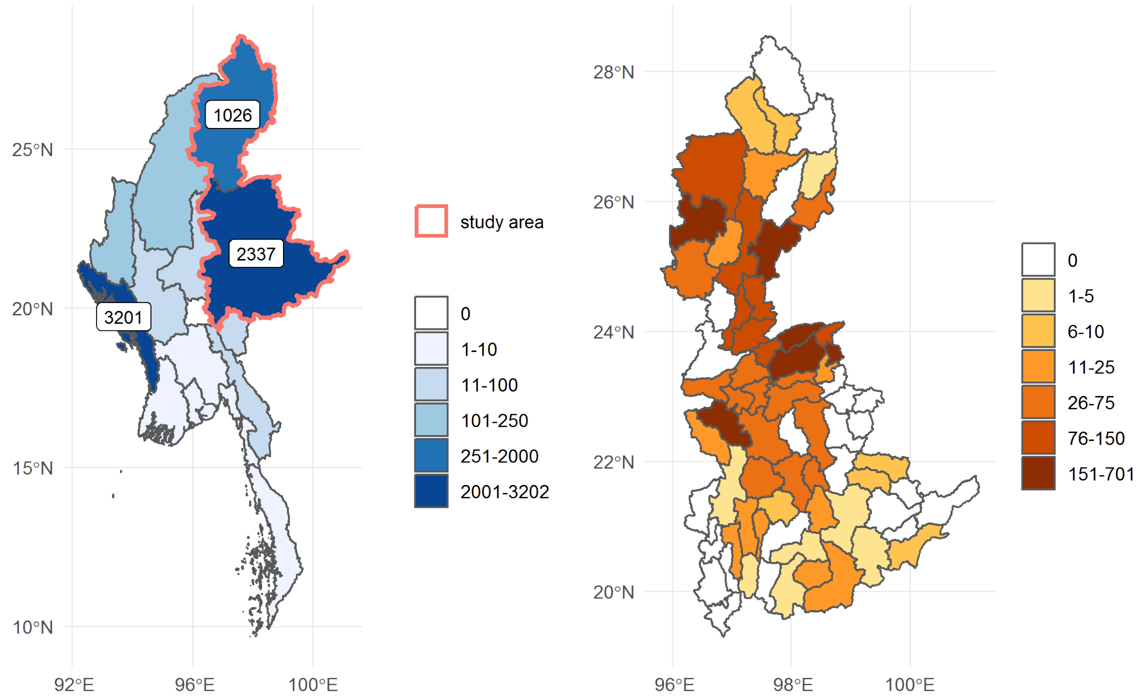
A Additional descriptive statistics

Figure A1: Number of conflict fatalities between 2012 and 2020



(a) by state

(b) by township in Kachin and Shan states

Figure A2: Presence of the ethnic majority (Bamar)

