# Trade Policy in the Shadow of Conflict: The Case of Dual-Use Goods\*

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January 3, 2025

[Most recent version]

#### **Abstract**

Policymakers increasingly use trade instruments to address national security concerns. This paper studies optimal policy for dual-use goods—items such as semiconductors or drones that have both military and civilian applications. We begin by empirically documenting that the regulation and trade flows of dual-use goods respond to changes in the security environment over time. To put structure on the national security externality, we introduce military procurement into a multi-country general equilibrium network model and add a military contest to the national welfare function. In a simple two-country case, optimal export taxes depend on a trade-off between the good's military centrality and its distortion centrality. Military centrality is a networkadjusted sales share to the foreign military; distortion centrality reflects taxation misallocation in the domestic economy from roundabout imports. Using U.S. defense procurement data, we construct a measure of military use across goods, which ranges from zero to one, by scaling the U.S. closed-economy military centrality by import demand elasticities. Our measure effectively evaluates policy restrictions and military content in trade flows. To quantify the macroeconomic magnitude of the consumption-security trade-off, we calibrate our model to a potential U.S.-China conflict. The revealed preference estimate of the value placed on the probability of winning the conflict equals 2.5 times the annual U.S. GDP.

<sup>\*</sup>We are indebted to Pol Antràs, Elhanan Helpman, and Marc Melitz for their continuous guidance and support. We extend our gratitude to the many individuals who helped with the creation of this paper (Appendix A). All errors are our own.

### 1 Introduction

A recent rise in geopolitical tensions has prompted policymakers to rethink trade policy in light of national security considerations. Evidence of how the Russian war effort in Ukraine relies on imported manufacturing components has emphasized the importance of trade in dual-use goods, items with both military and civilian applications. Amid growing concerns about future military confrontations with China, the U.S. Department of Commerce introduced a pre-emptive export ban on advanced NVIDIA chips. In policy discourse, the perspective that supply chains for goods of strategic importance should be restricted to friendly countries has been emerging as a new political consensus, gradually replacing previous free trade narratives.

Despite the policy interest, the field of international trade still lacks a concise summary defining dual-use goods and their role in trade policy.<sup>4</sup> Optimal tariff formulas have been derived for consumption goods across a variety of market structures (Helpman and Krugman, 1989). The literature has also explored how trade taxes should correct international externalities in the context of carbon emissions and climate change (e.g., Kortum and Weisbach, 2021). In response to the conflict in Ukraine, recent theoretical work has commented on the optimal sanctions design, drawing a parallel between sanctions and terms-of-trade manipulations (Becko, 2024). The quantitative treatment of military externalities, however, remains a gap in the literature, which we address.

Our paper characterizes the optimal trade policy for dual-use goods in a world with possible military conflicts. We motivate our inquiry by empirically documenting that the regulation and trade flows of critical goods respond to changes in the security environment over time. We then present a simple two-country model that formalizes a military contest externality and derive optimal trade taxes in that setup. We construct a measure of military use across goods between zero and one, which is based on the sufficient statistics for the military externality in our tax formulas, and show that it predicts policy targeting and changes in trade flows around conflicts. To quantify the consumption-security trade-off, we extend our baseline model to a multi-country general equilibrium setup and calibrate it to a potential U.S.-China conflict.

We begin our paper by establishing three motivating facts about dual-use goods. First, goods classified as dual-use by security authorities are often intermediate inputs. They are

<sup>&</sup>lt;sup>1</sup>The FT article "Type of Russian missile that struck Kyiv children's hospital uses Western components" (Miller et al., 2024) provides one piece of anecdotal evidence.

<sup>&</sup>lt;sup>2</sup>News coverage of the ban can be found in the article "U.S. Restricts Sales of Sophisticated Chips to China and Russia" in the New York Times (Clark & Swanson, 2022).

<sup>&</sup>lt;sup>3</sup>See "What is Friendshoring?" in the New York Times (Kessler, 2022).

<sup>&</sup>lt;sup>4</sup>For the supply chain analysis of dual-use goods, see, for example, reports by *Rhodus Intelligence* (Galeev et al., 2024).

concentrated in categories such as machine tools, aerospace, and chemicals, and are generally produced by industries located midstream in the U.S. input-output tables. Second, these goods have received more policy attention in recent years. The range of goods classified as dual-use for EU customs has doubled since 2007, with sharp increases around 2014 and 2022; security-related policy announcements targeting these goods have increased tenfold since 2019. Third, trade in dual-use goods responds to the security environment. The subsidy equivalent for dual-use trade within Cold War blocs peaked at 40% in 1990 and has been decreasing since then, but the Ukraine conflict reversed half of the post-1990 decrease in bloc importance. During war episodes between 1960 and today, dual-use imports have experienced, on average, a 10% subsidy equivalent for friends and a 10% tariff equivalent for enemies. Together, these facts suggest that trade in some goods responds to a time-varying national security externality and motivates our theoretical framework that takes production networks into account.

We formalize our concept of the defense externality in a simple two-country model. We begin with an Armington (1969) setup with a freely tradable outside good and then expand the model to incorporate production networks in the spirit of Baqaee and Farhi (2024). To these models, we add the defense department as a second final demand agent alongside households. The defense department procures physical goods and is financed by household taxes. The government calibrates defense spending to balance household consumption with the expected payoff of a contest with the foreign military. In our two-country setup, the contest payoff is a function of a simple ratio of domestic military to foreign, which we later generalize. We solve for the optimal taxes across goods, keeping in mind that the observed national security bans might be a second-best outcome if policy instruments are restricted to zero or infinite taxes only.

In this setup, optimal export taxes depend on a trade-off between foreign military centrality and domestic distortion centrality. Military centrality is a network-adjusted sales share to the foreign military, which is scaled by a macro shifter that captures the importance of winning the military contest relative to domestic consumption. Distortion centrality is a network-adjusted domestic sales share via roundabout imports. The trade-off depends on the import demand elasticity, which enters as a denominator that scales the centrality difference. The trade-off is thus more significant for less substitutable goods. It serves as a Pigouvian addition to standard terms-of-trade components in the optimal tax formulas. In our calibration exercise, we extend our model to include production factors in fixed supply and find that the generalized optimal tax formulas feature a similar factor

 $<sup>^5</sup>$ Here and henceforth, subsidy equivalent or tariff equivalent simply means the coefficient on the gravity equation right-hand-side indicator variable for dual-use  $\times$  diplomatic relationship conditional on exporter-importer, exporter-product, and importer-product fixed effects and a diplomatic relationship dummy variable.

centrality trade-off that is multiplied by the price reaction of each factor.

As an illustration of our model's mechanism, consider U.S. chip exports to China. Taxing chip exports increases their price for the Chinese military but also increases the price of re-imported electronics containing these chips for American buyers. For \$1 of U.S. export sales, foreign military centrality is roughly the 20 cents that go to the Chinese military, and domestic distortion centrality is roughly the 10 cents that return to the U.S. via electronics. The U.S. government prefers higher export taxes on chips when military tensions with China are high relative to the domestic consumption weight. If China can easily substitute American chips with home-produced ones, the trade-off matters less, and consequently, the U.S. chip exports should be taxed less. If trade instruments for national security are limited to export bans, we will observe a chip ban as a second-best solution if the optimal export tax is high enough.

To quantify which goods matter for defense in practice, we develop an empirical measure of military use, ranging between 0 and 1, inspired by our optimal tax formulas. We first provide historical and anecdotal evidence that regulators consider the relative use of goods by military and households. Then we construct our military use measure by calculating military centrality across goods for the U.S. closed-economy network and scaling it by import demand elasticities, estimated in the trade literature. The intuition behind this statistic emerges from our optimal tax formulas and reflects the trade-off between the sectoral size of the military externality and production base non-substitutability. Military use provides a product-level characteristic applicable to a variety of contexts. The goods that score the highest on this metric are aluminum, warships, tanks, aircraft engines, and various shipbuilding inputs.

Our measure of military use predicts targeting by trade policies, as well as changes in import flows around conflicts. For policy outcomes, we examine entries in dual-use lists, U.S. export non-tariff measures after 2022, and global export policy announcements over time. We observe a pronounced change in the policy gradient: goods in the top percentile of our military use measure faced 40% fewer export policy announcements over 2018-2019

<sup>&</sup>lt;sup>6</sup>The remaining 70 cents constitute foreign consumption centrality, which appear in the trade-off along-side domestic distortion centrality when the U.S. government places a positive weight on foreign consumption. All the sales values mentioned should also be adjusted by taxation along the network in a way that the main text clarifies. The numbers in this example are hypothetical. For more concrete examples, we provide several firm-level case studies of critical supply chains in our motivating facts section.

<sup>&</sup>lt;sup>7</sup>The closed economy benchmark enables us to understand existing levels of trade regulation, whereas international centralities are calculated conditional on existing regulation and act as a normative prescription for future regulatory changes.

<sup>&</sup>lt;sup>8</sup>The dual-use nature of shipbuilding aligns with the account by Barwick et al. (2024), which overviews the history of industrial policy in the sector. Ding (2023) shows that the largest economies of scope in joint production are found in electronics, aerospace, and optical equipment, which are also military-centric sectors.

compared to goods in the bottom percentile, 7% more over 2020-2021, and 100% more over 2022-2023. Military use is a strong and robust predictor of inclusion in trade restrictions. It yields a better fit ( $R^2 = 0.85$ ) than a simple military sales share ( $R^2 = 0.35$ ) and military centrality without elasticity scaling ( $R^2 = 0.59$ ). It also wins a horse race against the latter, and maintains the same magnitude and significance conditional on sales share polynomials and other product-level controls.

For trade flow outcomes, we analyze conflict events and decompose changes in the average military use of imports across source countries and individual goods. In the case of Ukraine, for a 1pp increase in military use, a good sees a 5% increase in imports after 2022. The leading military contributors are Poland (weapons), Slovakia (ammunition), and Canada (tanks), which are offset by Russia (fossil fuels), China (electrical apparatus, steel), and Belarus (petroleum). We perform similar decompositions for Russia after 2022 and China between 2016 and the present. Intriguingly, we spot a trend of Chinese military-adjacent decoupling since 2016, driven by a decrease in imports of aerospace components, semiconductors, and optical equipment from the West.

The empirical validation of our military use measure enables us to apply it in a variety of policy and trade settings. In one exercise, we quantify to what extent various sanction lists target military enterprises, as measured by the military centrality rank of their industry of operation. We find that the U.S. Bureau of Industry Security lists follow an intuitive order, from the Military End Use list bans (average military centrality percentile of 77%) to less military-centric licensing lists (52%). There is also an intuitive clustering in terms of countries, with a targeted group (>75%: e.g., Latin America and Northern Europe), an expanded group (50%-75%: e.g., China, UAE, and Turkey), and a blanket sanctions group (<50%: e.g., Armenia, Serbia, and Iran). Across countries, a 1% increase in sanctions intensity, measured by the ratio of targeted entities to total entity records in a country, is associated with an  $\approx$  3% decrease in the average military centrality percentile. We observe similar consumption-security trade-offs by analyzing the EU critical goods lists and sanctions against Russia.

Our military use measure is a helpful indicator of military intensity for country-level trade flows both over time and in the cross-section. Tracking average military use for goods on a given exporter-importer link allows us to detect conflict shocks, such as Opération

<sup>&</sup>lt;sup>9</sup>Policy announcements reflect changes in policy, not levels. One potential reason why high military use goods were targeted less before 2019 is that they are inputs; see Antràs et al. (2024). Another reason would be that the military domain lacked the need for adjustment close to the steady state relative to other domains in peacetime or, more behaviorally, had no salience for policymakers. National security gained prominence following the Covid-19 outbreak, alongside concerns about supply chain resilience. In 2020, 800 DJI drones were grounded in the U.S. over the spying fears (Friedman & McCabe, 2020), and the U.S. introduced restrictions on the export of semiconductors and artificial intelligence software, contributing to an increase in the gradient.

Lamantin in the Western Saharan War, and secular trends, such as Russia's increasing dependency on the German industrial base after 1995. In the cross-section, it allows us to identify trade flows with the most military content. Between 1995 and 2015, China saw the largest export gains (+13pp) in military-adjacent industries, making it the biggest global contributor (17%) in terms of cumulative military export content at present, comparable to the military export contributions of the U.S. (9%) and Germany (8%) jointly. Our product-level characteristic thus provides helpful policy metrics for various settings.

In the final part of the paper, we evaluate the macroeconomic magnitude of the national security externality. To that end, we calibrate our model to a potential U.S.-China conflict, with the rest of the world as a bystander country. We first extend our theory to a general equilibrium framework, developing compact propagation matrix formulas for factor price changes. We also extend our data by assembling Chinese input-output tables and constructing final military demand based on the revenue of publicly-traded firms in the defense sector. We parametrize national welfare as a function of domestic consumption, foreign consumption with a weight, and a generalized contest function of domestic and foreign militaries with a weight. The generalized contest function captures the probability of winning the conflict, and the weight can be interpreted as the conflict prize. The contest elasticity parameter  $\gamma$  governs the returns to scale when the military good converts into the probability of winning, with values below one dampening military advantage and above one amplifying it.

The structural parameters are disciplined using a revealed preference approach. The contest elasticity parameter  $\gamma$  rationalizes how the U.S. adjusts its military spending in response to the evolution of the Eastern Bloc military spending over time. We find that the parameter equals  $\gamma \approx 0.5$  across specifications, suggesting that the military good translates into the probability of winning with decreasing returns to scale. The welfare weight on the military contest, or what we call the conflict prize, is estimated from the military spending levels: a marginal tax dollar going to the military should be as valuable as a marginal tax dollar left to households. Our estimate of the conflict prize amounts to 2.5 times of the annual U.S. GDP. Factor price adjustments affect this estimate by about 0.7-0.9 annual U.S. GDP. The estimate also depends on our assumptions about existing military stockpiles, which we derive using book values from accounting statements. The prize reflects a dynamic continuation value of winning the contest projected onto a static model.

Given our structural fit, we evaluate how home military advantage ( $m_{\rm HOME}/m_{\rm FRGN}$ ) can be increased at the expense of the consumption ratio ( $c_{\rm FRGN}/c_{\rm HOME}$ ) across various scenar-

<sup>&</sup>lt;sup>10</sup>Historically, when stockpiles decrease, military spending increases. During the World War 2, military spending reached 40% of the domestic GDP for the U.S.. Separating the effects on military spending of changes in stockpiles from the effects of changes in the externality might require more empirical analysis in the future.

ios. In the baseline scenario, with export taxes and zero welfare weights on foreign households, the U.S. increases its military advantage by 1.7% and decreases its consumption ratio by 1.5%; the numbers for China are 2.1% (>1.7%) and -4.9% (<-1.5%), revealing a stronger export policy impact. Potential smuggling via the Rest of the World reduces these effects by more than half for both countries. When military stockpiles are depleted, incentives to block exports increase, multiplying the U.S. effects by  $\approx$ 1.25. Import taxes serve as a stronger military deterrent for the U.S. compared to the export policy, primarily through decreasing Chinese defense budget. For China, however, import policy has a near-zero impact since China does not import significant quantities of American goods. The U.S. export policy implemented jointly with the Western coalition has a five times stronger impact than the U.S. acting on its own; similar enforcement by the Eastern coalition helps China very modestly by a factor of 1.25. Finally, industrial policy is a much more potent tool compared to trade policy. It performs a static terms-of-trade manipulation by redistributing from export-oriented sectors toward domestic military sectors.

Overall, military can be thought of as an interest group that shapes policy and trade outcomes in a way that is relevant on a macro scale. The static optimal tariff approach, which usually requires modeling modifications to explain policy for consumer goods, describes trade restrictions well in the military domain, where incentives are closer to the unilateral benchmark. Our military use measure that we develop based on sufficient statistics in our optimal tax formulas can be helpful for policy and trade evaluations. Across a variety of settings, when the weight on the national security increases, less military-centric dual-use items become targeted by policy. Our modeling architecture allows researchers to conduct general equilibrium policy evaluations with adversarial contests in mind. Factor price adjustments materially affect various statistics of interest. We discuss potential research follow-ups at the very end.

The remainder of the paper proceeds as follows. Section 2 contextualizes our contribution within the broader literature. Section 3 presents motivating facts on trade in dual-use goods. Section 4 provides insight through a simple two-country model. Section 5 develops our empirical measure of military use. Section 6 extends and calibrates the model. Section 7 concludes.

### 2 Related literature

Our paper studies optimal trade policy for dual-use goods in the presence of a military contest externality. From a thematic perspective, it continues the line of work that studies the role of interest groups in international trade, examining it through a national security

<sup>&</sup>lt;sup>11</sup>For empirical evidence and modern treatment of the Heckscher-Ohlin framework, see Kikuchi (2024).

lens. The paper makes theoretical contributions to the optimal tariff literature and the literature on wedges in production networks. On the empirical front, it quantifies industry network positions by incorporating defense procurement into input-output tables, while analyzing the associated trade and industrial policies.

We continue the tradition of research on interest groups in international trade starting from Grossman and Helpman (1994). The literature began with the influence of domestic lobbies on trade policy but has expanded to consider the influence of foreign lobbies (Antràs and Padró i Miquel, 2011, 2023); some recent quantitative treatments include Ossa (2014), Méndez and Van Patten (2022), Adão et al. (2023, 2024), Kleinman et al. (2023), Hsiao et al. (2024). Our study is distinct in that we quantitively examine military contests rather than domestic elections or other diplomatic actions.

More broadly, our paper is related to research on geoeconomics. Earlier work in this area used parsimonious setups to understand price incentives relating to conflict, production, and exchange (Skaperdas and Syropoulos, 2001, Kaempfer and Lowenberg, 2007, Acemoglu et al., 2012) and examine links between trade and conflicts empirically (Martin, Mayer, et al., 2008, 2012; Martin, Thoenig, et al., 2008, Acemoglu and Yared, 2010, Wen, 2012, Rohner et al., 2013, Chatagnier and Kavakl, 2017). Recent work deepens our understanding of mechanisms behind international coercion (Itskhoki and Mukhin, 2022, 2023, Becko, 2023, Bianchi and Sosa-Padilla, 2023, Clayton et al., 2023, 2024, Becko and O'Connor, 2024, Eichengreen et al., 2024, Kooi, 2024, E. Liu and Yang, 2024) and delivers structural estimates of various conflict parameters (Kang, 2016, König et al., 2017, Couttenier et al., 2023, Thoenig, 2023). We do not model game theory behind conflict realization but instead treat conflict probability as given. Therefore, we consider our approach to be closer to the interest group literature.<sup>12</sup>

We solve for optimal taxes in a multi-agent network economy with distortions and externalities. Optimal tariff formulas have been derived for consumption goods for a variety of market structures (Helpman and Krugman, 1989); most recently, for a Ricardian setup with a continuum of goods (Costinot et al., 2015), under monopolistic competition with firm heterogeneity (Costinot et al., 2020), and in the presence of economies of scale (Lashkaripour & Lugovskyy, 2022). Becko (2024) showed that the optimal sanctions problem is a scaled terms-of-trade manipulation problem. An extensive literature has studied optimal trade taxes under climate production externalities (e.g., Farrokhi and Lashkaripour,

<sup>&</sup>lt;sup>12</sup>Another way to classify the literature is to say that Adão et al. (2023), Adão et al. (2024), Hsiao et al. (2024) and others non-parametrically recover reduced-form utility weights on various interest groups by projecting data onto a minimalist static model; Thoenig (2023), Clayton et al. (2023, 2024), E. Liu and Yang (2024) and others impose various forms of game protocols (e.g., Nash-in-Nash bargaining or first-degree monopoly discrimination) before market clearing. We follow a classic markup approach (optimal trade taxes) with general welfare weights and use some structure to impose functional forms on utility Jacobians.

2021, Kortum and Weisbach, 2021; more broadly, Golosov et al., 2014, Conte et al., 2022, Cruz and Rossi-Hansberg, 2022, 2023, Hsiao, 2022, Acemoglu et al., 2023, Bilal and Rossi-Hansberg, 2023). Building upon the production networks literature following Long and Plosser (1983), researchers have developed theoretical tools for input-output accounting and optimal wedge-setting on networks (e.g., E. Liu, 2019, Bigio and La'O, 2020, Galeotti et al., 2020, Lashkaripour and Beshkar, 2020, Wu, 2022, Baqaee and Farhi, 2024, E. Liu and Tsyvinski, 2024). Our contribution to these lines of research includes optimal tax expressions under arbitrary network distortions, compact formulas for factor price adjustments, and reformulations of centrality in terms of sales shares for multi-agent economies.

Our quantification of industry positions in input-output networks follows a long tradition starting from Leontief (1936), and has been most recently exemplified by the work on global value chains (Jones, 1976, Antràs et al., 2012, Antràs and Chor, 2013, 2018, Hausmann et al., 2014, Antràs, 2016, Grassi, 2018, Alfaro et al., 2019, Grassi and Sauvagnat, 2019). Our research examines applications of trade and industrial policies similar to Evenett (2019), Bai et al. (2022), Copeland et al. (2022), Juhász et al. (2022), and Goldberg et al. (2024). We extend this analysis to military goods by working with government procurement contracts following Auerbach and Gorodnichenko (2012), Belenzon and Cioaca (2021), and Cox et al. (2023). Our conflict event studies add to the work on the economic consequences of war (Chupilkin and Koczan, 2022, Davis et al., 2023, Federle et al., 2024, Neri-Laine, 2024, Horn et al., 2024, Gopinath et al., 2024). Various security implications of trade in services in the context of surveillance AI are discussed in Beraja, Kao, et al. (2023a, 2023b), Beraja, Yang, et al. (2023). Our calibration exercises are similar to recent work on sanctions (e.g., Ghironi et al., 2023, de Souza et al., 2024); future models might benefit from matching empirical estimates of various elasticities (e.g., Chupilkin et al., 2024, Crosignani et al., 2024, Egorov et al., 2024, Li et al., 2024, Teti et al., 2024. X. Liu et al., 2024). Having established this context, we now turn to the main text.

## 3 Motivating facts

What goods can be put to both military and civilian uses? Rare-earth magnets produced in Chengdu, China, are used as inputs in the U.S. F-35 fighter jet radars and Tesla car seats. Ship engines produced by a German Rolls-Royce subsidiary power both the PLA Navy's missile destroyers and cruise ships across Lake Michigan. Computer numerical control (CNC) machines are used to make parts for both Iskander missiles and golf clubs. Inexpensive drones, originally designed for amateur photography, are repurposed for trench warfare in

Ukraine. Examples of such manufacturing inputs and equipment are abundant. <sup>13</sup>

Governments have historically intervened in the free exchange of dual-use items. Military considerations dominated over the design of export control policies directed to the Soviet Union during the Cold War (Gustafson, 1981). The 1721 Naval Stores Act, passed by the British Parliament, incentivized the production and import of timber from the North American colonies. Inexpensive timber was a strategic input to strengthen the British hegemony at sea, while also inadvertently sparking a boom in London furniture making (Bowett, 1994). In 1076, a Song court decree banned exports of gunpowder components, saltpeter and sulfur, to neighboring Liao and Western Xia to protect its military advantage (Andrade, 2016). The design of national security interventions has become more challenging in the modern world of global value chains and reshipping, where imprecise policy tools affect third parties and generate unintended adjustments (Itskhoki and Ribakova, 2024, Iyoha et al., 2024, X. Liu et al., 2024).

In this section, we document three stylized facts about dual-use goods, as classified by security experts. First, dual-use goods are overwhelmingly intermediate inputs. Second, trade in dual-use goods is increasingly regulated. Third, dual-use trade responds to changes in the security environment. These facts will motivate our theoretical framework going forward.

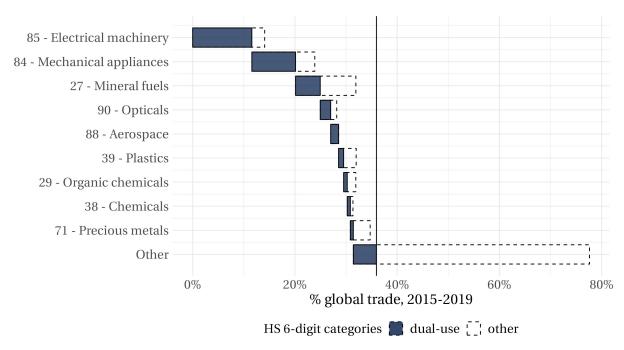
#### Fact #1. Dual-use goods are overwhelmingly intermediate inputs

Customs authorities implement strategic trade control to ensure that goods critical to national security do not cross international borders. The EU customs authorities provide correlation tables that link traditional Harmonized System 6-digit codes with the Export Control Classification Numbers (ECCN), flagging which goods should be subject to additional checks and licensing.<sup>14</sup> For the purposes of this section, our formal definition of dual-use goods refers to a set of HS 6-digit commodities listed in those tables.

Many commodities flagged as dual-use serve as inputs into manufacturing production. Two main HS 2-digit categories containing dual-use goods are electrical equipment (85) and mechanical machinery (84). Dual-use goods within these categories jointly account for more than 20% of global trade between 2015 and 2019 (Figure 1). Other prominent categories are opticals (90), aerospace (88), and mineral fuels (27), each representing 2% of global trade, as well as plastics (39), organic chemicals (29), and chemicals (38), accounting

<sup>&</sup>lt;sup>13</sup>See Appendix B.1 for our firm-level supply chain reconstructions behind the examples in this paragraph; examples for German ship engines, CNCs, and the Gustafson (1981) reference are borrowed from the OSINT analysis by *Rhodus Intelligence* and Kamil Galeev.

<sup>&</sup>lt;sup>14</sup>Appendix C.1.1 provides some institutional details.



*Notes:* Data for dual-use categories are taken from the 2018 vintage of the EU TARIC dual-use correlation tables. Data on trade flows from 2015 to 2019 are from the CEPII BACI (HS Rev. 4, 2012) dataset (Gaulier & Zignago, 2010). Blue bars show the share of global trade accounted by the dual-use goods within broader 2-digit categories; those bars are stacked to resemble a cumulative distribution function. Larger dashed white bars reflect the trade share of all the goods within each category. As such, blue bars sum horizontally to the total dual-use share of 36.3%, but white bars do not sum to 100% because they are placed in relation to blue bars. Figure C.1 provides a similar breakdown for the underlying ECN security codes.

Figure 1: Dual-use goods (2018 vintage) breakdown by HS2 codes

for 1%. Together commodities flagged as dual-use cover 36.3% of global trade. 15

In Appendix C.1.2, we link these HS 6-digit categories to NAICS industries that produce them and find that dual-use goods are located in midstream industries, as characterized by the ratio of their intermediate to total sales. Downstream industries either sell directly to civilians or, in a few special cases, are governed by the munitions lists rather than the dual-use lists. <sup>16</sup> Upstream industries, such as logging (113310) or industrial sand mining

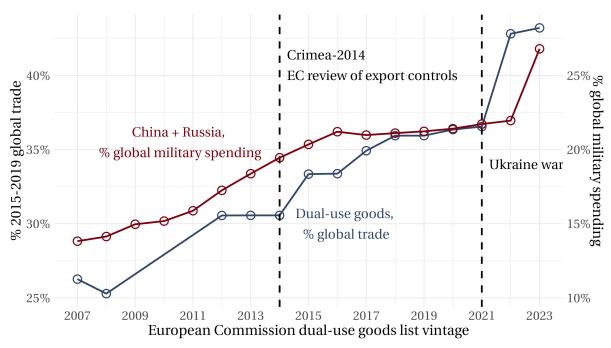
<sup>&</sup>lt;sup>15</sup>The reader should be careful in interpreting this number. First, this is not the same as saying that 36.3% of global trade is used in military production. These figures reflect commodities that might be used as military inputs, including raw materials such as oil and steel, but that in practice are mostly used for civilian purposes. Second, it would be incorrect to say that every item shipped within flagged categories could be used in military production. Not every chip can be put into a missile. These dual-use classifications are developed with customs' goals in mind and as such exhibit type-I and type-II errors driven by institutional objectives. Chatelus and Heine (2016) presents a more nuanced discussion of these issues. Therefore, the only way to treat our dual-use goods definition is to treat it in a formal sense. We will later demonstrate that this definition is helpful for policy analysis.

 $<sup>^{16}</sup>$ The HS codes governed by the munitions lists are 93XXXX (arms and ammunition), 8710XX (tanks), and

(212322), produce items that are too generic to be targeted by trade controls. These patterns in the data suggest that our model would benefit from a production networks treatment.

#### Fact #2. Trade in dual-use goods is increasingly regulated

The official customs definition of dual-use goods that we have selected as our benchmark has evolved over time. The set of commodities classified as dual-use has grown steadily since 2008, with sharp increases in 2015 and 2022 (Figure 2). The dual-use filter has expanded from covering 25% of global trade in 2007 to 45% in 2023. When expressed in terms of raw HS code count, the number of listed codes has doubled from 600 to 1,200 items (11.5% and 23% out of 5,205 goods in total; see Figure C.3).



*Notes:* Data for dual-use categories are taken from the EU TARIC dual-use correlation tables. Data on trade flows from 2015 to 2019 are from the CEPII BACI (HS Rev. 4, 2012) dataset (Gaulier & Zignago, 2010). Military spending data, which we use to measure China's and Russia's military spending as a percent of global military spending, come from SIPRI; 2023 values are estimated.

Figure 2: Dual-use goods coverage over time

The rise in dual-use coverage coincides with increases in military spending by China and Russia, and the timing follows the two acts of Russian aggression in Europe. In 2015, the European Commission ordered to review and modernize the export control system following increased national security threats; the list was updated to incorporate industrial ma-

<sup>890610 (</sup>warships). When y-variable monotonicity becomes important in our analysis, we add these HS6 codes to the dual-use lists manually; for descriptive purposes, we exclude them.

chinery. In 2022, following the start of the war in Ukraine, the list extended the machinery restrictions but also incorporated more household-oriented items such as air-conditioners and refrigerators (Supplementary Appendix Tables S.A.B1, S.A.B2). These facts suggest that the classification threshold might expand toward more household-oriented items in response to changes in the national security externality; a conjecture that we will examine in section 5.4 when discussing policy evaluations.

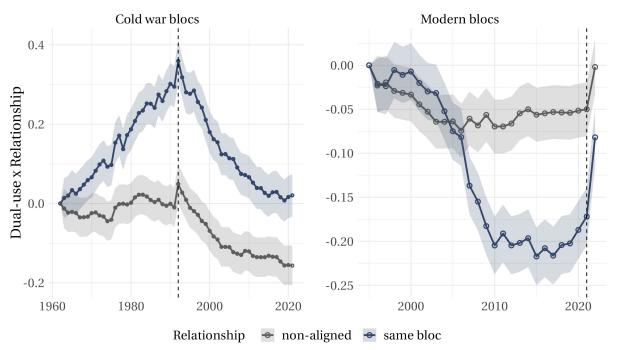
While the scope of customs controls has been expanding, the intensity of trade and industrial policies in this area has also been on the rise. In Appendix C.1.4, we document that "ringfencing" trade and industrial policies that restrict foreign access, such as foreign customer limits, local operations requirements, and intellectual property protections, disproportionately target dual-use goods when compared to a random draw benchmark or standard market-based instruments such as import tariffs. We also show that such policies have gained popularity since 2019, with a tenfold increase in new policy announcements in 2023 relative to the pre-pandemic period. Section 5 will examine policy targeting more formally; subsequently, we will analyze whether policy targeting translates into changes in trade flows.

#### Fact #3. Dual-use trade responds to changes in the security environment over time

The state of international security has varied historically, and those variations are reflected in the trade patterns of dual-use goods. In 1990, dual-use trade within Cold War blocs had a 40% subsidy equivalent<sup>17</sup> compared to all other trade links, as captured by a gravity equation at the exporter-importer-product-year level with a rich set of fixed effects (Figure 3; for details of the gravity specification and country bloc definitions, please refer to the note below the figure). The importance of the Cold War blocs has been gradually decreasing since then, and by 2019 the relative subsidy on the same-bloc×dual-use trade links has vanished altogether.

The decreasing trade relevance of country blocs has been partially reversed by the Ukraine war, which has rolled back half of the implicit subsidy decrease for same-bloc $\times$ dual-use trade links among modern geopolitical blocs since 1995. The Ukraine war has also emphasized the significance of dual-use trade between aligned/non-aligned country pairs; these trade links have witnessed a 5% subsidy equivalent. Our findings provide additional context to the results of Gopinath et al. (2024), who have established similar patterns for aggregate trade flows.

 $<sup>^{17}</sup>$ A reminder that subsidy equivalent or tariff equivalent simply means the coefficient on the gravity equation right-hand-side indicator variable for dual-use  $\times$  diplomatic relationship conditional on exporter-importer, exporter-product, and importer-product fixed effects and a diplomatic relationship dummy variable.



*Notes*: The trade data for the Cold War (1962-2021) come from the Atlas of Economic Complexity and are at the SITC Rev. 2 (1975) level. The trade data for the modern period (1995-2022) are from the UNComtrade database via BACI CEPII and are at the HS Rev. 0 (1992) level.

Our specification of choice is a triple-difference regression at the exporter-importer-product-year level that compares (1) trade in dual-use goods versus trade in other goods; (2) transactions within links of a given country-to-country relationship type versus all other trade links; and (3) periods of high bloc tension vesus other years. The regression equation is

$$\log y_{ijkt} = \alpha_{ijk}^{\mathcal{T}} + \alpha_{ikt}^{\mathcal{X}} + \alpha_{jkt}^{\mathcal{M}} + \gamma_{t,R} \times \text{Relationship}_{ij} + \beta_{t,R} \times \text{Relationship}_{ij} \times \text{Dual-use}_k + \varepsilon_{ijkt},$$

where  $\alpha_{ijk}^{\mathcal{T}}$ ,  $\alpha_{ikt}^{\mathcal{X}}$ , and  $\alpha_{jkt}^{\mathcal{M}}$  are a set of exporter-importer-product, exporter-product-time, and importer-product-time fixed effects. Relationship<sub>ij</sub> captures the diplomatic relationship between countries i and j. The year 1960 serves as the baseline, and we place no weight on the extensive margin when  $y_{ijkt} = 0$  by setting the left-hand side to zero following Chen and Roth (2024). An ijkt observation is included in the regression if both countries i and j have available data for year t.

Country classifications into the Western and Eastern blocs during the Cold War and in modern times are listed in Table SA.B.4. Links within the same bloc are defined as connections within the Western bloc or within the Eastern bloc. Non-aligned links are defined as connections between the Western bloc countries and the Rest of the World, as well as the Eastern bloc and the Rest of the World, with flows in both directions. Same bloc and non-aligned links are included in gravity regressions simultaneously.

Figures plot triple-difference coefficients  $\beta_{t,R}$  with 95% confidence intervals based on heteroskedasticity-robust standard errors. Figure C.6 plots  $\gamma_{t,R}$ , while Figures SA.B.3 and SA.B.4 present additional robustness checks.

Figure 3: Trade in dual-use goods by diplomatic relationship

In Appendix C.1.5, we show that shocks to the national security environment cause trade in dual-use goods to react in the short run. Analyzing wars between 1960 and to-day, dual-use imports for war participants undergo a 10% subsidy equivalent shock from their diplomatic friends and a 10% tariff equivalent shock from their diplomatic enemies. This occurs on top of a 30% subsidy shock and 30% tariff shock for all imports. The results suggest that following changes in national security, trade can adjust along geopolitical lines relatively quickly; we will examine conflict shocks in greater detail in section 5.

Together, our three facts suggest an existence of a time-varying national security externality, whereby trade in goods with military uses responds more strongly than trade in other goods. The next section formalizes this externality in a simple modeling framework and prepares theoretical foundations for our military use measure.

## 4 A simple two-country model

To capture our notion of the national security externality, we build a simple two-country model. We begin with a standard Armington (1969) setup with a freely tradeable outside good that serves as a numeraire. Additional model components include a tax-financed defense department that buys goods, and a military contest in the welfare function. The latter is a function of the ratio of home military good to that of the foreign country. We first consider a game where home and foreign governments simultaneously pick trade taxes and defense spending in a unilateral way to maximize domestic welfare. Subsequently, we consider a variation where trade and industrial policy moves before defense spending for both countries, adding a precautionary motive similar to Becko and O'Connor (2024). We end the section with a full setup that incorporates production networks in the spirit of Baqaee and Farhi (2024).

For every setup, we solve for the optimal taxes across goods. With no welfare weight on national security, the optimal export tax equals the monopoly markup (or the inverse demand elasticity), while the optimal import tariff is flat and equal to zero. Once security begins to matter, the export tax formula gains an additional Pigouvian term that multiplies a sales share going to foreign military by a country-level macro shifter. When the game becomes two-stage, the macro shifter incorporates an additional dynamic term that depends on the behavioral response of countries' defense spending in the second period. Due to

<sup>&</sup>lt;sup>18</sup>Here and henceforth, trade taxes also incorporate domestic industrial policy subsidies.

<sup>&</sup>lt;sup>19</sup>The level of import tariffs and export taxes is pinned down by the existence of a freely tradable outside good. In its absence, the Lerner symmetry holds and the flat level of import tariffs and export taxes is determined up to a constant (Lerner, 1936, Costinot et al., 2015, Costinot and Werning, 2019, Itskhoki and Mukhin, 2023).

that new dynamic component, domestic and import subsidies become positive and start playing a deterrence role. Once we extend the model to production networks, instead of a simple foreign military sales share, optimal tax formulas include a trade-off between the network-adjusted sales share to foreign military and the domestic sales share arising from roundabout imports. In section 6, we dispense with the freely tradable outside good and show that an additional factor centrality trade-off, multiplied by the factor price response, emerges.

### 4.1 Armington setup

Our baseline model sets up a simplified environment for tractability. We consider a world with two countries, home (H) and foreign (F). Each country has six key agents: a local representative firm, two local aggregators (one for the local consumption good and one for the military good), a representative household, the defense department, and the government. (Figure D.1 illustrates the structure schematically.) The local firm uses local labor to produce a local variety; the remaining labor not used by the firm transforms into a homogenous, freely tradable outside good. The local aggregators combine home and foreign varieties into both the local consumption good and the local military good. The household purchases the local consumption good and the freely tradable outside good with its income, which is derived from labor earnings and trade tax revenues net of a military lump-sum tax. The defense department utilizes government lump-sum transfers from households to fund the military good. The government determines trade policy and defense spending to maximize welfare, which consists of a sum of household utility and a national security term.

**Firms.** Every country has one firm producing a local variety with a constant-returns-to-scale labor technology  $q_k = z_k^q L_k$ ,  $k \in \{H, F\}$ . Here  $z_k^q$  is a technology shifter. The firms set their prices as

$$p_k = w_k / z_k^q. (1)$$

Every country-variety on the supply side will be later combined into a local consumption good and military good via demand aggregators, mirroring Armington (1969) model structure.

In addition to varieties produced by firms, there is also one freely tradable outside good that is produced only with labor:  $B=L^B$ . We normalize its price to 1,  $p^B=1$ . If both countries produce the freely tradable outside good, labor wages are pinned down by  $w_H=w_F=1$ , which shuts down general equilibrium wage effects. Our later assumptions on household utility and labor endowments will ensure that this would indeed be the case.

**Aggregators.** In every country  $i \in \{H, F\}$ , there are consumption and military aggregators. These aggregators transform varieties produced by firms into final consumption goods and military goods. To buy from firm k, the aggregator in country i pays the price

$$p_{ik} = \tau_{ik}^{\mathcal{X}} \tau_{ik}^{\mathcal{M}} d_{ik} p_k, \tag{2}$$

where  $(\tau_{ik}^{\mathcal{X}}-1)$  is an export tax (or subsidy) by a country k,  $(\tau_{ik}^{\mathcal{M}}-1)$  is an import tariff by country i, and  $d_{ik}$  are gravity frictions.