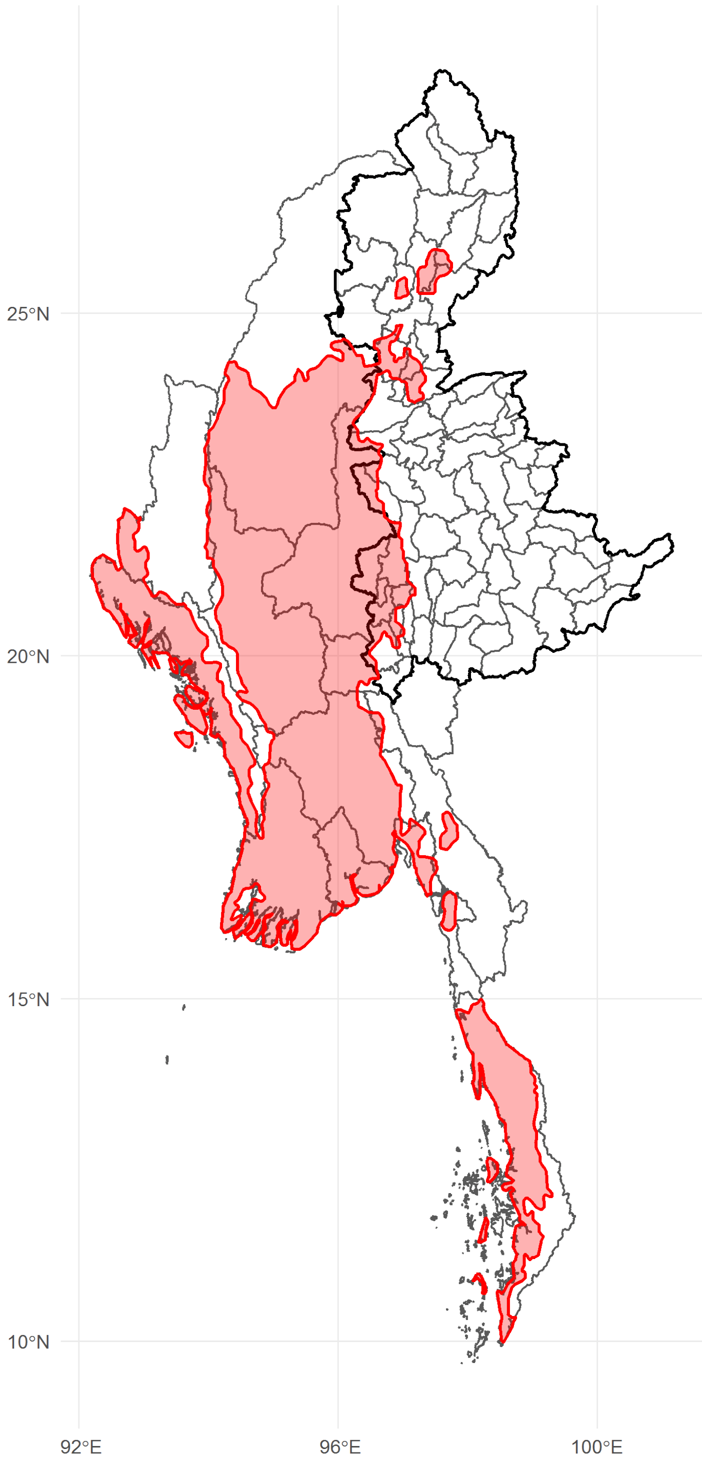


Table A1: Mapping harmonized system (96) codes to metals.

HS6 Code	Description	Assigned to
261710	Antimony ores and concentrates	Antimony
251110	Barium sulphate (barytes): natural	Baryte
261000	Chromium ores and concentrates	Chromium
270112	Coal: bituminous, whether or not pulverised, but not agglomerated	Coal
270119	Coal: (other than anthracite and bituminous), whether or not pulverised but not agglomerated	Coal
260300	Copper ores and concentrates	Copper
262030	Ash and residues: (not from the manufacture of iron or steel), containing mainly copper	Copper
740400	Copper: waste and scrap	Copper
251810	Dolomite: (not calcined), roughly trimmed or merely cut, by sawing or otherwise, into blocks or slabs of a rectangular (including square) shape	Dolomite
252010	Gypsum: anhydrite	Gypsum
260111	Iron ores and concentrates: non-agglomerated	Iron
260112	Iron ores and concentrates: agglomerated (excluding roasted iron pyrites)	Iron
260120	Iron pyrites: roasted	Iron
261900	Slag, dross: (other than granulated slag), scalings and other waste from the manufacture of iron or steel	Iron
720429	Ferrous waste and scrap: of alloy steel (excluding stainless)	Iron
720449	Ferrous waste and scrap: n.e.s. in heading no. 7204	Iron
260700	Lead ores and concentrates	Lead & Zinc
260800	Zinc ores and concentrates	Lead & Zinc
262019	Ash and residues: (not from the manufacture of iron or steel), containing mainly zinc, other than hard zinc spelter	Lead & Zinc
262020	Ash and residues: (not from the manufacture of iron or steel), containing mainly lead	Lead & Zinc
780200	Lead: waste and scrap	Lead & Zinc
252100	Limestone flux: limestone and other calcareous stone, of a kind used for the manufacture of lime or cement	Limestone
260200	Manganese ores and concentrates, including ferruginous manganese ores and concentrates with a manganese content of 20% or more, calculated on the dry weight	Manganese Dioxide
251511	Marble and travertine: having a specific gravity of 2.5 or more, crude or roughly trimmed by sawing or otherwise, into blocks or slabs of a rectangular (including square) shape	Marble
251512	Marble and travertine: merely cut, by sawing or otherwise, into blocks or slabs of a rectangular (including square) shape, having a specific gravity of 2.5 or more	Marble
251741	Stones: of marble, in granules, chippings and powder, whether or not heat-treated	Marble Marble
250510	Sands: natural, silica and quartz sands, whether or not coloured	Quartzite
250610	Quartz: other than natural sands	Quartzite
250621	Quartzite: crude or roughly trimmed	Quartzite