Aggregators combine firm output into final goods. To deliver  $c_i$  units of a local consumer good, the consumption aggregator combines  $c_{ik}$  units of firm k's output,  $k \in \{H, F\}$ , using a function  $\mathcal{F}^C$ . Similarly, to deliver  $m_i$  military units, the military aggregator combines  $m_{ik}$  units of firm k's output,  $k \in \{H, F\}$ , using a function  $\mathcal{F}^M$ :

$$c_i = \mathcal{F}_i^C(\{c_{ik}\}), \quad m_i = \mathcal{F}_i^M(\{m_{ik}\}).$$
 (3)

The functions  $\mathcal{F}^C$ ,  $\mathcal{F}^M$  are continuously differentiable, increasing, and concave in their arguments. They exhibit constant or decreasing returns to scale. Aggregators minimize their unit cost given firm prices  $p_{ik}$ :

$$P_i^C = \min_{\{c_{ik}\}} \left\{ \sum_{k=1}^K p_{ik} c_{ik} \right\} \quad \text{subject to} \quad c_i = 1, \tag{4}$$

$$P_i^M = \min_{\{m_{ik}\}} \left\{ \sum_{k=1}^K p_{ik} m_{ik} \right\} \quad \text{subject to} \quad m_i = 1.$$
 (5)

We denote the consumption aggregator's expenditure by  $C_i$  and the military aggregator's expenditure by  $M_i$ .

$$C_i \equiv P_i^C c_i, \quad M_i \equiv P_i^M m_i. \tag{6}$$

The resulting expenditure shares are

$$s_{ik}^C \equiv \frac{p_{ik}c_{ik}}{C_i}, \quad s_{ik}^M \equiv \frac{p_{ik}m_{ik}}{M_i}.$$
 (7)

The total expenditure on the good k is given by  $E_{ik}$ :

$$E_{ik} \equiv s_{ik}^C C_i + s_{ik}^M M_i, \tag{8}$$

while an after-tax expenditure is  $\tilde{E}_{ik} \equiv E_{ik}/(\tau_{ik}^{\mathcal{X}}\tau_{ik}^{\mathcal{M}})$ . We define the sales shares of firm k that go toward the military and consumption aggregators in country i as

$$S_{ik}^{C} \equiv \frac{s_{ik}^{C} C_{i}}{s_{ik}^{C} C_{i} + s_{ik}^{M} M_{i}}, \quad S_{ik}^{M} \equiv \frac{s_{ik}^{M} M_{i}}{s_{ik}^{C} C_{i} + s_{ik}^{M} M_{i}}.$$
 (9)

**Households.** A representative household in every country maximizes its utility that depends on its consumption of a freely tradable outside good ( $B_i$ ) and a local consumer good ( $c_i$ )

$$\max_{B_i, y_i} B_i + \frac{\eta_i}{\eta_i - 1} c_i^{\frac{\eta_i - 1}{\eta_i}} \tag{10}$$

subject to its budget constraint

$$B_i + C_i \le \mathcal{I}_i. \tag{11}$$

Household income  $\mathcal{I}_i$  equals labor income  $w_iL_i$  and tax revenues  $R_i$  net of government lump-sum taxes  $M_i$  that go toward the defense department:

$$\mathcal{I}_i = w_i L_i + R_i - M_i. \tag{12}$$

We assume that the labor endowment  $L_i$  is large enough to generate sufficient income for consuming the freely tradable outside good (which could otherwise lead to a corner solution under quasi-linear preferences). We also ensure that the labor endowment in both countries is large enough for the demand for the freely tradable outside good to drive both countries to produce it. This condition ensures  $w_H = w_F = p^M = 1$ , shutting down the general equilibrium effects. The quasi-linear structure also eliminates the income effect of the tax revenue  $R_i$  on household consumption spending  $C_i$ , simplifying our analysis in this section.

**Defense department.** Government lump-sum taxes  $M_i$  go toward defense spending. The defense department purchases  $m_i$  units of the military good to maximize national security

$$\max_{m_i} \frac{\zeta_i}{\zeta_i - 1} \left( \frac{m_i}{m_{-i}} \right)^{\frac{\zeta_i - 1}{\zeta_i}} \tag{13}$$

subject to the budget constraint

$$P_i^M m_i < M_i. (14)$$

The national security term depends not only on the military  $m_i$  at home but also on the military  $m_{-i}$  abroad. The higher the relative buildup  $(m_i/m_{-i})$  is, the more secure the country becomes. One can treat this functional form as a local approximation of more general contest functions (Tullock, 1980), which we will consider in section 6. Its role in this section is to simplify analytical expressions for utility Jacobians.

**Equilibrium.** Given government policies  $\mathcal{P} = (\{\tau_{ik}^{\mathcal{X}}\}, \{\tau_{ik}^{\mathcal{M}}\}, \{M_i\})$ ,  $\mathbf{E}_{\mathcal{P}} = (\{q_k\}, \{p_k\}, \{c_i\}, \{P_i^C\}, \{m_i\}, \{P_i^M\})$  is an equilibrium if

(1) firm optimizations (1), aggregator optimizations (4)-(5), household optimizations (10)-(11), and defense department optimizations (13)-(14) hold,

(2) goods markets clear

$$q_k = \sum_{i \in \{H,F\}} c_{ik} + \sum_{i \in \{H,F\}} m_{ik}.$$
 (15)

Country-specific policies will be denoted as  $\mathcal{P}^{(i)} = (\{\tau_{ik}^{\mathcal{M}}\}, \tau_{-i,i}^{\mathcal{X}}, M_i)$ . Hereafter, policies marked by  $\{\tau_{ik}^{\mathcal{M}}\}$  incorporate **both trade and industrial policies**.

**Welfare.** Governments set trade and defense spending policy variables contained in  $\mathcal{P}^{(i)} = (\{\tau_{ik}^{\mathcal{M}}\}, \tau_{-i,i}^{\mathcal{X}}, M_i)$ . Each country's national welfare payoff equals the sum of household utility and national security,

$$W_{i} = B_{i} + \frac{\eta_{i}}{\eta_{i} - 1} c_{i}^{\frac{\eta_{i} - 1}{\eta_{i}}} + \beta_{i} \frac{\zeta_{i}}{\zeta_{i} - 1} \left(\frac{m_{i}}{m_{-i}}\right)^{\frac{\zeta_{i} - 1}{\zeta_{i}}}, \tag{16}$$

where  $\beta_i$  is a weight that a country places on national security.

**Game.** The two governments simultaneously set their trade and defense spending policies  $(\mathcal{P}^{(H)}, \mathcal{P}^{(F)})$ . Based on  $\mathcal{P}$ , households, firms, and aggregators make their decisions, and the equilibrium  $\mathcal{E}_{\mathcal{P}}$  realizes. The governments subsequently collect welfare payoffs  $(W_H, W_F)$ .

The choice of the optimal trade policy  $\mathcal{P}_{\tau}$  is sensitive to assumptions on the game structure. We assume that setting trade policy entails setting linear ad-valorem taxes  $\tau_{ik}$  that are not a function of foreign trade policy or foreign defense spending. In the simultaneous-move game described above, the home government takes the foreign defense spending  $M_{-i}$  as given. In a sequential-move game where governments first set trade policy  $\mathcal{P}_{\tau}$  and then defense spending  $\mathcal{P}_{M}$ , the home government would take into account the foreign reaction to its trade policy. We will consider a sequential game variation to gain dynamic insights as an extension. The simultaneous-move game remains our benchmark and will be used for our quantitative analysis.

## 4.2 Optimal trade policy

We characterize the optimal trade policy in the environment specified above. We begin with the household and government spending problems. For households, a marginal dollar spent on a freely tradable outside good should be as beneficial as a marginal dollar spent on consumption, which allows us to characterize consumption spending given policies  $\mathcal{P}$ :

$$1 = c_i^{-1/\eta_i}/P_i^C, \quad c_i = (P_i^C)^{-\eta_i}, \quad C_i = (P_i^C)^{1-\eta_i}.$$
(17)

For governments, a marginal dollar spent on defense should be as beneficial as a marginal dollar left to households. This allows us to characterize defense spending given trade policies  $\mathcal{P}_{\tau}$ :

$$1 = \beta_i \frac{m_i^{-\frac{1}{\zeta_i}} m_{-i}^{\frac{1-\zeta_i}{\zeta_i}}}{P_i^M}, \quad m_i = (P_i^M/\beta_i)^{-\zeta_i} m_{-i}^{1-\zeta_i}, \quad M_i = \beta_i^{\zeta_i} \left(m_{-i} P_i^M\right)^{1-\zeta_i}$$
 (18)

Plugging (17), (18) into (16) allows to recast welfare in the optimum as

$$W_i = wL_i + R_i + \frac{C_i}{\eta_i - 1} + \frac{M_i}{\zeta_i - 1}.$$
 (19)

With these expressions in hand, we are now ready to characterize the optimal trade policy  $\mathcal{P}_{\tau}$ .

**Proposition 1.** The trade taxes for country  $i \in \{H, F\}$  in the Nash equilibrium satisfy

$$\tau_{ik}^{\mathcal{M}} = 1, \quad k \in \{H, F\},\tag{20}$$

$$\frac{\tau_{-i,i}^{\mathcal{X}} - 1}{\tau_{-i,i}^{\mathcal{X}}} = -\frac{1 + \left(\frac{M_i}{M_{-i}}\right) S_{-i,i}^M}{\mathcal{E}_{-i,i}^{-i,i} - 1}, \quad S_{ik}^M \equiv \frac{s_{ik}^M M_i}{s_{ik}^C C_i + s_{ik}^M M_i},\tag{21}$$

where elasticity  $\mathcal{E}_{-i,i}^{-i,i} \equiv d \log E_{-i,i}/d \log \tau_{-i,i}^{\mathcal{X}}$  is the import demand elasticity.

The proof of the proposition is given in Appendix D.1. It follows the Ramsey approach and serves as a template for other similar derivations in this paper, which are relegated to the Supplementary Appendix. Given a small policy change, the change in the national welfare function can be expressed as

$$dW_{i} = \underbrace{dR_{i}}_{\text{revenue}} + \underbrace{M_{i}d\log P_{-i}^{M}}_{\text{foreign military}} - \underbrace{\left(C_{i}d\log P_{i}^{C} + M_{i}d\log P_{i}^{M}\right)}_{\text{domestic distortion}}$$
(22)

The remainder of our proof expands these elements in terms of tax changes to solve for the optimum.

At the optimum, the export tax corrects a Pigouvian externality by internalizing the cost that every unit sold to the foreign military imposes on domestic welfare. Here  $(M_i/M_{-i})$  is a national security macro shifter that depends on the utility functional forms;  $S_{-i,i}^M$ , however, is a fundamental price-theoretic term that remains invariant across setups. Setting  $S_{-i,i}^M=0$  isolates the standard terms-of-trade export tax formula  $[-1/(\mathcal{E}_{-i,i}^{-i,i}-1)]$  that extracts the monopoly mark-up. Any non-zero import tax is distortionary because there are no market failures on the import side.

<sup>&</sup>lt;sup>20</sup>Alternatively, one can fix foreign military spending  $M_{-i}$  and examine the best response under  $\beta_i=0$  (zero weight on national security in national welfare). This would result in  $M_i=0$  and no Pigouvian externality in the optimal export tax.

We now proceed to the case of a sequential game in which trade policy is chosen before defense spending. Such a game presents a reduced-form way of modeling dynamics if one believes that trade policy choices made today can affect military build-up tomorrow (e.g. through resource stockpiling, military investment, or delays in observing foreign military strategies). In Supplementary Appendix A.2, we show that the following proposition holds.

**Proposition 2.** Consider the game in which governments set trade policies  $(\mathcal{P}_{\tau}^{(H)}, \mathcal{P}_{\tau}^{(F)})$  first and defense spending  $(\mathcal{P}_{M}^{(H)}, \mathcal{P}_{M}^{(F)})$  second. The trade taxes for country  $i \in \{H, F\}$  in the subgame perfect Nash equilibrium are characterized by

$$\frac{\tau_{-i,i}^{\mathcal{X}} - 1}{\tau_{-i,i}^{\mathcal{X}}} = -\frac{\mathcal{T}_{-i,i}^{\mathcal{X}} + \zeta_{i,-i}\tau_{-i,i}^{\mathcal{M}}(M_i/M_{-i})S_{-i,i}^{M}}{\mathcal{E}_{-i,i}^{-i,i} - 1},$$
(23)

$$\frac{\tau_{ik}^{\mathcal{M}} - 1}{\tau_{ik}^{\mathcal{M}}} = -\frac{\mathcal{T}_{ik}^{\mathcal{M}} + (1 - \zeta_{i,-i})S_{ik}^{M}}{\mathcal{E}_{ik}^{ik} - 1}, \quad k \in \{H, F\},$$

$$(24)$$

where  $\mathcal{T}^{\mathcal{X}}$  and  $\mathcal{T}^{\mathcal{M}}$  are the usual terms-of-trade components featuring revenue spillovers following trade diversion, and  $\zeta_{i,-i} \equiv \zeta_{-i}/(\zeta_i + \zeta_{-i} - \zeta_i \zeta_{-i})$  is the conflict elasticity. The terms-of-trade components can be expanded as

$$\mathcal{T}_{-i,i}^{\mathcal{X}} \equiv 1 + (E_{-i,i}/\tau_{-i,i}^{\mathcal{M}})^{-1} \sum_{k \in \{H,F\}} \frac{\tau_{ik}^{\mathcal{M}} - 1}{\tau_{ik}^{\mathcal{M}}} E_{ik} \mathcal{E}_{-i,i}^{ik}, \tag{25}$$

$$\mathcal{T}_{ik}^{\mathcal{M}} \equiv E_{ik}^{-1} \left[ \frac{\tau_{-i,i}^{\mathcal{X}} - 1}{\tau_{-i,i}^{\mathcal{X}} \tau_{-i,i}^{\mathcal{M}}} E_{-i,i} \mathcal{E}_{ik}^{-i,i} + \frac{\tau_{ik}^{\mathcal{M}} - 1}{\tau_{ik}^{\mathcal{M}}} E_{ik} \mathcal{E}_{ik}^{-i,i} \right]. \tag{26}$$

In addition to correcting the Pigouvian externality, trade interventions now have an additional strategic dimension. Export taxes and domestic subsidies act as deterrents, tilting the price ratio to affect the second stage of the game. The welfare choice in the first stage is now characterized by

$$dW_{i} = dR_{i} + M_{i}\zeta_{i,-i}d\log P_{-i}^{M} - C_{i}d\log P_{i}^{C} - M_{i}\zeta_{i,-i}d\log P_{i}^{M}.$$
 (27)

The degree of the strategic force is characterized by the conflict elasticity  $\zeta_{i,-i}$ , which reflects how sensitive foreign military spending is to the military price ratio. Under  $\zeta_{i,-i}=1$ , when nominal military spending is not sensitive to price ratio, Propositions 1 and 2 yield the same formulas. Under  $\zeta_{i,-i}>1$ , when nominal military spending decreases when price ratio moves unfavorably, strategic incentives both amplify export taxes and generate domestic subsidies. Another way to interpret this is to see that the strategic force modifies

<sup>&</sup>lt;sup>21</sup>Under  $\zeta_{i,-i}$  < 1, the foreign government decreases its military spending when the military price ratio becomes more favorable to it. For the home government, taxing home military goods becomes the optimal policy, as it both raises domestic revenues and deters foreign military spending.

the macro shifter  $(M_i/M_{-i})$  from Proposition 1, while keeping sectoral shifters  $S^M$  intact.<sup>22</sup> Proposition 2 thus demonstrates how dynamic incentives can make a case for trade policy as a strategic deterrent; for a more in-depth treatment of this topic, see Becko and O'Connor (2024).

We have gained some intuition about how taxation should function under the horizontal production case. In a simultaneous move game, governments correct a Pigouvian externality by imposing higher export taxes on goods with a higher sales share to the foreign military. In a two-stage game, the dynamic deterrence incentive makes the case for domestic subsidies. Yet this analysis has not touched upon how to treat inputs with complex downstream propagation, such as CNC machines or semiconductors. The following subsection examines how trade policy should operate in the context when inputs have intermediate uses.

#### 4.3 Military centrality in production networks

We extend our trade policy analysis to an environment with production networks. We show that the optimal trade taxes balance military centrality and distortion centrality of a trade flow, scaled by the trade flow elasticity. Military centrality is a network- and taxation-adjusted share of sales to the foreign military; distortion centrality is a similar statistic for the domestic economy that measures roundabout imports.

Our setup now features firm-level networks. The set of firms is  $\mathcal{K}$  with a set  $\mathcal{K}_H$  of home firms and a set  $\mathcal{K}_F$  of foreign firms,  $\mathcal{K}_H \cup \mathcal{K}_F = \mathcal{K}$ . To produce  $q_k$  units of output, firm  $k \in \mathcal{K}$  combines  $L_k$  units of local labor with inputs  $q_{kl}$  from firm l's output,  $l \in \mathcal{K}$ , according to production aggregator  $\mathcal{F}_k$ :

$$q_k = \mathcal{F}_k(L_k, \{q_{kl}\}). \tag{28}$$

Aggregators  $\mathcal{F}_k$  are continuously differentiable, increasing, and concave in arguments. They exhibit constant or decreasing returns to scale.

Firms minimize their unit costs given procurement prices  $p_{kl}$ :

$$p_k = \min_{L_k, \{q_{kl}\}} \left\{ w_k L_k + \sum_{l=1}^K p_{kl} q_{kl} \right\}$$
 subject to  $q_k = 1$ . (29)

The resulting procurement shares are denoted by

$$\Omega_{kl} = \frac{p_{kl}q_{kl}}{p_kq_k}. (30)$$

<sup>&</sup>lt;sup>22</sup>It also modifies terms-of-trade components. This occurs because trade policy now affects final demand, which means that taxes make import demand elasticities, which previously were zero, non-zero. (For example, import taxes for a country now affect export flows.)

Aggregators combine the output of all firms. The market clearing condition is now

$$q_k = \sum_{l \in \mathcal{K}} q_{lk} + \sum_{i \in \{H, F\}} c_{ik} + \sum_{i \in \{H, F\}} m_{ik}$$
(31)

For notational simplicity, we assume that all the cross-border transactions are firm-to-firm, while aggregators purchase only from local firms. This assumption is without loss of generality because, in a situation where a home firm sells directly to a foreign aggregator, we can always create a hypothetical importing node in the other country and assume that the firm sells to that node, which then sells to the foreign aggregator.

Before characterizing the optimal trade policy, we introduce some network definitions. We begin with standard definitions of the *Leontief* and *inverse Leontief matrices* and present some helpful facts about these. Then we introduce the concepts of *pull weights* and a *distortion matrix*. We use those concepts to introduce *military centrality*, which is the main focus of our analysis.

**Definition 1** (Leontief matrices). The cost-based Leontief matrix is  $\Omega = (\Omega_{kl})$ . The revenue-based Leontief matrix is  $\tilde{\Omega} = (\tilde{\Omega}_{kl})$ ,  $\tilde{\Omega}_{kl} = \Omega_{kl}/(\tau_{kl}^{\mathcal{X}}\tau_{kl}^{\mathcal{M}})$ .

**Definition 2** (Inverse Leontief matrices). The inverse cost-based Leontief matrix  $\Psi = (\Psi_{kl})$  and the inverse revenue-based Leontief matrix  $\tilde{\Psi} = (\tilde{\Psi}_{kl})$  are defined as

$$\Psi \equiv (\mathbf{I} - \mathbf{\Omega})^{-1}, \quad \tilde{\Psi} \equiv (\mathbf{I} - \tilde{\mathbf{\Omega}})^{-1}.$$
 (32)

The following two facts about Leontief matrices will be helpful for subsequent definitions. First, all the elements of inverse Leontief matrices  $\Psi_{kl}$ ,  $\tilde{\Psi}_{kl}$  are non-negative, since  $\Psi = \sum_{n=0}^{\infty} \Omega^n$ ,  $\tilde{\Psi} = \sum_{n=0}^{\infty} \tilde{\Omega}^n$ . Second, one can rewrite the market clearing condition for goods as

$$\mathbf{X} = \tilde{\mathbf{\Psi}}' \sum_{i \in \{H, F\}} \tilde{\mathbf{E}}_i. \tag{33}$$

One can see it by multiplying both sides of equation (31) by  $p_k$  and recasting in matrix form:

$$X_k = \sum_{l=1}^K \tilde{\Omega}_{lk} X_l + \sum_{i \in \{H,F\}} \tilde{E}_{ik}, \quad \mathbf{X} = \tilde{\mathbf{\Omega}}' \mathbf{X} + \sum_{i \in \{H,F\}} \tilde{\mathbf{E}}_i.$$
(34)

These facts will be helpful for the next two definitions.