250629	Quartzite: cut, by sawing or otherwise, into blocks or slabs of a rectangular (including square) shape, (excluding crude or roughly trimmed)	Quartzite
260900	Tin ores and concentrates	Tin & Tungsten
261100	Tungsten ores and concentrates	Tin & Tungsten
800200	Tin: waste and scrap	Tin & Tungsten

B Approximating export exposure in opium

The Myanmar Opium Survey 2020 (UNODC, 2021, p. 3) includes a map which describes the average cultivation density of opium between 2014 and 2020. This map contains four classes of density. To get a measure of opium production by township, I trace this map and take the following steps:

1. For each class, the UNODC report gives a bracket of cultivation density. For the low (0 - 0.01 ha/km^2), medium (0.01 - 0.1 ha/km^2), and high (0.1 - 1 ha/km^2) class, I take the average of this bracket (0.005, 0.055, and 0.55 ha/km^2 respectively). For the very high class ($>$ 1 ha/km^2), I assume a value of 2 ha/km^2.
2. I assume that areas outside the survey area of the UNODC report have no opium production. UNODC (2021, p. 33) provides support for this assumption.
3. I compute the overlapping area between each township and each of the four density classes.
4. I estimate the total opium cultivation in a township by multiplying the area of the township that is covered by a class with that class's cultivation density and then summing up the corresponding values for all classes that are present in the township.
5. To calculate the share of opium production of a township, I divide that township's opium production by the sum of opium production across all townships (divided by 31900/33100, as UNODC (2021) estimates that 1'200 ha of the opium cultivation area located outside Kachin and Shan states).

I then use this share of opium production by township to disaggregate the value generated from each year's nationwide export of opium. Estimates of the latter can also be found in the yearly UNODC reports. Unfortunately, the reports for the years 2016 (UNODC, 2017a) and 2017 UNODC (2017b) do not contain information about the value of opium production. Moreover, not all reports estimate the same matter. To make the different numbers comparable, I take the following additional assumptions:

1. The reports concerning the years 2012-2015 (UNODC (2012), UNODC (2013), UNODC (2014), UNODC (2015)) always provide point estimates as well as brackets of values for the relevant variables. This is not true for the years 2018-2020 (UNODC (2018), UNODC (2019), UNODC (2021)), which only report brackets for some values. In these cases, I take the middle of the brackets as point estimates. I also use the middle of the bracket to correct the farm-gate value in 2020. In this case the report provides a mid-point which is, however, outside of the bracket.
2. To make the values for different years comparable, I convert them to the farm-gate value in a first step. While the reports contain farm-gate values for the years 2018-2020, they only have an estimate of the "total potential wholesale value" for 2012-2015. However, there are estimates for both terms in 2011, once from the 2011 report (UNODC, 2011, farm-gate value) and once from the 2012 report (wholesale value). As the latter is 1.2 times as large as the former, I divide the wholesale value by 1.2 to get estimates for the

farm-gate value for 2012-2015.

3. The reports for the years 2018-2020 include an estimate of the "farm-gate value of opium" as well an estimate of the "value of opiates potentially available for export" (at the border). On average, the latter is ≈ 11.3 times as large as the former. As the interest of this exercise is export exposure, I scale the farm-gate values for 2012-2015 by ≈ 11.3.