**Definition 3** (Final demand weights). *Final demand weights* for firm k from expenditures of country j on firm l's output are

$$\omega_{kl}^{(j)} \equiv \frac{\tilde{E}_{jl}\tilde{\Psi}_{lk}}{X_k} \tag{35}$$

Intuitively,  $\omega_{kl}^{(j)}$  is a network-adjusted sales share that goes to country j through final demand for firm l's goods;  $\sum_{l\in\mathcal{K}}\omega_{kl}^{(j)}$  is the overall sales share to country j, and  $\sum_{j\in\{H,F\}}\sum_{l\in\mathcal{K}}\omega_{kl}^{(j)}=1$  represents the total sales share, which must sum to 1. This can be verified by observing that

$$X_k = \sum_{j \in \{H,F\}} \sum_{l=1}^K \tilde{E}_{jl} \tilde{\Psi}_{lk} \quad \Rightarrow \quad \sum_{j \in \{H,F\}} \sum_{l \in \mathcal{K}} \omega_{kl}^{(j)} = 1.$$
 (36)

**Definition 4** (Distortion matrix). *Distortion matrix*  $\delta^{(j)} = (\delta_{kl}^{(j)})$  is defined as

$$\delta_{kl}^{(j)} \equiv \frac{\tau_{jl} \Psi_{lk}}{\tilde{\Psi}_{lk}}, \quad \tau_{jl} \equiv \tau_{jl}^{\mathcal{X}} \tau_{jl}^{\mathcal{M}}. \tag{37}$$

The distortion matrix equals the matrix of ones when there are no taxes. In the economy with non-negative taxes, distortions are all greater or equal to 1. In the economy with nonnegative subsidies, distortions are all less or equal to 1. These two statements can be verified by showing that

$$\Psi - \tilde{\Psi} = \Psi(\Omega - \tilde{\Omega})\tilde{\Psi}. \tag{38}$$

After introducing these definitions, we proceed with our concepts of firm-level *centrality*.

**Definition 5** (Centrality). We define distortion centrality, consumption centrality, and military centrality of firm k for country j as

$$C_{jk}^{D} \equiv \sum_{l \in \mathcal{K}_{j}} \omega_{kl}^{(j)} \delta_{kl}^{(j)}, \tag{39}$$

$$C_{jk}^{C} = \sum_{l \in \mathcal{K}_{j}} \omega_{kl}^{(j)} \delta_{kl}^{(j)} S_{jl}^{C}, \qquad S_{ik}^{C} \equiv \frac{s_{ik}^{C} C_{i}}{s_{ik}^{C} C_{i} + s_{ik}^{M} M_{i}}, \tag{40}$$

$$C_{jk}^{M} = \sum_{l \in \mathcal{K}_{j}} \omega_{kl}^{(j)} \delta_{kl}^{(j)} S_{jl}^{M}, \qquad S_{ik}^{M} \equiv \frac{s_{ik}^{M} M_{i}}{s_{ik}^{C} C_{i} + s_{ik}^{M} M_{i}}.$$
 (41)

Intuitively,  $\omega_{kl}^{(j)}$  stands for the network adjustment, and  $\delta_{kl}^{(j)}$  for the taxation adjustment. An alternative interpretation of these definitions is that nodes with some final sales to country j have a military sales share characteristic  $S_{jl}^M$  with  $S_{jl}^M + S_{jl}^C = 1$ . The pull weights  $\omega$  and the distortion matrix  $\delta$  amplify these characteristics:

$$C_j^D \equiv (\boldsymbol{\omega}^{(j)} \otimes \boldsymbol{\delta}^{(j)}) \mathbf{1}, \quad C_j^M \equiv (\boldsymbol{\omega}^{(j)} \otimes \boldsymbol{\delta}^{(j)}) \mathbf{S}_j^M, \quad C_j^C \equiv (\boldsymbol{\omega}^{(j)} \otimes \boldsymbol{\delta}^{(j)}) \mathbf{S}_j^C.$$
 (42)

One can see that the sum of consumption and military centralities yield distortion centrality:

$$\mathcal{C}_{jk}^C + \mathcal{C}_{jk}^M = \mathcal{C}_{jk}^D. \tag{43}$$

In an economy with no taxes, distortion centrality equals a network-adjusted sales share to a given country,  $\sum_{l \in \mathcal{K}} \omega_{kl}^{(j)} \leq 1$ . In a closed economy with no taxes, distortion centrality equals 1. The following lemma provides a more intuitive way to express our centrality measures.

Lemma 1 (Centrality equivalence). Centrality can be restated as

$$C_{jk}^{M} = \frac{[\mathbf{\Psi}'\mathbf{s}^{\mathbf{M}}]_{jk}M_{j}}{[\tilde{\mathbf{\Psi}}'\mathbf{s}^{\mathbf{M}}]_{jk}M_{j} + [\tilde{\mathbf{\Psi}}'\mathbf{s}^{\mathbf{C}}]_{jk}C_{j}}, \qquad C_{jk}^{C} = \frac{[\mathbf{\Psi}'\mathbf{s}^{\mathbf{C}}]_{jk}C_{j}}{[\tilde{\mathbf{\Psi}}'\mathbf{s}^{\mathbf{M}}]_{jk}M_{j} + [\tilde{\mathbf{\Psi}}'\mathbf{s}^{\mathbf{C}}]_{jk}C_{j}}.$$
 (44)

Proof.

$$C_{jk}^{M} = \sum_{l} \frac{E_{jl} \Psi_{lk}}{X_{k}} S_{jl}^{M} = \frac{[\mathbf{\Psi}' \mathbf{s}^{\mathbf{M}}]_{jk} M_{j}}{[\mathbf{\tilde{\Psi}'} \mathbf{s}^{\mathbf{M}}]_{jk} M_{j} + [\mathbf{\tilde{\Psi}'} \mathbf{s}^{\mathbf{C}}]_{jk} C_{j}}.$$
(45)

As such, in an economy with no taxes,  $\mathbf{\Psi} = \tilde{\mathbf{\Psi}} \Rightarrow \mathcal{C}_{ik}^M \in [0,1].$ 

Another property of this centrality measure is rank invariance in a constant-returns-to-scale economy conditional on factor prices and trade taxes. Regardless of how one scales final agents' income, the relative rankings of firms remain the same. This property is helpful for empirical analysis.

**Lemma 2** (Rank invariance). Consider two economies A', A'' with identical factor prices and no taxation but different values of final demand M and C (e.g., driven by external endowments). Then, for any two industries k and l,

$$\mathcal{C}_{ik}^{M'} \geq \mathcal{C}_{il}^{M'} \qquad \Leftrightarrow \qquad \mathcal{C}_{ik}^{M''} \geq \mathcal{C}_{il}^{M''}$$

*Proof.* The rankings of centrality are the same as the rankings of military specialization:

$$C_k^M \ge C_l^M \quad \Leftrightarrow \quad \frac{1}{1 + ([\mathbf{\Psi}'\mathbf{s}^{\mathbf{C}}]_k/[\mathbf{\Psi}'\mathbf{s}^{\mathbf{M}}]_k)(C/M)} \ge \frac{1}{1 + ([\mathbf{\Psi}'\mathbf{s}^{\mathbf{C}}]_l/[\mathbf{\Psi}'\mathbf{s}^{\mathbf{M}}]_l)(C/M)}. \quad (46)$$

The latter inequality can be recast as

$$\frac{[\mathbf{\Psi}'\mathbf{s}^{\mathbf{C}}]_k}{[\mathbf{\Psi}'\mathbf{s}^{\mathbf{M}}]_k} \le \frac{[\mathbf{\Psi}'\mathbf{s}^{\mathbf{C}}]_l}{[\mathbf{\Psi}'\mathbf{s}^{\mathbf{M}}]_l}.$$
(47)

The terms here depend only on the network structure but not on the final demand M and C. Hence, centrality rankings are invariant to the scale of final demand as long as factor prices are kept constant.

After having defined and explored our centrality concepts, we can proceed with the proposition for the optimal network taxes. (Details of the proof are relegated to Supplementary Appendix A.3.)

**Proposition 3.** The trade taxes for country  $i \in \{H, F\}$  and firm  $k \in K_i$  in the Nash equilibrium satisfy

$$\frac{\tau_{-i,k}^{\mathcal{X}} - 1}{\tau_{-i,k}^{\mathcal{X}}} = -\frac{\overbrace{\tau_{-i,k}^{\mathcal{X}} + \tau_{-i,k}^{\mathcal{M}} \left[ \left(\frac{M_i}{M_{-i}}\right) \mathcal{C}_{-i,k}^{M} - \mathcal{C}_{i,k}^{D} \right]}^{centrality trade-off}}{\mathcal{E}_{-i,k}^{-i,k} - 1},$$

$$(48)$$

$$\frac{\tau_{ik}^{\mathcal{M}} - 1}{\tau_{ik}^{\mathcal{M}}} = -\frac{\overbrace{\mathcal{T}_{ik}^{\mathcal{M}}}^{ToT} + \overbrace{\left(\frac{M_i}{M_{-i}}\right)\mathcal{C}_{-i,i}^{M} - \mathcal{C}_{ik}^{D}}^{C_{-i,i}} - \mathcal{C}_{ik}^{D}}{\mathcal{E}_{ik}^{ik} - 1}.$$
(49)

where  $\mathcal{T}_{-i,k}^{\mathcal{X}}$  and  $\mathcal{T}_{ik}^{\mathcal{M}}$  are terms-of-trade components,  $\mathcal{E}_{ik}^{ik}$  and  $\mathcal{E}_{-i,k}^{-i,k}$  are import demand elasticities. These terms-of-trade components can be expanded as

$$\mathcal{T}_{-i,k}^{\mathcal{X}} \equiv 1 + \left[ \frac{F_{-i,k}}{\tau_{-i,k}^{\mathcal{M}}} \right]^{-1} \left( \sum_{l \in \mathcal{K}_i \setminus \{k\}} \frac{\tau_{-i,l}^{\mathcal{X}} - 1}{\tau_{-i,l}^{\mathcal{X}} \tau_{-i,l}^{\mathcal{M}}} F_{-i,l} \mathcal{E}_{-i,k}^{-i,l} + \sum_{l \in \mathcal{K}} \frac{\tau_{il}^{\mathcal{M}} - 1}{\tau_{il}^{\mathcal{M}}} F_{il} \mathcal{E}_{-i,k}^{il} \right), \tag{50}$$

$$\mathcal{T}_{ik}^{\mathcal{M}} \equiv F_{ik}^{-1} \left( \sum_{l \in \mathcal{K}_i} \frac{(\tau_{-i,l}^{\mathcal{X}} - 1) F_{-i,l}}{\tau_{-i,l}^{\mathcal{X}} \tau_{-i,l}^{\mathcal{M}}} \mathcal{E}_{ik}^{-i,l} + \sum_{l \in \mathcal{K} \setminus \{k\}} \frac{\tau_{il}^{\mathcal{M}} - 1}{\tau_{il}^{\mathcal{M}}} F_{il} \mathcal{E}_{ik}^{il} \right), \tag{51}$$

where  $F_{jk}$  is the total cross-border flow from firm k to country j.

Proposition 3 subsumes Proposition 1. There are two key changes in the tax formulas compared to Proposition 1. First, the final sales share  $S^M$  is replaced by the military centrality  $\mathcal{C}^M$ . In the horizontal case, one can verify that military centrality equals the sales share exactly. Second, there is the addition of a new distortion centrality term  $\mathcal{C}^D$ . This term captures the impact of roundabout imports. In the horizontal case with no roundabout component, distortion centrality equals zero, as exported goods never return as re-imports into the domestic economy.

This section has solved for the optimal trade taxes in a simple two-country economy with production networks. We have introduced the concept of military centrality. Proposition 3 has shown that trade policy serves a dual role in balancing foreign military centrality and domestic distortion centrality. With this baseline in mind, we can now proceed with our empirical applications.

### 5 Empirical measurement

Our simple model suggests that military centrality, distortion centrality, and import demand elasticities are the key sufficient statistics for determining optimal taxes that should

inform national security aspects of trade policy. This section aims to examine to what extent one can determine which goods pose military threats from economic data alone, without relying on security experts' lists.

We begin by developing a military use measure, inspired by our optimal tax formulas, which is defined as the U.S. closed-economy military centrality divided by import demand elasticities. Then we validate this measure using various outcomes, demonstrating that it predicts policy targeting and trade flow responses around conflicts. Given the predictive performance of our military use measure, we apply it to quantify various trade-related statistics. Specifically, we use it to evaluate the U.S. entity lists, the EU critical goods lists, and sanctions against Russia. We conclude by providing some summaries of trade flows in the cross-section and over time.

Before presenting our data, in Appendix B.2 we provide descriptive evidence that statistics such as military sales share are important factors in policymakers' decisions. We show an excerpt from a BIS conference that debated whether to continue regulating carbon fiber given its increased use in sporting and automobile applications. We also examine several technological transitions that decreased the military use of certain items, such as the post-WW2 phase-out of internal combustion engines from battlefield vehicles. We demonstrate that, historically, those episodes coincided with increases in international trade in the affected items. Our paper aims to provide a quantitative framework for analyzing such trade policy decisions.

### 5.1 Military use measure

Our centrality measures are written in terms of endogenous sales shares and, as such, already reflect existing policy interventions. If we were to ask what exports to China the U.S. should tax next, given all the regulations already in place, we would construct the U.S. distortion and Chinese military centrality measures for U.S. export flows and plug those into our formulas. This approach, however, works poorly for generating a policy-independent metric that predicts existing levels of regulation. For example, the American nuclear warhead centrality for China is zero not because nuclear warheads are not military-centric but because trade policy on both sides has already made this link infeasible.

To approximate economic production fundamentals, we pick an environment with minimal trade regulation and focus on the U.S. closed-economy setup. Our preferred empirical measure of military use is

$$0 \le \mathcal{C}_{\mathrm{US},k}^M / \sigma_k \le 1,\tag{52}$$

where  $\mathcal{C}^M_{\mathrm{US},k} \equiv \frac{[\Psi'\mathbf{s^M}]_{jk}M_j}{[\Psi'\mathbf{s^M}]_{jk}M_j + [\Psi'\mathbf{s^C}]_{jk}C_j} \in [0,1]$  represents the U.S. closed-economy military centrality of good k and  $\sigma_k \geq 1$  is its import demand elasticity. The intuition for this

statistic arises from the Pigouvian term in our optimal tax formulas. It reflects the tradeoff between the potential military externality magnitude  $C_{\text{US},k}^M$  and production base nonsubstitutability, as captured by import demand elasticities  $\sigma_k$ .

Military centrality  $\mathcal{C}_{jk}^M$  reflects the network-adjusted sales share of the U.S. NAICS industries to the Department of Defense. Industries are mapped to HS 6-digit commodities to obtain the product-level measure. Some industries, such as missile production or tank manufacturing, primarily serve the Department of Defense. Others, like automobile manufacturing or pharmaceuticals, predominantly sell to households. A range of input industries, such as semiconductors or the production of plastics, cater to both. Figure 4 displays total sales to both agents by industry. We set C and M to the empirical values of the U.S. annual national income and military spending, respectively, with  $M \approx 0.03C$ , keeping in mind that the rank of  $\mathcal{C}_{\mathrm{US},k}^M$  is scale-invariant with respect to the choice of M (Lemma 2).<sup>23</sup>

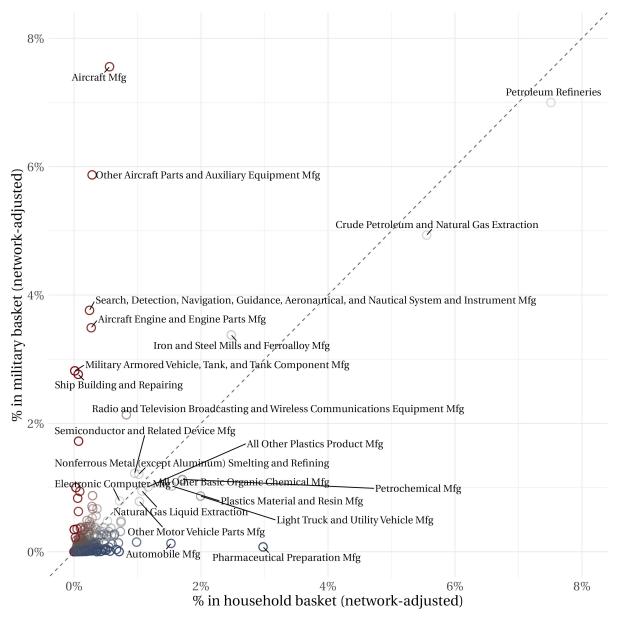
Import demand elasticities  $\sigma_k$  are the CES elasticities of substitution for a given good between export origins. They serve as empirical proxies for demand elasticity  $(\mathcal{E}_k-1)$  with networks and general equilibrium dependencies in our optimal tax formulas. We use LIML estimates, which are robust to outliers in trade flows, computed by Soderbery (2015), based on the Broda and Weinstein (2006) procedure, which extends Feenstra (1994). Supplementary Appendix B.2 discusses various trade elasticities and shows that our results hold under alternative elasticity measures. We treat these import demand elasticities as proxies for both technological substitutability and various dynamic forces, such as depreciation and stockpiling, insofar as these intertemporal phenomena are projected onto a static estimation strategy.

Table 1 lists fifteen goods with the highest military use. The highest-scoring goods are aluminum, warships, tanks, aircraft engines, and various shipbuilding inputs. Out of the 15 items, 12 belong to the EU dual-use list or are military items governed by the munitions list. We report changes in the optimal export tax rates for those good, assuming a starting point  $\tau=1$  (no terms-of-trade) and  $M_i/M_{-i}=1$  for the Jacobian. For this starting point, optimal taxes turn out to be of reasonable magnitudes, ranging from 200% on aluminum powders (highest) to 40% on aircraft engines (lowest).

## 5.2 Policy targeting

We compare our military use measure to three policy outcomes: EU dual-use lists, U.S. export restrictions after 2022, and global export policy announcements. Moving from the

 $<sup>^{23}</sup>$ A related question is whether annual M and annual elasticities are picked using the right time horizon given the presence of dynamic forces such as stockpiling. In the absence of a dynamic model, annual values are a natural choice that also happen to deliver decent predictability.



Notes: Data for the U.S. input-output table are taken for 2018 from the Bureau of Economic Analysis, with additional information from the Survey of U.S. Businesses by the U.S. Census. Data for military final demand come from procurement contracts accessed via USASpending. The military and household network-adjusted sales on the plot are  $\Psi'\mathbf{s}^{\mathbf{M}}M$  and  $\Psi'\mathbf{s}^{\mathbf{C}}C$ , with the basket normalization performed by setting  $C = 1/(\Psi'\mathbf{s}_{\mathbf{C}}\mathbf{1})$  and  $M = 1/(\Psi'\mathbf{s}_{\mathbf{M}}\mathbf{1})$ .

Figure 4: The 2018 U.S. input-output table

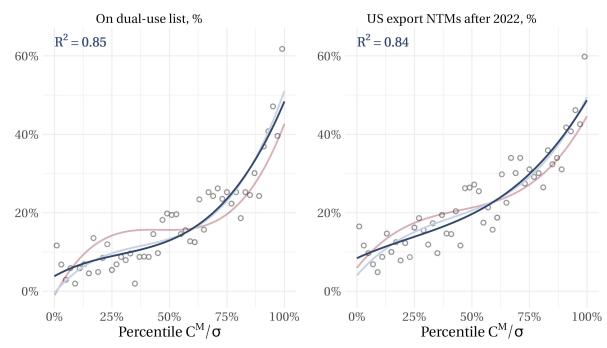
HS code	Description	$\mathcal{C}_{ ext{US},k}^{M}/\sigma_{k}$	$\Delta \tau (\%)$	D-U
760310	Aluminium; powders of non-lamellar structure	0.66	196.38	✓
760320	Aluminium; powders of lamellar structure, flakes	0.64	178.63	✓
890610	Vessels; warships	0.58	136.19	✓
871000	Tanks and other armoured fighting vehicles; motorised, whether or	0.56	129.46	✓
	not fitted with weapons, and parts of such vehicles			
890110	Cruise ships, excursion boats and similar vessels, principally de-	0.40	67.07	✓
	signed for the transport of persons, ferry boats of all kinds			
890120	Tankers	0.40	66.32	✓
890130	Vessels, refrigerated; other than tankers	0.40	66.32	✓
890190	Vessels; n.e.c. in heading no. 8901, for the transport of goods and	0.40	65.58	✓
	other vessels for the transport of both persons and goods			
890690	Vessels; other, including lifeboats other than rowing boats, other	0.39	62.89	✓
	than warships			
880310	Aircraft and spacecraft; propellers and rotors and parts thereof	0.37	57.51	✓
890590	Vessels; light, fire-floats, floating cranes and other vessels, the navi-	0.36	57.30	✓
	gability of which is subsidiary to their main function, floating docks			
890520	Floating or submersible drilling or production platforms	0.36	56.66	X
890510	Dredgers	0.36	56.04	X
890400	Tugs and pusher craft	0.32	47.65	X
840910	Engines; parts of aircraft engines (spark-ignition reciprocating or ro-	0.29	40.11	✓
	tary internal combustion piston engines)			

Notes: The three last columns report our measure of military use, export tax prescription, and the presence on the EU dual-use list. Military use is an elasticity-adjusted military centrality. The associated export tax prescription is computed based on  $(\tau_k-1)/\tau_k=\mathcal{C}_{\text{US},k}/\sigma_k$ . The EU dual-use list is from 2018 and is augmented by munitions HS codes 93XXXX (arms and ammunition), 8710XX (tanks), and 890610 (warships). Table C.2 details keywords in the HS code descriptions within the defined buckets. Figure C.8 plots the centrality and elasticity distributions for the underlying NAICS industries. Table C.3 depicts the correlation table for key variables; Figure C.9 plots the cumulative distribution functions.