4. Finally, I linearly interpolate the values of 2015 and 2018 to get estimates for the missing years 2016 and 2017.

C Robustness checks

Table A2: Control variables

Dependent Variable:	ln(conflict events)			
Model:	(1) OLS	(2) IV	(3) OLS	(4) IV
Panel A: Only townships without jade or gems				
ln(export exposure metals)	0.42**	0.47*	0.67**	0.97***
	(0.17)	(0.22)	(0.22)	(0.28)
Bamar × ln(export exposure metals)			-0.72**	-1.49**
			(0.28)	(0.60)
ln(export exposure opium)	-0.46	-0.47	-0.33	-0.20
	(0.27)	(0.27)	(0.29)	(0.33)
Cragg-Donald Wald F statistic		192.81		93.51
Panel B: Not controlling for opium export exposure				
ln(export exposure metals)	0.42**	0.51*	0.74**	1.06***
	(0.17)	(0.26)	(0.22)	(0.28)
Bamar × ln(export exposure metals)			-0.86**	-1.57**
			(0.26)	(0.55)
ln(export exposure jade)	0.15	0.15	0.14	0.12
	(0.21)	(0.21)	(0.20)	(0.20)
Cragg-Donald Wald F statistic		206.78		98.50

Note: Panel A excludes three townships where MEITI reports licenses related to jade and/or gemstones. Panel B includes all townships, but does not control for export exposure in opium. The table shows regressions of violent conflict events on export exposure in primary sector mining goods. The balanced panel consists of 73 townships in Kachin and Shan and 9 years (657 observations). All specifications include township fixed effects and year fixed effects. The parentheses show standard errors, which are two-way clustered by township and by year. I obtain export exposure by disaggregating nationwide exports to the townships where the goods are produced, using the townships' share of the national production area. The export exposure in jade and in opium is computed in the same way. Specifications three and four consider heterogeneous effects by including an interaction term, with Bamar being an indicator variable for the presence of the ethnic majority in a township. For the IV specifications, I construct a shift-share instrument using Chinese imports from other low and middle-income countries, multiplied by the same shares of national production area as above. I take logs for all export exposures and conflict events to interpret the coefficients as elasticities. To keep observations with zero values, I add 0.1 to all variables before taking logs. The levels of significance are * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table A3: Allocation of national exports to townships

Dependent Variable:	ln(conflict events)			
Model:	(1) OLS	(2) IV	(3) OLS	(4) IV
Panel A: Exports allocated by mining area				
ln(export exposure metals)	0.47**	0.48	0.76**	1.02**
	(0.18)	(0.34)	(0.24)	(0.38)
Bamar × ln(export exposure metals)			-0.80**	-1.55**
			(0.31)	(0.65)
ln(export exposure jade)	0.16	0.16	0.14	0.13
	(0.20)	(0.21)	(0.20)	(0.20)
ln(export exposure opium)	-0.40	-0.40	-0.29	-0.19
	(0.26)	(0.26)	(0.28)	(0.30)
Cragg-Donald Wald F statistic		163.28		75.15
Panel B: Exports allocated by projected mining area				
ln(export exposure metals)	0.39*	0.56**	0.55**	1.08***
	(0.18)	(0.23)	(0.21)	(0.24)
Bamar × ln(export exposure metals)			-0.49	-1.67**
			(0.30)	(0.60)
ln(export exposure jade)	0.15	0.14	0.15	0.12
	(0.20)	(0.21)	(0.20)	(0.20)
ln(export exposure opium)	-0.40	-0.42	-0.33	-0.17
	(0.26)	(0.26)	(0.27)	(0.31)
Cragg-Donald Wald F statistic		183.14		87.72
Panel C: Exports allocated by number of mines				
ln(export exposure metals)	0.32*	0.48*	0.52**	0.93***
	(0.16)	(0.21)	(0.20)	(0.26)
Bamar × ln(export exposure metals)			-0.57*	-1.41**
			(0.25)	(0.56)
ln(export exposure jade)	0.16	0.15	0.15	0.12
	(0.20)	(0.20)	(0.20)	(0.19)
ln(export exposure opium)	-0.42	-0.45	-0.34	-0.24
	(0.26)	(0.26)	(0.27)	(0.31)
Cragg-Donald Wald F statistic		187.92		91.66