Table 1: Top-15 HS codes by military use

0th percentile to the 100th percentile of our measure increases the probability of being on the dual-use lists from 5% to 50% and the probability of facing a U.S. export restriction after 2022 from 9% to 50%. The policy gradient shows a striking evolution: goods in the top percentile of military use faced 40% fewer export policy announcements over 2018-2019 compared to goods in the bottom percentile, 7% more over 2020-2021, and 100% more over 2022-2023. As Supplementary Appendix B.2 shows, the measure's predictability is stronger when weighted by trade shares or collapsed at the 4-digit level. The results are robust across various military contract samples and trade elasticities.

We first show how military use relates to the probability of being on the critical goods lists. Figure 5 displays average policy outcomes for percentiles of three different sorting variables: military use  $(\mathcal{C}^M/\sigma)$ , in blue, military centrality  $(\mathcal{C}^M)$ , in light blue, and military

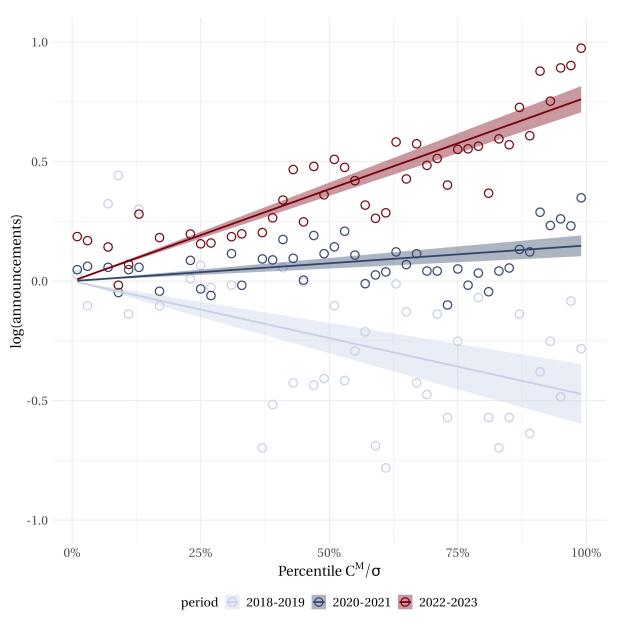


*Notes:* The colored lines display a cubic polynomial fit of the outcome onto the sorting variable percentiles: military use (blue), military centrality (light blue), and military sales share (red). Blue points reflect a bin-scatter with 50 bins of equal size for military use percentiles. The dual-use list is from 2018. The U.S. export non-tariff measures (NTMs) are taken from the *Global Trade Alert* data and cover U.S. announcements in the categories "Foreign customer limit," "Export licensing requirement," "Export ban," and "Export-related non-tariff measure, nes."

Figure 5: Military use and policy lists

sales ( $S^M$ , in red). While all the three variables exhibit monotonic behavior, military use provides the best sorting among the three. For the dual-use list, the  $R^2$  of the polynomial fit is 0.35 for  $S^M$ , 0.59 for  $\mathcal{C}^M$ , and 0.85 for  $\mathcal{C}^M/\sigma$ . For the U.S. export NTMs, the  $R^2$  is 0.29 for  $S^M$ , 0.45 for  $\mathcal{C}^M$ , and 0.84 for  $\mathcal{C}^M/\sigma$  (Figure C.10). It is worth emphasizing that both military centrality and import demand elasticities contribute to explaining policy targeting. Tables C.4-C.7 show that our military use measure wins a horse race against a simple military sales share and remains stable after including flexible sales share polynomials, trade controls, and HS2 fixed effects. Our model-guided  $\mathcal{C}^M/\sigma$  statistic thus delivers a superior prediction performance than  $S^M$  or  $s^M$  alone.

We then analyze global counts of export non-tariff measure announcements over time, noting that policy announcements reflect policy changes, not existing levels (Figure 6). In 2018-2019, goods in the top percentile of military use were subject to 50% less new export policies than those in the bottom percentile. This pattern evened out in 2020-2021, with goods covered almost uniformly. In 2022-2023, products in the top percentile received 100% more policies compared with the bottom percentile. This shift in policy focus is consistent with an increase in regulatory attention towards military-related industries.



Notes: The global export non-tariff measures (NTMs) are taken from the Global Trade Alert data and cover policy announcements in the categories "Foreign customer limit," "Export licensing requirement," "Export ban," and "Export-related non-tariff measure, nes." The figure presents a binscatter with 50 bins of equal size for military use percentiles. The regression lines plot a linear fit of  $\log(\operatorname{count}_{kt}) = \alpha_t + \beta_t \operatorname{bin} \operatorname{number}_k + \varepsilon_{kt}$  with an intercept normalized to zero.

Figure 6: Global policy counts

### 5.3 Trade flows

For trade flow outcomes, we examine import changes across goods following shifts in the security environment. We do that for three cases: Ukraine after 2022, Russia after 2022, and China after 2016. We then decompose military contributions across source countries and individual goods by measuring how much each trade flow contributes to cumulative military use of country imports and by analyzing changes in these shares over time. Finally, we observe that the average military use proves helpful for long-run analysis of trade flows over time.

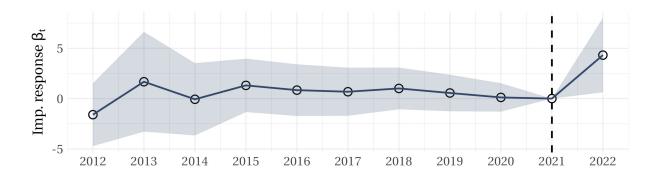
In the case of Ukraine, for a 1pp increase in military use, a good experiences a 5% increase in imports after 2022 (Figure 7). The leading military contributors are Poland (weapons), Slovakia (ammunition), and Canada (tanks), offset by Russia (fossil fuels), China (electrical apparatus, steel), and Belarus (petroleum). Increases in military use imports are driven by ammunition, tanks, weapons, warships, and electric generating sets (Appendix C.2.4).

For Russia after 2022, a 1pp increase in centrality leads to a 3.5% decrease in expected imports (Figure C.11). The leading military contributors are China (manufacturing), Kazakhstan (aluminum), and Turkey (vessels), offset by France, Germany, and the United States (primarily in aerospace and shipbuilding). Previously, Belarus functioned as a reshipping hub for European Union imports; consequently, it contributes less as well. The overall decline is linked to the import of aerospace and shipbuilding goods, as well as reception and transmission equipment.

A curious finding is the decoupling in military industries observed for China since 2016. For a 1pp increase in military use, China has witnessed an 8% decrease in expected imports between 2016 and the present. The decrease is driven by imports from the U.S., South Korea, France, Japan, and Taiwan, and is counterbalanced by increased imports from Vietnam, Indonesia, and Hong Kong.<sup>24</sup> The main drivers of the military import decrease are in aerospace, optical equipment, and various parts for the transmission and reception of data.<sup>25</sup> Whether this decoupling is a result of demand or supply factors, a by-product of Chinese industrial policies or an export policy intervention from source countries, remains a question for future research.

<sup>&</sup>lt;sup>24</sup>Given large flows associated with Hong Kong in the trade data, a significant part of these flows are due to reshipping.

<sup>&</sup>lt;sup>25</sup>This category includes displays, microchips, electric circuits, and semiconductors, as identified through the crosswalk with the latest HS Rev. 2022 set of codes.



#### (a) Impact of military use on imports



(b) Change between 2021 and 2022 in cumulative military use contribution shares across source countries

*Notes:* The top figure displays  $\beta_t$  from

$$\log y_{kt} = \alpha_k + \gamma_t + \beta_t \left[ \mathcal{C}_{\text{US},k}^M / \sigma_k \right] + \varepsilon_{kt},$$

where  $\alpha_k$  are good fixed effects and  $\gamma_t$  are year fixed effects. The year 2021 serves as the baseline. Standard errors are clustered at the good level.

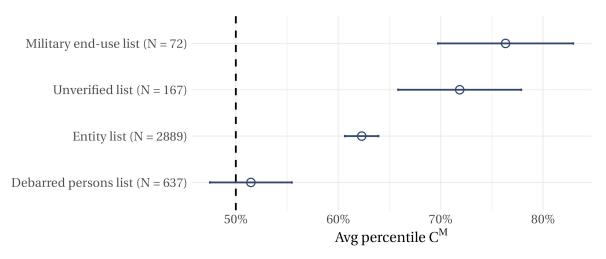
The bottom figure plots the change in cumulative military use contribution shares by source country, where the contribution share is measured as

$$\text{contribution}_{ijkt} = \frac{\sum_{k} y_{ijk} \left[ \mathcal{C}_{\text{US},k}^{M} / \sigma_{k} \right]}{\sum_{l} \sum_{k} y_{ilk} \left[ \mathcal{C}_{\text{US},k}^{M} / \sigma_{k} \right]}$$

Figure 7: Trade responses following geopolitical shocks: Ukraine-2022

### 5.4 Policy evaluation

Given that our military use measure passes some validation checks, we apply it to evaluate various security measures: the U.S. Bureau of Industry Security lists, the EU critical goods lists, and sanctions against Russia. For the entity lists, we link companies to their NAICS codes (when necessary, via matching with external datasets and using industry classification crosswalks) and report the centrality percentiles of associated industries. A recurring theme, observed both in the cross-section of policy targets and over time, is that more consumer-use goods and enterprises are targeted in less safe settings. Using the language of our theory, when a macro shifter on the security externality increases in size, more goods and enterprises pass the policy threshold.



*Notes*: The BIS Military End-Use List includes foreign parties that represent an unacceptable risk of use in or diversion to a "military end use" or "military end user" in countries subject to a U.S. arms embargo. The Unverified List contains names of foreign persons who are or have been parties to transactions involving U.S.-origin items and whose legitimacy have not been verified. The BIS Entity List includes the names of foreign persons, including businesses, research institutions, government and private organizations, individuals, and other types of legal persons that are subject to specific license requirements for the export, re-export, and/or transfer (in-country) of specified items. The Debarred Persons List includes individuals and entities that have been denied export privileges; they are matched only if an individual or entity that provides services is registered as a company.

The resulting lists of enterprises are matched with the universe of Orbis enterprises by country. The centrality rank is then determined for the industry of the matched enterprise, which is crosswalked into NAICS (Rev. 2012) classification code.

Figure 8: Military centrality of the Bureau of Industry Security categories

As a sanity check, we first report average centrality percentiles of targeted enterprises across BIS security lists by their type (Figure 8). The Military End-Use List (foreign enti-

<sup>&</sup>lt;sup>26</sup>Since we have industries and not goods, we report centrality instead of military use. This approach has the advantage of working for non-tradable industries as well.

ties that might divert goods to the military) has the average centrality percentile of around 76%, followed by the Unverified List (no bona fide; 73%), the Entity List (license needed; 62%), and the Debarred Persons List (no export privilege; 51%). Sorting by centrality thus generates an intuitive ranking of lists, serving as an indirect validation of our measure.<sup>27</sup>

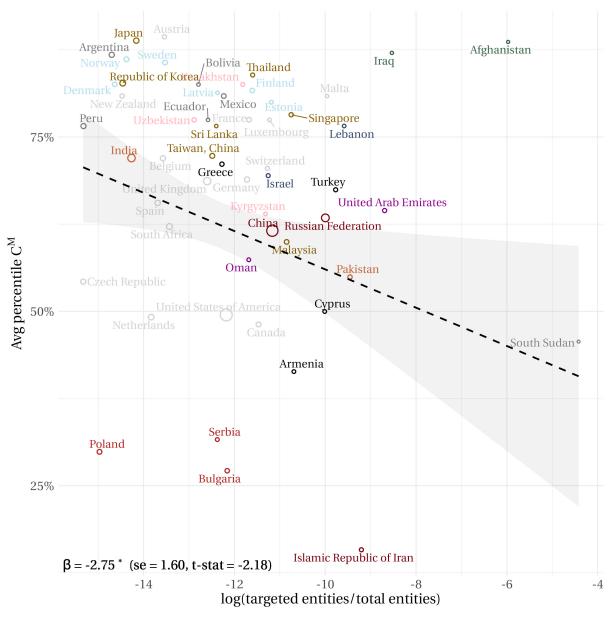
Figure 9 decomposes entity lists by country, plotting the average centrality percentile against sanctions intensity, as measured by the ratio of sanctioned entities to total entities. Scandinavian countries, Latin American countries, Iraq and Afghanistan, countries in the South China Sea except China, and most European countries are characterized by a limited number of restricted entities with a high military centrality (>75%), suggesting a targeted sanctions approach. Countries serving as entrepôts and countries in conflict-prone regions, such as the UAE, Oman, Turkey, and Pakistan, feature more entities on the lists and have average centrality between 50% and 75%. China and Russia, which lead in terms of the total number of applied restrictions, also fall into the 50%-75% zone. Outlier countries, like Serbia or Iran, feature a high number of restrictions and low centrality, reflecting a blanket sanctions approach (<50%). Across countries, a 1% increase in sanctions intensity is associated with an  $\approx$  3% decrease in average centrality percentile.

Similarly, we conduct an assessment of the EU critical goods lists. We first examine the EU dual-use lists (Fact #2, Figure 2) and evaluate how the average military use of the dual-use lists changed over time given the scope expansion. We find that targeting improved from 65.9% to 66.9% after the 2014 shock. In 2022, however, average military use decreased from 66.3% to 63.1%, marking a drastic adjustment toward more household-oriented items on the extensive margin (Figure C.15), in line with a shift in the security environment.

Besides the dual-use lists, since 2022 the EU Commission has compiled the list of critical battlefield items. The item groups are radioelectronics (95%; N=5 HS six-digit codes), semiconductors (74%; N=4), economically critical goods smuggled via third-party countries (68%; N=73), navigation & optics (62%; N=25), and manufacturing equipment (53%; N=16) (Figure C.16). Notably, semiconductors (74%), listed as Tier 1, score less on our measure than radioelectronics (95%), listed as Tier 2. This aligns with our understanding that semiconductors are substitutable with civilian versions and are easy to stockpile. While they might constitute an innovation chokepoint (e.g., NVIDIA AI chips), they do not necessarily constitute a physical production chokepoint. The high score of smuggled goods on our measure indicates that third-country imports might be used in military production, which is corroborated by the existing anecdotal evidence.

We conclude by evaluating various lists of sanctions applied against the Russian economy (Figure C.17). The bulk of broad-based war-related sanctions falls between 50% and

<sup>&</sup>lt;sup>27</sup>The Debarred Persons List contains cases of smuggling, where industry is often masked by the nature of the violation.



Notes: The countries are split and colored according to the following groups:  $Afghanistan \ and \ Iraq \ (dark \ green)$ ,  $Central \ Asia \ (Kazakhstan, \ Uzbekistan, \ Kyrgystan; pink)$ ,  $Israel \ and \ Lebanon \ (dark \ blue)$ ,  $Latin \ America \ (pale \ green)$ ,  $Nordic \ and \ Baltic \ countries \ (Sweden, \ Norway, \ Denmark, \ Finland, \ Estonia, \ Latvia; \ light \ blue)$ ,  $Asia \ Minor \ (Greece, \ Turkey, \ Cyprus, \ Armenia; \ black)$ ,  $China, \ Iran, \ and \ Russia \ (dark \ red)$ ,  $South \ Asia \ (India \ and \ Pakistan; \ saffron)$ ,  $South \ China \ Sea \ (Japan, \ Republic \ of \ Korea, \ Thailand, \ Sri \ Lanka, \ Singapore, \ Taiwan, \ Malaysia; \ gold)$ ,  $South \ Sudan \ (gray)$ ,  $UAE \ and \ Oman \ (magenta)$ ,  $Poland, \ Bulgaria, \ and \ Serbia \ (red)$ , other  $Western \ countries \ (light \ gray)$ . The size of points is proportional to the log(total entities), where total entities represents the number of entities for a given country recorded in Orbis. The regression line is weighted by total entities; results are robust when weighted by population, by targeted entities, and uniformly. Figures C.13 and C.14 plot average percentile  $C^M$  against targeted entities per capita and total targeted entities. Supplementary Appendix Figure SA.B.32 reports confidence intervals for the estimates.

Figure 9: Centrality by country: BIS targeted entities

65%: these include the Japanese METI end user list (61%; N = 38), the Canadian Consolidated Autonomous Sanctions list (59%; N = 346), and the Ukraine NSDC State Register of Sanctions (56%; N = 4298). Sanctions with very high (>70%) and very low (<50%) centrality tend to target fewer enterprises.

Access to micro-data and micro-level elasticities of adjustment is preferable for determining where sanctions should be tightened. Our calibration exercise demonstrates how our model can be brought to the data and handle certain extensions such as smuggling. While more nuanced models of incomplete information and uncertainty, and spatial link formation and goods' diffusion might be necessary for practical sanctions enforcement, our military use measure provides a helpful product-level statistic to guide macroeconomic evaluations even without access to the micro-data.

#### 5.5 Trade statistics

Average military use is a helpful summary statistic for the content of trade flows both over time and in the cross-section. Figure 10 gives a long-run perspective on the average military use of Iraq's imports and its response to various conflict events. Figure C.18 provides additional illustrative examples: (i) the emergence of Taiwan as a dual-use exporter, (ii) Russia's growing dependence on German machinery, (iii) the detection of French Opération Lamantin in the Western Saharan war, (iv) U.S. exports to Saudi Arabia, (v) shocks to Libyan imports, (vi) Yugoslavian imports, and (vii) Israeli imports. These case studies demonstrate how our measure can effectively trace the military content of trade flows over time.

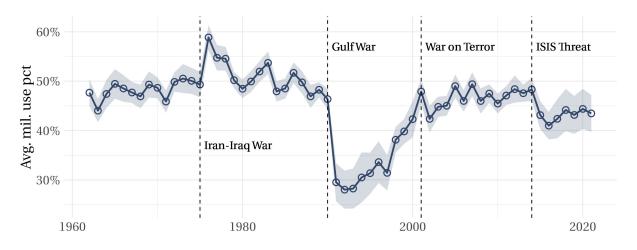


Figure 10: Imports of Iraq

We also summarize long-run changes in military contributions to global trade flows,

measured as cumulative military use content shares (see Figure 7 for our definition). Between 1965 and 1995, military contributions to global exports increased for East Asia, Mexico, and Spain, while decreasing for North America and Western Europe. The U.S. has experienced an increase in military-adjacent imports, paralleled by the rise of East Asian economies. Between 1995 and 2015, increases in military export contributions were driven almost exclusively by China. The downward trend for Western Europe continued, paralleled with a similar decline in Japan (Figures C.19-C.22). As of 2015-2019, China (17%), the U.S. (9%), and Germany (8%) are the three leading exporters in terms of cumulative military use content.