Note: Panel A disaggregates nationwide exports by mining area (without winsorizing). Panel B assigns to each mine the area of an average mine of the same type and metal. Panel C uses the number of mines to disaggregate exports. Export exposure in jade is disaggregated by area in Panels A and B, and by the number of mines in Panel C. The table shows regressions of violent conflict events on export exposure in primary sector mining goods. The balanced panel consists of 73 townships in Kachin and Shan and 9 years (657 observations). All specifications include township fixed effects and year fixed effects. The parentheses show standard errors, which are two-way clustered by township and by year. I obtain export exposure by disaggregating nationwide exports to the townships where the goods are produced, using the townships' share of the national production area. The export exposure in jade and in opium is computed in the same way. Specifications five and six consider heterogeneous effects by including an interaction term, with Bamar being an indicator variable for the presence of the ethnic majority in a township. For the IV specifications, I construct a shift-share instrument using Chinese imports from other low and middle-income countries, multiplied by the same shares of national production area as above. I take logs for all export exposures and conflict events to interpret the coefficients as elasticities. To keep observations with zero values, I add 0.1 to all variables before taking logs. The levels of significance are * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table A4: Different sets of countries for the instrument

Dependent Variable:	ln(conflict events)					
Subset:	All countries		Neighbors		Lmic ex neigh.	
Model:	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
ln(export exposure metals)	0.64	1.16**	0.67	1.18*	0.69**	1.11**
	(0.35)	(0.36)	(0.45)	(0.60)	(0.29)	(0.34)
Bamar × ln(export exposure metals)		-1.48**		-1.43		-1.32**
		(0.59)		(0.83)		(0.55)
ln(export exposure jade)	0.14	0.11	0.13	0.11	0.13	0.12
	(0.21)	(0.20)	(0.20)	(0.18)	(0.20)	(0.20)
ln(export exposure opium)	-0.46	-0.21	-0.46	-0.23	-0.46	-0.24
	(0.26)	(0.31)	(0.25)	(0.31)	(0.27)	(0.32)
Cragg-Donald Wald F statistic	164.48	76.46	169.36	83.28	178.42	88.45

Note: Columns (1) and (2) use Chinese imports from all countries (other than Myanmar) for the construction of the instrument. Columns (3) and (4) use imports from the neighboring countries of China. Columns (5) and (6) use imports from low and middle-income countries that are not neighbors of China. The table shows regressions of violent conflict events on export exposure in primary sector mining goods. The balanced panel consists of 73 townships in Kachin and Shan and 9 years (657 observations). All specifications include township fixed effects and year fixed effects. The parentheses show standard errors, which are two-way clustered by township and by year. I obtain export exposure by disaggregating nationwide exports to the townships where the goods are produced, using the townships' share of the national production area. The export exposure in jade and in opium is computed in the same way. Specifications two, four, and six consider heterogeneous effects by including an interaction term, with Bamar being an indicator variable for the presence of the ethnic majority in a township. For the IV specifications, I construct a shift-share instrument using Chinese imports from other low and middle-income countries, multiplied by the same shares of national production area as above. I take logs for all export exposures and conflict events to interpret the coefficients as elasticities. To keep observations with zero values, I add 0.1 to all variables before taking logs. The levels of significance are * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table A5: Conflict measures