We have thus constructed an empirical measure of military use that is rooted in sufficient statistics in our optimal tax formulas. Our measure effectively predicts policy targeting and trade flow changes following conflicts. We have used it to evaluate various policy lists and trade flows over time. As a product-level characteristic, military use can therefore serve many helpful purposes. While we have developed a cross-sectional understanding of what goods should be targeted, the next section uses our model's calibration to a potential U.S.-China conflict to evaluate the macroeconomic magnitude of the consumption-security trade-off.

## 6 Calibration

Our theoretical approach provides a structural framework to assess the military externality and its macroeconomic implications, enabling us to quantify the consumption-security trade-off. While we have developed a measure of military use across goods, we have not taken a quantitative stance on macroeconomic shifters in our optimal tax formulas. To do that, we calibrate our model to a potential U.S.-China conflict and explore various counterfactual scenarios.

To do that, we extend our theory from Section 4 to a general equilibrium setup with flexible functional forms and adjustable factor prices. Production networks data are augmented with input-output tables for China and trade with the Rest of the World; China's military basket is recovered from the revenues of publicly-traded firms in the defense sector. We take a stance on specific functional forms and estimate parameters of the contest block. We conclude with quantitative policy evaluations.

## 6.1 General equilibrium model

We make three amendments to the network model in section 4. First, we allow for N countries instead of just two. Second, we introduce general utility functions

$$U_i(\{c_j\}_{i=1}^N, \{m_j\}_{i=1}^N). (53)$$

Finally, we rule out the existence of a freely tradable outside good, incorporating potential factor price adjustments into our analysis.

In the absence of the outside good, the household budget constraint becomes

$$C_i = w_i L_i + D_i + R_i - M_i, (54)$$

and wages  $w_i$  cease to be a numeraire.<sup>28</sup> Here,  $D_i$  represents trade deficits, with  $\sum_{i=1}^{N} D_i = 0$ . The following proposition presents optimal tax formulas for a general equilibrium setup.

### **Proposition 4.**

$$\frac{\tau_{-i,k}^{\mathcal{X}} - 1}{\tau_{-i,k}^{\mathcal{X}}} = -\frac{\underbrace{\tau_{0}^{\mathcal{X}}}_{-i,k} + \underbrace{\tau_{-i,k}^{\mathcal{X}}}_{-i,k} + \underbrace{\tau_{-i,k}^{\mathcal{M}}}_{-i,k} \sum_{j} \underbrace{\left[w_{ij}^{C} \mathcal{C}_{jk}^{C} + w_{ij}^{M} \mathcal{C}_{jk}^{M}\right]}_{\left[w_{ij}^{C} + w_{ij}^{C} \mathcal{C}_{jk}^{C} + w_{ij}^{C} \mathcal{C}_{jk}^{C}\right]} + \underbrace{\tau_{-i,k}^{\mathcal{M}}}_{\left[w_{ij}^{C} \mathcal{C}_{jj'}^{C} + w_{ij}^{M} \mathcal{C}_{jj'}^{M}\right]}_{\left[v_{ij}^{C} \mathcal{C}_{jk}^{C} + w_{ij}^{C} \mathcal{C}_{jk}^{C}\right]} + \underbrace{\tau_{-i,k}^{\mathcal{M}}}_{\left[w_{ij}^{C} \mathcal{C}_{jj'}^{C} + w_{ij}^{M} \mathcal{C}_{jj'}^{M}\right]}_{\left[v_{ij}^{C} \mathcal{C}_{jk}^{C} + w_{ij}^{C} \mathcal{C}_{jk}^{C}\right]},$$
(55)

$$\frac{\tau_{ik}^{\mathcal{M}} - 1}{\tau_{ik}^{\mathcal{M}}} = -\frac{\overbrace{T_{ik}^{\mathcal{M}} + \overbrace{\mathcal{I}_{ik}^{\mathcal{M}}}^{budget} + \sum_{j} \underbrace{\left[w_{ij}^{C} \mathcal{C}_{jk}^{C} + w_{ij}^{M} \mathcal{C}_{jk}^{M}\right]}^{\text{centrality trade-off}} + \sum_{j,j'} \underbrace{\left[w_{ij}^{C} \mathcal{C}_{jj'}^{C} + w_{ij}^{M} \mathcal{C}_{jj'}^{M}\right] \widetilde{\mathcal{J}}_{j'k}^{i}}_{\mathcal{E}_{ik}^{ik} - 1}}, \quad (56)$$

where  $\mathcal{T}_{-i,k}^{\mathcal{X}}$ ,  $\mathcal{T}_{ik}^{\mathcal{M}}$  are terms-of-trade terms,  $\mathcal{I}_{-i,k}^{\mathcal{X}}$ ,  $\mathcal{I}_{ik}^{\mathcal{M}}$  are income effect terms, and  $\tilde{\mathcal{J}}_{j'k}^{j}$  is a wage-tax Jacobian adjusted by the inverse ratio of trade flows to factor payments  $(F_{jk}/(w_{j'}L_{j'}))$ . The centrality weights are given by utility Jacobians

$$w_{ij}^{C} = \left(\frac{U_{ic,j}}{P_{j}^{C}}\right) / \left(\frac{U_{ic,i}}{P_{i}^{C}}\right), \quad w_{ij}^{M} = \left(\frac{U_{ic,j}}{P_{j}^{M}}\right) / \left(\frac{U_{ic,i}}{P_{i}^{C}}\right). \tag{57}$$

Terms-of-trade terms can be rewritten as

$$\mathcal{T}_{-i,k}^{\mathcal{X}} \equiv 1 + \left[\frac{F_{-i,k}}{\tau_{-i,k}^{\mathcal{M}}}\right]^{-1} \left(\sum_{j \neq i,l \in \mathcal{K}_i}^{\neg (j=-i \wedge l=k)} \frac{\tau_{jl}^{\mathcal{X}} - 1}{\tau_{jl}^{\mathcal{X}} \tau_{jl}^{\mathcal{M}}} F_{jl} \mathcal{E}_{-i,k}^{jl} + \sum_{l} \frac{\tau_{il}^{\mathcal{M}} - 1}{\tau_{il}^{\mathcal{M}}} F_{il} \mathcal{E}_{-i,k}^{il}\right), \tag{58}$$

$$\mathcal{T}_{ik}^{\mathcal{M}} \equiv 1 + F_{ik}^{-1} \left( \sum_{j \neq i, l \in \mathcal{K}_i} \frac{\tau_{jl}^{\mathcal{X}} - 1}{\tau_{jl}^{\mathcal{X}} \tau_{jl}^{\mathcal{M}}} F_{jl} \mathcal{E}_{ik}^{jl} + \sum_{l \neq k} \frac{\tau_{il}^{\mathcal{M}} - 1}{\tau_{il}^{\mathcal{M}}} F_{il} \mathcal{E}_{ik}^{il} \right), \tag{59}$$

<sup>&</sup>lt;sup>28</sup>Our analysis extends to the case of multiple factors or when a factor is owned by multiple groups.

and income effect terms as

$$\mathcal{I}_{-i,k}^{\mathcal{X}} = \left[\frac{F_{-i,k}}{\tau_{-i,k}^{\mathcal{M}}}\right]^{-1} \left[\sum_{j \neq i} w_{ij}^{C} \mathcal{J}_{-i,k}^{R_{j}} + \sum_{j} w_{j} L_{j} \mathcal{J}_{-i,k}^{w_{j}}\right], \tag{60}$$

$$\mathcal{I}_{ik}^{\mathcal{M}} = F_{ik}^{-1} \left[ \sum_{j \neq i} w_{ij}^{C} \mathcal{J}_{ik}^{R_j} + \sum_{j} w_j L_j \mathcal{J}_{ik}^{w_j} \right], \tag{61}$$

with further expansions if necessary.

The proposition proof is given in Supplementary Appendix A.5. In the absence of a freely tradable good, the household budgets and factors in fixed supply generate changes in the price system. The new element in the optimal tax formulas emerges as a factor centrality trade-off, scaled by a factor price response. As in all previous cases, our formulas cover both trade and industrial policies.

One question that arises from Proposition 4 is how to recover the factor price tax Jacobian  $\mathcal{J}_{j'k}^w$ . For that purpose, we express the factor market clearing condition as a compact matrix expression

$$\Lambda^{L}wL = \Omega^{L'}\Lambda^{X}\tilde{\Psi}'(s^{C}(D-M) + s^{M}M), \tag{62}$$

where  $\Lambda^R$ ,  $\Lambda^X$ , and  $\Lambda^L$  satisfy

$$\mathbf{R} = \mathbf{\Lambda}^{\mathbf{R}} \mathbf{X}, \quad \mathbf{\Lambda}^{\mathbf{X}} \equiv (\mathbf{I} - \tilde{\mathbf{\Psi}}' \mathbf{s}^{\mathbf{C}} \mathbf{\Lambda}^{\mathbf{R}})^{-1}, \quad \mathbf{\Lambda}^{\mathbf{L}} \equiv \mathbf{I} - \mathbf{\Omega}^{\mathbf{L}} \mathbf{\Lambda}^{\mathbf{X}} \tilde{\mathbf{\Psi}}' \mathbf{s}^{\mathbf{C}}.$$
 (63)

Matrix  $\Lambda^{\mathbf{R}}$  converts firm sales into tax revenues. Matrix  $\Lambda^{\mathbf{X}}$  is the inverse that reflects the amplification of sales via tax revenues—tax revenues increase household budgets and lead to higher demand and more sales. Matrix  $\Lambda^{\mathbf{L}}$  captures the roundabout propagation of factor prices through the economy, serving as the analog of  $(\mathbf{I} - \Omega)$  in the Leontief inverse but for factor prices. Taking a first-order approximation following a small policy change allows us to back out  $\mathcal{J}^w_{j'k}$  (see Appendix D.2 for more details).

When it comes to solving the model numerically, we use an iterative algorithm, first solving for optimal taxes using (55)-(56) and then updating the equilibrium using (62). To calibrate the model, we need to take a stance on the utility functional forms and their associated parameters, which we address in the following subsection.

#### **6.2** Parameter fit

We calibrate our model to a three-country setup with the United States, China, and the Rest of the World. To do so, we assemble Chinese input-output tables (Figure C.23). The

differences in military sectors are primarily driven by the fact that we derive military demand from publicly traded Chinese firms in the defense sector (whereas for the U.S., publicly available contracts of the Department of Defense are observed). For the Rest of the World, we assume no military production and a horizontal production of export varieties that utilize only local labor, mapping networks only for import nests.

We also take a stance on the functional forms of the utility and production functions. Following Tullock (1980), we adopt a generalized contest function to model the military contest, resulting in the following national welfare function:

$$U_i(\{c_j\}_{i=1}^N, \{m_j\}_{i=1}^N) = c_i + \sum_{j \neq i} \alpha_{ij} c_j + \beta_i \frac{g(m_i)}{g(m_i) + \sum_{j \neq i} g(m_j)}.$$
 (64)

We will denote the expected prize share of a country in the conflict as  $\nu_i = g(m_i)/(g(m_i) + \sum_{j \neq i} g(m_j))$  and interpret  $\beta_i$  as the expected prize size for country i that pins down the marginal value of national security. We assume that the Rest of the World has no military capabilities and places no weight on national security, so that  $\nu_{\text{USA}} + \nu_{\text{CHN}} = 1$ . A large literature on generalized contest functions, starting from Tullock (1980), has extended the contest block to various scenarios, including conflict damages and military alliances (e.g., König et al., 2017). We include a derivation for military alliances in our Supplementary Appendix A.6 but reserve alliance quantifications for future work, keeping our contest block minimalist.

We further assume that  $g(m_i) = (m_{0i} + m_i)^{\gamma}$ , where  $m_{0i}$  is the existing national stockpile of the military good in fixed supply (determined by the Department of Defense assets from their accounting statements in the data). Parameter  $\gamma$  captures returns to scale for a military good, with values below one dampening military advantage (under  $\gamma \to 0$ , everyone gets an equal share regardless of military size) and above one amplifying it (under  $\gamma \to \infty$ , a small military advantage yields a certain victory).

Table 2 summarizes our parameter choices. The welfare weights on foreign consumption  $\alpha_{ij}$  are assumed to be  $\alpha_{ij}=0.01P_j^C$  or  $\alpha_{ij}=P_j^C$  across calibrations to contrast welfare under unilateral and universalist modes of trade policy. This parameter governs the strength of terms-of-trade versus Pigouvian incentives across goods; in theory, it could be recovered by fitting predicted taxes to observed policy decisions.

Our trade elasticities across broad nests come from the work of Fajgelbaum et al. (2020). We use  $\sigma=2.53$  for import nodes,  $\sigma=1.53$  for nodes that aggregate HS4 codes into imported NAICS, and  $\sigma=1.19$  for NAICS aggregators of domestic and foreign varieties. For all other nodes, including consumer and military final demand nodes, we assume unit elasticities. The heterogeneity in import demand elasticities thus arises only from the underlying network structure.

Country-specific prize size  $\beta_i$  is backed out using a revealed preference approach to fit

parameter	value
$\alpha_{ij}$	$\alpha_{ij} = 0.01 P_j^C / \alpha_{ij} = P_j^C$
$eta_i$	model inversion to fit 2018 military expenditure levels
$\gamma$	$\gamma = 0.5$ (estimated)
$\sigma$	from Fajgelbaum et al. (2020), unit otherwise

Notes:  $\alpha_{ij}$  is proportional to initial  $P_j^C$  with the idea of approximating weights  $(U_{jC}/P_j^C)^{-1}$ , under which optimal taxes are close to zero (not exactly zero due to general equilibrium effects).

Table 2: Calibration parameters

the first-order condition for 2018 observed military spending levels exactly. For exposition purposes only, we show that if one omits general equilibrium price effects coming from factor price adjustments, the first-order condition simplifies to a familiar marginal utility trade-off in fund allocation:<sup>29</sup>

$$\beta_i \frac{g'(m_i)}{g(m_i)} \frac{\nu_i (1 - \nu_i)}{P_i^M} = \frac{1}{P_i^C}.$$
 (66)

Substituting in  $g(m_i) = (m_{0i} + m_i)^{\gamma}$  further yields

$$\gamma \beta_i \kappa_i m_i^{-1} \frac{\nu_i (1 - \nu_i)}{P_i^M} = \frac{1}{P_i^C}, \qquad \kappa_i \equiv \frac{m_i}{m_{0i} + m_i}. \tag{67}$$

Plugging relevant values for 2018 allows us to recover  $\beta_i$ .

The value of  $\gamma$ , which is a prerequisite for recovering  $\beta_i$ , is estimated from the time series variation in military spending over time. We use military spending of the Western bloc and, at all points in time, treat it as the best response to the exogenous path of the Eastern bloc military spending, perhaps with some noise,

$$\log m_t - \log \nu_t(\gamma) - \log(1 - \nu_t(\gamma)) = \varepsilon_t, \qquad \varepsilon_t \equiv \log \left( \gamma \beta_t \kappa_t P_t^C / P_t^M \right), \tag{68}$$

with subscript i= USA omitted for convenience (derivation in Appendix D.3). We explain the residual variation in  $\varepsilon_t$  via changes in the security environment, controling for bloc contest importance and side conflicts, as well as other political and economic factors outside of our model. We pick  $\gamma$  for which the factors that we select can explain the most of the residual variation in terms of  $R^2$ :  $\varepsilon_t = \mathbf{X}_t' \boldsymbol{\beta}_t + \epsilon_t$ .

$$\beta_{i} = \frac{\frac{U_{i,ci}}{P_{i}^{C}} + \sum_{j} \frac{U_{i,cj}}{P_{j}^{C}} C_{j} \mathcal{J}_{M_{i}}^{P_{j}^{C}}}{\frac{U_{i,m_{i}}/\beta_{i}}{P_{i}^{M}} - \sum_{j} \frac{U_{i,m_{j}}/\beta_{i}}{P_{j}^{M}} M_{j} \mathcal{J}_{M_{i}}^{P_{j}^{M}}} = \frac{\frac{1}{P_{i}^{C}} + \sum_{j} \frac{\alpha_{ij}}{P_{j}^{C}} C_{j} \mathcal{J}_{M_{i}}^{P_{j}^{C}}}{\frac{g'(m_{i})}{g(m_{i})} \frac{\nu_{i}(1-\nu_{i})}{P_{i}^{M}} + \sum_{j} \frac{g'(m_{j})}{g(m_{j})} \frac{\nu_{i}\nu_{j}}{P_{j}^{M}} M_{j} \mathcal{J}_{M_{i}}^{P_{j}^{M}}}$$
(65)

<sup>&</sup>lt;sup>29</sup>The full formula that takes into account factor price adjustments is

Table 3 shows that the best fit across specifications is consistently obtained for values of  $\gamma$  around  $\gamma=0.5$ . We start by explaining  $\varepsilon_t$  solely with a year trend, which gives us an  $R^2$  of 0.86. To reflect stickiness in military spending decisions, we add an autoregressive component  $\log m_{t-1}$  with one lag, yielding  $R^2=0.96$ . We then add separate intercepts for geopolitical periods, include controls for active conflicts, and incorporate shocks for war onsets. Figure 11 plots the fit using our preferred specification with  $\gamma=0.463$  and war controls. The parameter value suggests decreasing returns to scale to the military good when it converts into the probability of winning.

	trend	trend + AR(1)	+ period dummies	+ war dummies	+ war start shocks
$\hat{\gamma}$	0.517	0.398	0.499	0.463	0.468
$\mathbb{R}^2$	0.860	0.957	0.960	0.968	0.971

The historical periods are the Cold War (1950-1989), the End of History (1990-2000), the War on Terror (2001-2013), and the New Cold War (2014-2021). The major wars during this time span include the Korean War (1950-1953), the Vietnam War (1965-1973), the Gulf War (1990-1991), the Afghanistan War (2001-2014), and the Iraq War (2003-2011). For our specification of preference,  $\gamma=0.463$ .

Table 3: Various specifications for  $\gamma$  estimation

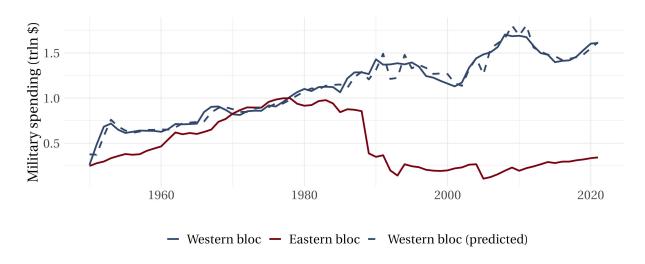


Figure 11: Military expenditures: Fitted values for  $\gamma = 0.463$ 

Country-specific conflict prizes  $\beta_i$  are equal to 250% of the U.S. annual GDP and 140% for China (Table 4). Those numbers can be interpreted as reduced-form welfare weights on the probability of winning projected onto our static model. The estimates, however, are sensitive to several assumptions. First, the values used for military stockpiles  $m_{0i}$  affect the estimates: whether one uses no stockpiles (36% annual U.S. GDP), domestic stockpiles (180% annual U.S. GDP), or includes stockpiles of allies (250% annual U.S. GDP) matters. We choose the upper-bound estimates as our baseline because the security environment

has deteriorated since 2018, military spending has increased, and the sizes of shadow military budgets are unknown. Another consideration is that general equilibrium effects materially change prize estimates: from 180% to 250% for the U.S. and from 225% to 140% for China. This occurs because military spending affects factor prices and, consequently, relative benefits of shifting tax dollars. An increase in Chinese military demand lowers home wages because military-adjacent sectors depend more on foreign imports than civilian ones; the opposite effect is observed for the U.S. (Table C.11). Adding quantitative details to factor utilization with plant-level production is an interesting problem in itself and could be the subject of future research.

	yearly budget		+ stock		+ allies' budgets		+ allies' stock	
	CHN	USA	CHN	USA	CHN	USA	CHN	USA
Military value	3.44	3.30	16.97	16.37	17.96	17.98	20.87	22.72
Partial equilibrium	37.10	26.59	182.94	131.80	193.62	144.78	225.07	182.97
General equilibrium	22.84	36.13	112.64	179.08	119.21	196.72	138.58	248.59

*Notes:* All numbers are reported as % of 2018 annual U.S. GDP. The dollar value conversion uses weighted industrial price indices for both consumer and military goods for both countries. Stockpiles refer to the assets of the Department of Defense as reported in their accounting statements.

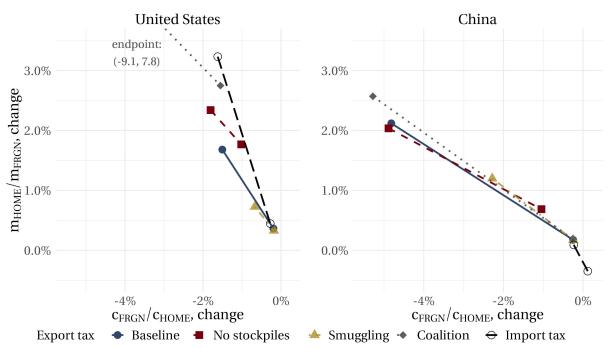
Table 4: Conflict prize, % annual U.S. GDP

#### 6.3 Results

Given our calibration fit, we analyze the impact of the optimal trade policies. We consider trade policies applied by the U.S. and China unilaterally and report changes in military advantage  $(m_{\rm HOME}/m_{\rm FRGN})$  and consumption ratio  $(c_{\rm FRGN}/c_{\rm HOME})$  relative to a zero-tax benchmark. Figure 12 plots segments with endpoints at  $\alpha_{\rm HOME,\,FRGN}=0.01P_{\rm FRGN}^C$  and  $\alpha_{\rm FRGN}=P_{\rm FRGN}^C$ ; the weights on the Rest of the World always follow a universalist benchmark  $(\alpha_{\rm ROW}=P_{\rm ROW}^C)$ . Both the slope and length of the segments provide insights into the policy impact.

As one can see from the graph, China has an upper hand compared to the U.S. when it comes to unilateral export policies (2.1% military advantage and -4.9% consumer advantage as opposed to 1.7% and -1.5% for the U.S.). However, under coalition export enforcement, the U.S. trade impact becomes three times larger than that of China. Smuggling more than halves these impact magnitudes. <sup>30</sup> The drawdown of stockpiles increases incentives to

<sup>&</sup>lt;sup>30</sup>If one allows for targeting exports to the Rest of the World, optimal export taxes across destinations become closer together. Welfare is lower in that scenario compared to a benchmark with no reshipping and possible export taxes on the Rest of the World. This occurs due to implicit constraints on taxes across export destinations that reshipping sets.



Notes: Baseline stands for a unilateral application of export taxes, for the U.S. against China and for China against the U.S. (but not the Rest of the World). No stockpiles refers to the scenario when  $m_{i0}=0$ . Smuggling is modeled as an additional CES nest for a direct route versus the route via the Rest of the World with  $\sigma=8.0$  and the cost of reshipping  $\tau=2.0$ . Coalition means joint export tax setting with allies. Import tax means unilateral import tax enforcement.

Figure 12: Policy impact plot

target exports and makes export taxation more aggressive. Import tariffs are a more powerful instrument for the U.S., but have almost no impact on China, as China does not import much from the U.S.. However, one should keep in mind that import tariff deterrence works mostly through the budget constraint and not through the production price margin.

An important qualification is that Figure 12 considers scenarios when the foreign military tax is fixed as a share of household budget. Once we allow government flexibility in setting lump sum taxes, the impact of policy on military advantage is dampened due to budget redistribution; foreign households take a stronger hit  $(\Delta_{\alpha}^2(m_{\text{HOME}}/m_{\text{FRGN}}) = 0.3\%$  and  $\Delta_{\alpha}^2(c_{\text{HOME}}/c_{\text{FRGN}}) = -1.4\%$ ). If the foreign government can tax households without limits, the problem reduces to lowering the foreign economy-wide budget constraint.

In terms of welfare outcomes, the U.S. unilateral export policy at its baseline improves the U.S. national welfare by 0.2%; the analogous Chinese policy improves its domestic welfare by 1.5% (Table C.12). The larger magnitudes for China reflect more redistribution from foreign to domestic consumers and a different starting point in terms of consumption.

Finally, and perhaps most importantly, industrial policy is a much more potent tool compared to trade policy. Under a universalist benchmark  $\alpha_{ij}=P_j^C$  and a balanced-

budget constraint on taxation, optimal industrial policy moves military advantage by 11% while keeping consumption sharing at just 0.7% (Table C.13). The optimal policy redistributes resources from export-oriented sectors toward the defense sector, which is mostly domestic, thus performing an indirect terms-of-trade manipulation similar to Ottonello et al. (2024).<sup>31</sup> During conflict, our model prescribes ramping up military spending and subsidizing military sectors at the expense of export-oriented ones. The use of redistributive domestic taxation is an indirect way to impact conflicts when the first-best solution is unattainable due to various constraints.

## 7 Conclusion

National security shapes the regulation and trade flows of military inputs. In our model, an input should be subject to scrutiny if it is what the foreign military buys, it is not heavily utilized in roundabout imports, and it is difficult to substitute. Policy efforts to increase prices for foreign military should begin with sectors that satisfy these conditions in input-output networks. The extent to which inputs should be restricted depends on policymakers' position on the consumption-security trade-off. Our macroeconomic framework offers an architecture to quantify this trade-off.

Our contribution to the literature is threefold. First, we extend optimal tariff theories by demonstrating how sufficient statistics from the optimal tax formulas can explain trade policies in the national security domain. Second, we develop a novel product-level measure of military use that establishes the consumption-security trade-off in international policy settings. Finally, we introduce a parsimonious structural framework that can handle factor price adjustments in general equilibrium.

Some research topics naturally follow from our paper. First, an important issue is that of conflict dynamics: the speed of goods' production versus destruction, and the build-up, scaling, and replacement of the durable manufacturing base. Second, the value of military capabilities is inherently state-contingent: it is high during conflict but low during peacetime. This state contingency adversely affects incentives for peacetime military build-up, which is meant to deter wars. Third, our framework could be extended to include innovation and knowledge flows, similar to E. Liu and Ma (2021). The prevention of critical technology diffusion with military applications is a highly policy-relevant problem; such technologies can be identified in a network setup similar to ours.

More broadly, the nuances of dynamic games and the subtleties of diplomatic com-

<sup>&</sup>lt;sup>31</sup>In a closed economy with a flexible defense budget, there is no need for industrial policy since defense spending is a first-best lever of addressing variations in national security environment. The only rationale for industrial policy in our setting comes from the fact that the economy is open.

munications make international political economy an exciting area of study. Estimation of policy functions for military spending, stockpiles, and diplomacy is one empirical exercise out of many. Similarly, conflict game theory contains interesting problems: whether a country should let aggression slide, respond in kind, or respond harshly, and in which domain (military, trade, finance, etc). On the data front, measures tracking attitudes, political support, and information flows become increasingly available, opening up new opportunities for creative work that combines structural models with data.

The quantitative economic models of military production would benefit from firm- and plant-level data, a richer spatial setup, and "engineering" elasticities of production for the supply and demand sides. Similarly, studying the industrial organization of dual-use sectors such as space, drones, cyber, AI, and nuclear technology is an exciting direction full of granular settings to examine innovation, competition, and externalities with national security in mind. Overall, there are unlimited opportunities for applied national security research by economists, with the ultimate goal of developing a new security framework that prevents military conflicts from ever happening again.

<sup>&</sup>lt;sup>32</sup>One study that constructs alternative input-output tables using large language models is Fetzer et al. (2024). Alfaro et al. (2024) constructs input-output tables that incorporate rare earth commodities.

## References

- Acemoglu, D., Aghion, P., Barrage, L., & Hémous, D. (2023). Climate Change, Directed Innovation, and Energy Transition: The Long-run Consequences of the Shale Gas Revolution.
- Acemoglu, D., Golosov, M., Tsyvinski, A., & Yared, P. (2012). A Dynamic Theory of Resource Wars \*. *The Quarterly Journal of Economics*, 127(1), 283–331.
- Acemoglu, D., & Yared, P. (2010). Political Limits to Globalization. *American Economic Review*, 100(2), 83–88.
- Adão, R., Becko, J. S., Costinot, A., & Donaldson, D. (2023). Why is Trade Not Free? A Revealed Preference Approach.
- Adão, R., Becko, J. S., Costinot, A., & Donaldson, D. (2024). A World Trading System For Whom? Evidence from Global Tariffs.
- Alfaro, L., Antràs, P., Chor, D., & Conconi, P. (2019). Internalizing Global Value Chains: A Firm-Level Analysis. *Journal of Political Economy*, 127(2), 508–559.
- Alfaro, L., Fadinger, H., Schymik, J., & Virananda, G. (2024). Industrial and Trade Policy in Supply Chains: The Case of Rare Earth Elements.
- Andrade, T. (2016). *The Gunpowder Age: China, Military Innovation, and the Rise of the West in World History*. Princeton University Press.
- $Antr\`{a}s, P. (2016). \textit{ Global Production: Firms, Contracts, and Trade Structure}. Princeton University Press.$
- Antràs, P., & Chor, D. (2013). Organizing the Global Value Chain. *Econometrica*, 81(6), 2127–2204.
- Antràs, P., & Chor, D. (2018). On the Measurement of Upstreamness and Downstreamness in Global Value Chains. *NBER Working Papers*.
- Antràs, P., Chor, D., Fally, T., & Hillberry, R. (2012). Measuring the Upstreamness of Production and Trade Flows. *American Economic Review*, 102(3), 412–416.
- Antràs, P., Fort, T. C., Gutiérrez, A., & Tintelnot, F. (2024). Trade Policy and Global Sourcing: An Efficiency Rationale for Tariff Escalation. *Journal of Political Economy Macroeconomics*, *2*(1), 1–44.
- Antràs, P., & Padró i Miquel, G. (2011). Foreign influence and welfare. *Journal of International Economics*, 84(2), 135–148.
- Antràs, P., & Padró i Miquel, G. (2023). Exporting Ideology: The Right and Left of Foreign Influence.
- Armington, P. S. (1969). A Theory of Demand for Products Distinguished by Place of Production (Une théorie de la demande de produits différenciés d'après leur origine) (Una teoría de la demanda de productos distinguiéndolos según el lugar de producción). *Staff Papers (International Monetary Fund)*, 16(1), 159–178.
- Auerbach, A. J., & Gorodnichenko, Y. (2012). Measuring the Output Responses to Fiscal Policy. *American Economic Journal: Economic Policy*, 4(2), 1–27.
- Austal Launches Largest Vessel to Date Lake Express High-Speed Vehicle-Passenger Ferry. (2004).
- Bai, J., Bernstein, S., Dev, A., & Lerner, J. (2022). The Dance Between Government and Private Investors: Public Entrepreneurial Finance around the Globe.
- Baqaee, D. R., & Farhi, E. (2024). Networks, Barriers, and Trade. Econometrica, 92(2), 505–541.

- Barwick, P. J., Kalouptsidi, M., & Bin Zahur, N. (2024). Industrial Policy: Lessons from Shipbuilding. *Journal of Economic Perspectives*, *38*(4), 55–80.
- Becko, J. S. (2023). How Should Sanctions Account for Bystander Countries? *AEA Papers and Proceedings*, 113, 39–42.
- Becko, J. S. (2024). A theory of economic sanctions as terms-of-trade manipulation. *Journal of International Economics*, 150, 103898.
- Becko, J. S., & O'Connor, D. G. (2024). Strategic (Dis) Integration.
- Belenzon, S., & Cioaca, L. C. (2021). Guaranteed Markets and Corporate Scientific Research.
- Beraja, M., Kao, A., Yang, D. Y., & Yuchtman, N. (2023a). AI-tocracy\*. *The Quarterly Journal of Economics*, *138*(3), 1349–1402.
- Beraja, M., Kao, A., Yang, D. Y., & Yuchtman, N. (2023b). Exporting the Surveillance State via Trade in AI.
- Beraja, M., Yang, D. Y., & Yuchtman, N. (2023). Data-intensive Innovation and the State: Evidence from AI Firms in China. *The Review of Economic Studies*, 90(4), 1701–1723.
- Bianchi, J., & Sosa-Padilla, C. (2023). International Sanctions and Dollar Dominance.
- Bigio, S., & La'O, J. (2020). Distortions in Production Networks\*. *The Quarterly Journal of Economics*, 135(4), 2187–2253.
- Bilal, A., & Rossi-Hansberg, E. (2023). Anticipating Climate Change Across the United States.
- BIS Annual Conference. (2018).
- Bowett, A. (1994). The Commercial Introduction of Mahogany and the Naval Stores Act of 1721. *Furniture History*, *30*, 43–56.
- Broda, C., & Weinstein, D. E. (2006). Globalization and the Gains From Variety\*. *The Quarterly Journal of Economics*, 121(2), 541–585.
- Chatagnier, J. T., & Kavakl, K. C. (2017). From Economic Competition to Military Combat: Export Similarity and International Conflict. *Journal of Conflict Resolution*, *61*(7), 1510–1536.
- Chatelus, R., & Heine, P. (2016). Rating Correlations Between Customs Codes and Export Control Lists: Assessing the Needs and Challenges. *Strategic Trade Review*, 2(3).
- Chen, J., & Roth, J. (2024). Logs with Zeros? Some Problems and Solutions\*. *The Quarterly Journal of Economics*, 139(2), 891–936.
- Chupilkin, M., Javorcik, B., Peeva, A., & Plekhanov, A. (2024). Decision to Leave: Economic Sanctions and Intermediated Trade.
- Chupilkin, M., & Koczan, Z. (2022). The economic consequences of war: Estimates using synthetic controls.
- Clark, D., & Swanson, A. (2022). U.S. Restricts Sales of Sophisticated Chips to China and Russia. *The New York Times*.
- Clayton, C., Maggiori, M., & Schreger, J. (2023). A Framework for Geopolitics and Economics.
- Clayton, C., Maggiori, M., & Schreger, J. (2024). A Theory of Economic Coercion and Fragmentation. *SocArXiv*.
- Conte, B., Desmet, K., & Rossi-Hansberg, E. (2022). On the Geographic Implications of Carbon Taxes.
- Copeland, B. R., Shapiro, J. S., & Scott Taylor, M. (2022). Globalization and the environment. In *Hand-book of International Economics* (pp. 61–146). Elsevier.

- Costinot, A., Donaldson, D., Vogel, J., & Werning, I. (2015). Comparative Advantage and Optimal Trade Policy \*. *The Quarterly Journal of Economics*, *130*(2), 659–702.
- Costinot, A., Rodríguez-Clare, A., & Werning, I. (2020). Micro to Macro: Optimal Trade Policy With Firm Heterogeneity. *Econometrica*, 88(6), 2739–2776.
- Costinot, A., & Werning, I. (2019). Lerner Symmetry: A Modern Treatment. *American Economic Review: Insights, 1*(1), 13–26.
- Couttenier, M., Marcoux, J., Mayer, T., & Thoenig, M. (2023). The Gravity of Violence.
- Cox, L., Müller, G. J., Pasten, E., Schoenle, R., & Weber, M. (2023). Big G.
- Crosignani, M., Han, L., Macchiavelli, M., & Silva, A. F. (2024). Geopolitical Risk and Decoupling: Evidence from U.S. Export Controls. *Federal Reserve Bank of New York Staff Reports*, (1096).
- Cruz, J.-L., & Rossi-Hansberg, E. (2022). Local Carbon Policy.
- Cruz, J.-L., & Rossi-Hansberg, E. (2023). The Economic Geography of Global Warming. *The Review of Economic Studies*, rdad042.
- Davis, A., Lopez-Pena, P., Mobarak, M., & Wen, J. (2023). Causes and Consequences of State Violence against Civilians: The Rohingya of Myanmar.
- de Souza, G., Hu, N., Li, H., & Mei, Y. (2024). (Trade) War and peace: How to impose international trade sanctions. *Journal of Monetary Economics*, *146*, 103572.
- Ding, X. (2023). Industry Linkages from Joint Production.
- Egorov, K., Korovkin, V., Makarin, A., & Nigmatulina, D. (2024). Trade Sanctions.
- Eichengreen, B., Ferrari Minesso, M., Mehl, A., Vansteenkiste, I., & Vicquéry, R. (2024). Sanctions and the exchange rate in time. *Economic Policy*, 39(118), 323–354.
- Evenett, S. J. (2019). Protectionism, state discrimination, and international business since the onset of the Global Financial Crisis. *Journal of International Business Policy*, *2*(1), 9–36.
- Fajgelbaum, P. D., Goldberg, P. K., Kennedy, P. J., & Khandelwal, A. K. (2020). The Return to Protectionism\*. *The Quarterly Journal of Economics*, 135(1), 1–55.
- Farrokhi, F., & Lashkaripour, A. (2021). Can Trade Policy Mitigate Climate Change? Working paper.
- Federle, J., Meier, A., Muller, G., Mutschler, W., & Schularick, M. (2024). The Price of War. CEPR.
- Feenstra, R. C. (1994). New Product Varieties and the Measurement of International Prices. *The American Economic Review*, 84(1), 157–177.
- Fetzer, T., Lambert, P. J., Feld, B., & Garg, P. (2024). AI-Generated Production Networks: Measurement and Applications to Global Trade.
- Friedman, L., & McCabe, D. (2020). Interior Dept. Grounds Its Drones Over Chinese Spying Fears. *The New York Times*.
- Galeev, K., Smolina, O., Makhonin, O., & Mikhalevska, K. (2024). How Does Russia Make Missiles?
- Galeotti, A., Golub, B., & Goyal, S. (2020). Targeting Interventions in Networks. *Econometrica*, 88(6), 2445–2471.
- Gaulier, G., & Zignago, S. (2010). *BACI: International Trade Database at the Product-Level. The 1994-2007 Version* (Working Paper). CEPII research center.
- Ghironi, F., Kim, D., & Ozhan, G. K. (2023). International Economic Sanctions and Third-Country Effects.

- Goldberg, P. K., Juhász, R., Lane, N. J., Lo Forte, G., & Thurk, J. (2024). Industrial Policy in the Global Semiconductor Sector.
- Golosov, M., Hassler, J., Krusell, P., & Tsyvinski, A. (2014). Optimal Taxes on Fossil Fuel in General Equilibrium. *Econometrica*, 82(1), 41–88.
- Gopinath, G., Gourinchas, P.-O., Presbitero, A., & Topalova, P. B. (2024). Changing Global Linkages: A New Cold War?
- Grassi, B. (2018). IO in I-O: Size, Industrial Organization, and the Input-Output NetworkMake a Firm Structurally Important. *Working Papers*.
- Grassi, B., & Sauvagnat, J. (2019). Production networks and economic policy. *Oxford Review of Economic Policy*, 35(4), 638–677.
- Grossman, G. M., & Helpman, E. (1994). Protection for Sale. *The American Economic Review, 84*(4), 833–850.
- Grubel, H. G., & Lloyd, P. J. (1975). *Intra-industry Trade: The Theory and Measurement of International Trade in Differentiated Products.* Macmillan.
- Gustafson, T. (1981). *Selling the Russians the Rope?*: *Soviet Technology Policy and U.S. Export Controls* (tech. rep.). RAND Corporation.
- Hausmann, R., Hidalgo, C. A., Bustos, S., Coscia, M., & Simoes, A. (2014). *The Atlas of Economic Complexity: Mapping Paths to Prosperity*. MIT Press.
- Helpman, E., & Krugman, P. (1989). Trade Policy and Market Structure.
- Horn, S., Reinhart, C., & Trebesch, C. (2024). International Lending in War and Peace.
- Hsiao, A. (2022). Coordination and Commitment in International Climate Action: Evidence from Palm Oil.
- Hsiao, A., Moscona, J., & Sastry, K. (2024). Food Policy in a Warming World.
- Itskhoki, O., & Mukhin, D. (2022). Sanctions and the Exchange Rate.
- Itskhoki, O., & Mukhin, D. (2023). International Sanctions and Limits of Lerner Symmetry. *AEA Papers and Proceedings*, 113, 33–38.
- Itskhoki, O., & Ribakova, E. (2024). The economics of sanctions: From theory into practice.
- Iyoha, E., Malesky, E. J., Wen, J., Wu, S.-J., & Feng, B. (2024). Exports in Disguise: Trade Re-Routing During the U.S.-China Trade War.
- Jones, L. P. (1976). The Measurement of Hirschmanian Linkages\*. *The Quarterly Journal of Economics*, 90(2), 323–333.
- Juhász, R., Lane, N., Oehlsen, E., & Pérez, V. C. (2022). The Who, What, When, and How of Industrial Policy: A Text-Based Approach.
- Kaempfer, W. H., & Lowenberg, A. D. (2007). Chapter 27. The Political Economy of Economic Sanctions. In T. Sandler & K. Hartley (Eds.), *Handbook of Defense Economics* (pp. 867–911). Elsevier.
- Kang, K. (2016). Policy Influence and Private Returns from Lobbying in the Energy Sector. *The Review of Economic Studies*, 83(1), 269–305.
- Kessler, S. (2022). What Is Friendshoring? *The New York Times*.
- Kikuchi, S. (2024). Does Skill Abundance Still Matter? The Evolution of Comparative Advantage in the 21st Century.