Model:	(1) OLS	(2) IV	(3) OLS	(4) IV
Dependent Variable:	ln(fatalities)			
Panel A: Fatalities				
ln(export exposure metals)	0.41**	0.32	0.51*	0.55
	(0.17)	(0.40)	(0.23)	(0.38)
Bamar × ln(export exposure metals)			-0.28	-0.70
			(0.38)	(0.74)
ln(export exposure jade)	0.15	0.16	0.15	0.15
	(0.26)	(0.28)	(0.26)	(0.27)
ln(export exposure opium)	-0.30	-0.29	-0.26	-0.17
	(0.24)	(0.23)	(0.21)	(0.22)
Cragg-Donald Wald F statistic		203.16		98.49
Dependent Variable:	ln(fatal events)			
Panel B: Fatal events				
ln(export exposure metals)	0.33**	0.30	0.40	0.50*
	(0.14)	(0.27)	(0.21)	(0.22)
Bamar × ln(export exposure metals)			-0.19	-0.59
			(0.34)	(0.56)
ln(export exposure jade)	0.10	0.10	0.09	0.09
	(0.22)	(0.23)	(0.22)	(0.23)
ln(export exposure opium)	-0.37*	-0.36*	-0.34*	-0.26
	(0.17)	(0.17)	(0.16)	(0.17)
Cragg-Donald Wald F statistic		203.16		98.49
Dependent Variable:	has conflict event			
Panel C: Binary indicator, at least one violent conflict event				
ln(export exposure metals)	0.10*	0.16*	0.14**	0.27**
	(0.05)	(0.09)	(0.06)	(0.11)
Bamar × ln(export exposure metals)			-0.11*	-0.32*
			(0.05)	(0.17)
ln(export exposure jade)	0.05	0.04	0.04	0.04
	(0.03)	(0.03)	(0.03)	(0.03)
ln(export exposure opium)	-0.04	-0.05	-0.02	0.00
	(0.07)	(0.07)	(0.08)	(0.10)
Cragg-Donald Wald F statistic		203.16		98.49

Note: Panel A uses the number of fatalities in a township and year as the dependent variable. Panel B uses the number of events with at least one fatality. Panel C uses a binary variable, indicating whether there has been at least one violent conflict event. The main variable of interest is export exposure in primary sector mining goods. The balanced panel consists of 73 townships in Kachin and Shan and 9 years (657 observations). All specifications include township fixed effects and year fixed effects. The parentheses show standard errors, which are two-way clustered by township and by year. I obtain export exposure by disaggregating nationwide exports to the townships where the goods are produced, using the townships' share of the national production area. The export exposure in jade and in opium is computed in the same way. Specifications three and four consider heterogeneous effects by including an interaction term, with Bamar being an indicator variable for the presence of the ethnic majority in a township. For the IV specifications, I construct a shift-share instrument using Chinese imports from other low and middle-income countries, multiplied by the same shares of national production area as above. I take logs for all export exposures and conflict events to interpret the coefficients as elasticities. To keep observations with zero values, I add 0.1 to all variables before taking logs. The levels of significance are * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table A6: Government participation

Dependent Variable:	ln(conflict events)			
Model:	(1) OLS	(2) IV	(3) OLS	(4) IV
Panel A: Events with government participation				
ln(export exposure metals)	0.19	0.30	0.42	0.83
	(0.19)	(0.43)	(0.29)	(0.52)
Bamar × ln(export exposure metals)			-0.63	-1.59**
			(0.35)	(0.58)
ln(export exposure jade)	0.17	0.16	0.16	0.14
	(0.20)	(0.21)	(0.20)	(0.21)
ln(export exposure opium)	-0.28	-0.29	-0.17	-0.03
	(0.29)	(0.30)	(0.31)	(0.34)
Cragg-Donald		203.16		98.49
Panel B: Events without government participation				
ln(export exposure metals)	0.69***	0.51*	0.93**	0.74*
	(0.20)	(0.27)	(0.28)	(0.39)
Bamar × ln(export exposure metals)			-0.67	-0.69
			(0.36)	(0.50)
ln(export exposure jade)	-0.15***	-0.14**	-0.16***	-0.14***
	(0.03)	(0.04)	(0.02)	(0.03)
ln(export exposure opium)	-0.78***	-0.75***	-0.67***	-0.64***
	(0.19)	(0.18)	(0.17)	(0.14)
Cragg-Donald		203.16		98.49

Note: Panel A includes all violent events in which at least one of the conflict parties was coded as state forces by ACLED, including military and police forces. Panel B includes all other violent events, where none of the parties was coded as belonging to the state forces. The table shows regressions of violent conflict events on export exposure in primary sector mining goods. The balanced panel consists of 73 townships in Kachin and Shan and 9 years (657 observations). All specifications include township fixed effects and year fixed effects. The parentheses show standard errors, which are two-way clustered by township and by year. I obtain export exposure by disaggregating nationwide exports to the townships where the goods are produced, using the townships' share of the national production area. The export exposure in jade and in opium is computed in the same way. Specifications three and four consider heterogeneous effects by including an interaction term, with Bamar being an indicator variable for the presence of the ethnic majority in a township. For the IV specifications, I construct a shift-share instrument using Chinese imports from other low and middle-income countries, multiplied by the same shares of national production area as above. I take logs for all export exposures and conflict events to interpret the coefficients as elasticities. To keep observations with zero values, I add 0.1 to all variables before taking logs. The levels of significance are * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table A7: Mapping of metals to goods of similar value for placebo test

Metal	HS6 code and description of matched placebo good		Mio USD (2011*) Metal	Placebo
Antimony	080300	Fruit, edible: bananas, (including plantains), fresh or dried	7.40	7.57
Baryte	620291	Anoraks (including ski-jackets), wind-cheaters, wind-jackets and similar articles: women's or girls', of wool or fine animal hair, other than those of heading no. 6204 (not knitted or crocheted)	0.04	0.04
Chromium	530310	Jute and other textile bast fibres: raw or retted, but not spun, (excluding flax, hemp (cannabis sativa L.), and ramie)	0.02	0.01
Coal	240210	Cigars, cheroots and cigarillos: containing tobacco including the weight of every band, wrapper or attachment thereto	0.01	0.01
Copper	400129	Rubber: natural (excluding latex, technically specified natural rubber and smoked sheets), in primary forms or in plates, sheets or strip	10.53	10.54
Dolomite	030749	Molluscs: cuttle fish and squid, frozen, dried, salted or in brine (whether in shell or not)	0.42	0.42
Gypsum	841990	Machinery, plant and laboratory equipment: parts of equipment for treating materials by a process involving a change of temperature	0.00	0.00
Iron	440349	Wood, tropical: (as specified in subheading note 1, chapter 44, customs tariff), n.e.s. in item no. 4403.41, in the rough, whether or not stripped of bark or sapwood, or roughly squared, untreated	87.47	87.94
Lead & Zinc	121299	Vegetable products (including unroasted chicory roots, chicorium intybus sativum variety): n.e.s. in chapter 12, fresh, chilled, frozen or dried, ground or unground, primarily for human consumption	21.48	21.92
Limestone	070490	Vegetables, brassica: edible, n.e.s. in heading no. 0704, fresh or chilled	0.00	0.00
Manganese Dioxide	400122	Rubber: technically specified natural rubber (TSNR), in primary forms or in plates, sheets or strip (excluding latex and smoked sheets)	43.57	39.82
Marble	030559	Fish: dried (whether or not salted but not smoked), n.e.s. in item no. 0305.51	1.10	1.13
Quartzite	410619	Leather: goat or kid skin, without hair on, tanned or retanned but not further prepared, whether or not split, n.e.s. in heading no. 4106 (not pre-tanned), excluding leather of heading no. 4108 and 4109	0.38	0.39
Tin & Tungsten	100510	Cereals: maize (corn), seed	31.82	35.60

Note: Matched such that the difference in export value to China in the last pre-study year of 2011 is minimized. The following two goods were disregarded, as they are related to metals: "830220 Castors: with mountings, of base metal" and "970300 Sculptures and statuary: original, in any material". Both would have been matched to marble. The following metals were not exported from Myanmar to China in 2011 and are therefore matched by the difference in export value in the first year after 2011 in which there are exports: Chromium (matched in 2012), Baryte (2013), Limestone (2014), and Gypsum (2017).