- Kleinman, B., Liu, E., & Redding, S. J. (2023). International Friends and Enemies. *American Economic Journal: Macroeconomics*.
- König, M. D., Rohner, D., Thoenig, M., & Zilibotti, F. (2017). Networks in Conflict: Theory and Evidence From the Great War of Africa. *Econometrica*, 85(4), 1093–1132.
- Kooi, O. (2024). Power and Resilience: An Economic Approach to National Security Policy.
- Kortum, S. S., & Weisbach, D. A. (2021). Optimal Unilateral Carbon Policy.
- Lashkaripour, A., & Beshkar, M. (2020). *The Cost of Dissolving the WTO: The Role of Global Value Chains* (CAEPR Working Paper 2020-005 Classification-). Center for Applied Economics and Policy Research, Department of Economics, Indiana University Bloomington.
- Lashkaripour, A., & Lugovskyy, V. (2022). Profits, Scale Economies, and the Gains from Trade and Industrial Policy.
- Leontief, W. W. (1936). Quantitative Input and Output Relations in the Economic Systems of the United States. *The Review of Economics and Statistics*, *18*(3), 105–125.
- Lerner, A. P. (1936). The Symmetry between Import and Export Taxes. *Economica*, 3(11), 306–313.
- Li, H., Li, Z., Park, Z., Wang, Y., & Wu, J. (2024). To Comply or Not to Comply: Understanding Neutral Country Supply Chain Responses to Russian Sanctions.
- Liu, E. (2019). Industrial Policies in Production Networks\*. *The Quarterly Journal of Economics*, 134(4), 1883–1948.
- Liu, E., & Ma, S. (2021). Innovation Networks and R&D Allocation.
- Liu, E., & Tsyvinski, A. (2024). A Dynamic Model of Input-Output Networks.
- Liu, E., & Yang, D. (2024). International Power.
- Liu, X., Liu, Y., & Wen, J. Y. (2024). The Consequences of Export Controls in Target Countries.
- Long, J. B., & Plosser, C. I. (1983). Real Business Cycles. *Journal of Political Economy*, 91(1), 39–69.
- Martin, P., Mayer, T., & Thoenig, M. (2008). Make Trade Not War? *The Review of Economic Studies*, 75(3), 865–900.
- Martin, P., Mayer, T., & Thoenig, M. (2012). The Geography of Conflicts and Regional Trade Agreements. *American Economic Journal: Macroeconomics*, 4(4), 1–35.
- Martin, P., Thoenig, M., & Mayer, T. (2008). Civil Wars and International Trade. *Journal of the European Economic Association*, 6(2/3), 541–550.
- Méndez, E., & Van Patten, D. (2022). Voting on a Trade Agreement: Firm Networks and Attitudes Toward Openness.
- Miller, C., Tsunashima, T., Seddon, M., Joiner, S., Campbell, C., & Cook, C. (2024). Type of Russian missile that struck Kyiv childrens hospital uses Western components. *Financial Times*.
- Mozur, P., & Hopkins, V. (2023). Ukraines War of Drones Runs Into an Obstacle: China. *The New York Times*.
- Neri-Laine, M. (2024). Sovereign Gravity: The Military Alliances' Effect on Trade.
- Ossa, R. (2014). Trade Wars and Trade Talks with Data. *American Economic Review, 104*(12), 4104–4146.
- Ottonello, P., Perez, D. J., & Witheridge, W. (2024). The Exchange Rate as an Industrial Policy.
- Pitron, G. (2020). *The Rare Metals War: The dark side of clean energy and digital technologies*. Scribe Publications Pty Limited.

- Rivkin, A. (2021). German technology found in China's warships: Report. Deutsche Welle.
- Rohner, D., Thoenig, M., & Zilibotti, F. (2013). War Signals: A Theory of Trade, Trust, and Conflict. *The Review of Economic Studies*, 80(3), 1114–1147.
- Sarkees, M., & Wayman, F. (2010). Resort to War, 1816-2007.
- Shiffman, J., & Shalal-Esa, A. (2014). Exclusive: U.S. waived laws to keep F-35 on track with Chinamade parts. *Reuters*.
- Skaperdas, S., & Syropoulos, C. (2001). Guns, Butter, and Openness: On the Relationship between Security and Trade. *American Economic Review*, *91*(2), 353–357.
- Soderbery, A. (2015). Estimating import supply and demand elasticities: Analysis and implications. *Journal of International Economics*, *96*(1), 1–17.
- Teti, F., Scheckenhofer, L., & Wanner, J. (2024). Trade Sanctions against Russia: Light Strokes or Massive Blows?
- Thoenig, M. (2023). Trade policy in the shadow of war: A quantitative toolkit for geoeconomics.
- Tullock, G. (1980). Efficient Rent Seeking. In J. Buchanan, G. Tullock, & R. Tollison (Eds.), *Toward a Theory of the Rent-Seeking Society* (pp. 97–112). Texas A&M University Press.
- Wen, J. (2012). Industry-Level Supply-Side Market Concentration and the Price of Military Conflict. *Conflict Management and Peace Science*, 29(1), 79–92.
- Wu, L. (2022). Network Lerner Index: Demand and Distortions across Industries.

# A Acknowledgements

We are indebted to Pol Antràs, Elhanan Helpman, and Marc Melitz for their continuous guidance and support.

We thank Adrien Bilal, Gabriel Chodorow-Reich, Xavier Gabaix, Edward Glaeser, Oleg Itskhoki, Kenneth Rogoff, Jesse Shapiro, Ludwig Straub, Jaya Wen, David Yang, together with fellow students Constanza Abuin, Anhua Chen, Leonardo D'Amico, Raul Duarte, Tilman Graff, Adrien Kulesza, Caleb Kwon, Marcela Mello, Ewan Rawcliffe, Kunal Sangani, Lina Thomas, Wilbur Townsend, Lingxuan Wu, and especially Jeff Gortmaker and Namrata Narain, for their helpful suggestions and feedback.

We also thank Rodrigo Adão, Fernando Alvarez, Jonathan Dingel, Lars Peter Hansen, Mikhail Golosov, Aleksei Oskolkov, Konstantin Sonin, Esteban Rossi-Hansberg, Elisa Rubbo, Felix Tintelnot, Juanma Vincenzi-Castro, as well as Thomas Bourany, Marcos Sora, Olivier Kooi, and Xiaoyang Li for their comments during Maxim's two-month visit to UChicago.

We gratefully acknowledge the financial support of the Molly and Domenic Ferrante Family Foundation and the HBS Doctoral Fund.

We thank Dmitry Gvozdev, Irina Linevich, Alexander Lutsenko, Anastasia Nebolsina, Rithwik Ramkumar, Kirill Safonov, Daniil Starikov, and Victoria Shumilova for their excellent research assistance.

We appreciate the help of Davin Chor, Kalina Manova, and Zhihong Yu, as well as Bing Zhang and Daxuan Zhao, who shared their crosswalks for Chinese industry classifications with us.

All errors are our own.

# **B** Examples

## **B.1** Dual-use goods examples

#### **B.1.1** Rare-earths magnets in F-35 and Tesla

The annual budget of the U.S. Air Force is  $\approx$ \$215 bln. Every year, it is used to procure  $\approx$ 70 F-35 fighter jets from Lockheed Martin, which cost more than \$100 mln per jet. Around \$10 mln USD of those \$100 mln is the cost of a high-precision radar AN/APG-81 that Lockheed Martin subcontracts to Northrop Grumman. The high-precision radar technology makes use of neodymium permanent magnets, which Northrop Grumman, as the 2012 Pentagon investigation showed, procures from Chengdu Magnetic Material Science and Technology, located in an industrial hub near rare earths deposits in Sichuan, China. (Shiffman & Shalal-Esa, 2014)

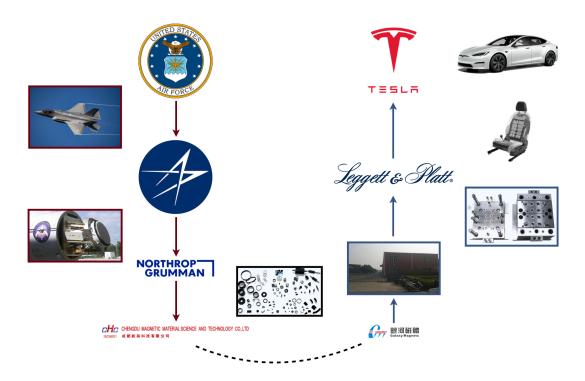


Figure B.1: Neodymium magnets as components of F-35 fighter jet and Tesla cars

Located some 30 minutes away is Chengdu Galaxy Magnets, which also sells permanent magnets made of neodymium. One of its customers is Guangdong Zhaoqing LV, a subsidiary of the furniture company Leggett & Platt (Factset). The automotive branch of the company sells car seats to Tesla (Factset), where permanent magnets power the engineering mechanism controlling the seat adjustment and recline. Similar \$2 neodymium

magnets are therefore used in both \$100 mln fighter jets of the U.S. military and Tesla cars purchased by American consumers.

Why would the U.S. military subject itself to a potential supply chain and security vulnerability? "Kendall [Frank Kendall, the chief U.S. Arms buyer] said the waivers were needed to keep production, testing, and training of the Pentagon's newest warplane on track; avert millions of dollars in retrofit costs; and prevent delays in the Marine Corps' plan to start using the jets in combat from mid-2015, according to the documents. [...] In one case [of an F-35 jet], it would cost \$10.8 million and take about 25,000 man-hours to remove the Chinese-made magnets and replace them with American ones." (Shiffman & Shalal-Esa, 2014). According to Anthony Marchese, the CEO of Texas Mineral Resources, who is leading efforts to re-shore the rare earth supply chain, "the manufacturers of the F-35 still buy rare earths in China. Period." (Pitron, 2020).

#### **B.1.2** Engines in PRC navy ships and Lake Express

PRC missile destroyer Luyang II is powered by two MTU 20V-956-TB92 diesel engines produced by MTU Friedrichshafen, a German company that is now a part of Rolls-Royce Holdings (Rivkin, 2021). A similar, slightly less powerful engine, the MTU 16V-4000-M70 is installed in *Lake Express* that carries passengers across Lake Michigan ("Austal Launches Largest Vessel to Date - Lake Express High-Speed Vehicle-Passenger Ferry", 2004).







Figure B.2: MTU engines in PRC navy ships and Lake Express

### **B.1.3** CNC machines producing Iskander missiles and Top Flite golf clubs

HAAS VF2SS milling machine is used both to produce custom golf clubs (Custom Golf Club Putter Made With CNC Machining — Star Rapid, 2017) and Iskander missiles on the Titan-Barikadnyy plant (Galeev et al., 2024)







Figure B.3: CNC machines producing Iskander missiles and Top Flite golf clubs

### **B.1.4** Drones in amateur photography and trench warfare

\$500 DJI drones, purposed for amateur photography, have been used by the Ukrainian armed forces in trench warfare (Mozur & Hopkins, 2023).







Figure B.4: DJI drones in trench warfare and amateur photography

## **B.2** Descriptive evidence for sufficient statistics

Figure B.5 displays a slide on the uses of carbon fiber from the Bureau of Industry Security conference, which suggests that regulators indeed consider the distribution of product's sales across two sectors. Regulatory authorities are uncertain whether they should control carbon fiber exports, given its increased prevalence in non-military applications. This is exactly the type of question our research aims to resolve quantitatively.

We examine several anecdotal episodes where certain goods were phased out in military production and analyze how international trade in those goods evolved. The three technological transitions we consider are the phase-out of combustion piston engines in military vehicles, the replacement of analog manufacturing by high-precision CNC machines, and the microelectronics revolution. With the advent of gas turbines and alternative propulsion systems, internal combustion piston engines gradually ceased to be used in battle-field vehicles, particularly in aerospace and naval applications.<sup>33</sup> During the 1970-1980s,

<sup>&</sup>lt;sup>33</sup>Some first models that replaced internal combustion engines are Bell UH-1 Iroquois (1959; gas turbine;

# Future TEG Topics – Carbon Fiber?

- Carbon fiber was once the exotic material of aerospace, rocket motor cases, and centrifuge rotors. Now many of these early fibers/grades are obsolete with newer and better grades commonly used in sporting good and automobile applications.
- Given that these materials continue to have strategic applications, should the growing world wide availability and ever increasing civil and consumer uses force the NSG to look for innovative ways to address these concerns?

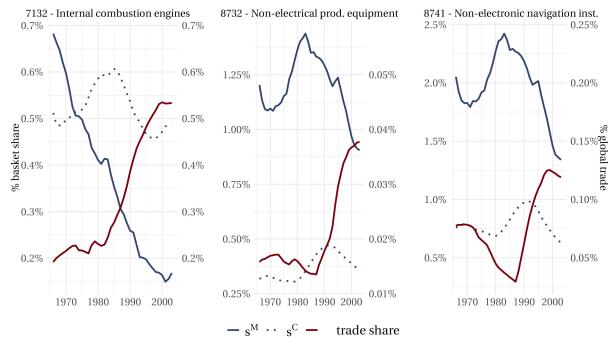


Notes: Slide from the 2018 discussion from the Bureau of Industry Security ("BIS Annual Conference", 2018).

Figure B.5: Policymakers discuss relative uses: The case of carbon fiber

high-precision manufacturing began replacing analog instruments with CNCs, leading to the latter's phase-out from military procurement. The microelectronics revolution, occuring around the same time, decreased military reliance on non-electronic navigation instruments. Despite military phase-out and stable US consumer shares, international trade in those goods increased, not decreased, providing suggestive evidence in favor of more lax trade regulation (Figure B.6).

replaced Bell H-13 with piston engines), jet-powered Boeing B-47 Stratojet (1951; replaced B-29 Superfortress with piston engines), nuclear-powered USS Enterprise CVN-65 (1961; replaced the USS Essex CV-9 driven by piston-engines), nuclear-powered USS Nautilus SSN-571 (1954; replaced the diesel-electric USS Gato-class submarines), and M1 Abrams (1980; gas turbine; replaced diesel-powered M60 Patton).



*Notes:* The trade data for the Cold War (1962-2021) are from the Atlas of Economic Complexity and are classified at the SITC Rev. 2 (1975) level. The military procurement share has been reconstructed from the National Archives (1966-2006) and crosswalked from FSC (Federal Supply Codes) to SITC Rev. 2. The consumer share is reconstructed using value-added numbers from NBER manufacturing database and crosswalked from NAICS to SITC Rev. 2. Supplementary Appendix Figure SA.B.7 provides additional figures for components of internal combustion engines, SITC 7139 "Parts of internal combustion engines" and SITC 7783 "Electrical equipment for internal combustion engines," showing analogous patterns in these categories.

Figure B.6: Cases of technological transitions

## **C** Empirics

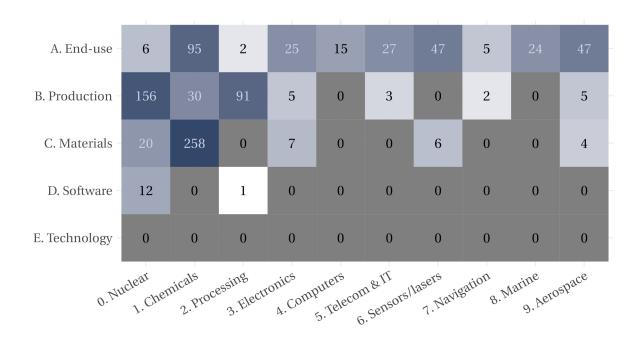
## C.1 Motivating facts

#### C.1.1 Institutional details

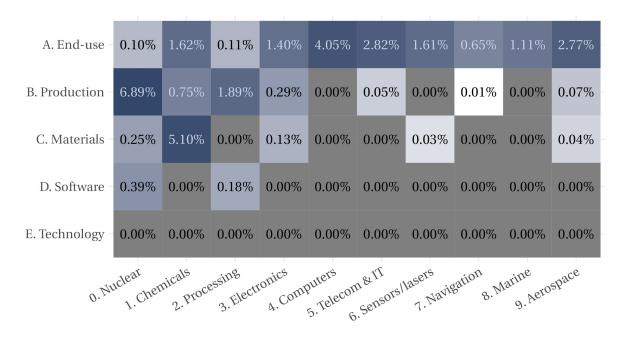
For the purpose of our analysis, we adopt a formal "legal" definition of dual-use goods as items identified by security regulators. Table C.1 summarizes the institutional details of the U.S. export control enforcement. Our attention is focused on dual-use lists rather than munitions lists, as the former have more civilian overlap and, as a consequence, cover more civilian goods in the Harmonized System classification. The HS codes covered by munitions lists, in contrast to dual-use lists, are 93XXXX (arms and ammunition), 8710XX (tanks), and 890610 (warships). When monotonicity becomes important in our regression analysis, we add those HS6 codes manually. The underlying security classification for dual-use goods is the Export Control Classification Number (ECCN); Figure C.1 displays the coverage in the ECCN classification.

The export clearance procedure for dual-use goods follows a typical sequence. Exporters must first classify their good under a relevant ECCN. Then, they file documentation for a license, reporting details such as technical specifications, destination, counterparties, and the intended use. Upon obtaining the license, they must keep records of the export and sometimes must provide declarations from the end user regarding the intended final use. Non-compliance with any of those steps can lead to sanctions such as fines or permanent bans on exporting.

The EU TARIC, the integrated Tariff of the European Union, is a multilingual database integrating all measures relating to the EU customs tariff, commercial, and agricultural legislation. It provides correlation tables between traditional Harmonized System codes and the Export Control Classification Numbers (ECN), largely mirroring those of the Wassegnaar Arrangement or the Bureau of Industry Security (ECCN). As Chatelus and Heine (2016) note, "in the EU, the TARIC correlation table does not determine when exporters must request a permit, but it does determine when exporters must assess whether their exported commodity requires a permit or not. When the customs tariff number indicates a correlation with the dual-use list, EU exporters must fill in code X002 (controlled) or code Y901 (not controlled) in Box 44 of the Single Administrative Document (i.e., the customs declaration)." Consequently, the EU TARIC system governs the degree of the customs oversight.



(a) Raw HS6 code counts



(b) Global trade share, 2015-19

Figure C.1: ECCN classification: categories (x-axis) and subcategories (y-axis)

	Dual-use goods	Munitions
List	Commerce Control List (CCL)	U.S. Munitions List (USML)
Categories	Export Control Classification Number (ECCN), 5+ symbols	21 categories; see Federal Code 22.I.M.121
Code	Export Administration Regulations (EAR)	International Traffic in Arms Regulations (ITAR)
Agency	Bureau of Industry Security (BIS)	Directorate of Defense Trade Controls (DDTC)
Ministry	Department of Commerce	Department of State
Consults	Multilateral export control regimes*, DoD	Department of Defense (DoD)

Note: Multilateral export control regimes are informal clubs of countries that coordinate on export control and enforcement, including: (i) the Wassenaar Arrangement (WA) on Export Controls for Conventional Arms and Dual-Use Goods and Technologies, (ii) the Nuclear Suppliers Group (NSG), for the control of nuclear and nuclear-related technology, (iii) the Australia Group (AG) for the control of chemical and biological technology that could be weaponized, and (iv) the Missile Technology Control Regime (MTCR) for the control of rockets and other aerial vehicles capable of delivering weapons of mass destruction. ECCN codes used for dual-use items in the U.S. largely overlap with the Wassegnaar Arrangement lists and the EU control classification. The Wassenaar Arrangement is the successor to the Cold War-era Coordinating Committee for Multilateral Export Controls (CoCom). The Wassenaar Arrangement is more lenient than its predecessor, having been designed with the primary goal of ensuring transparency in national export control regimes.

Table C.1: U.S. institutional regulations on arms-related items

### C.1.2 Fact #1. Dual-use goods are overwhelmingly intermediate inputs

To understand the positioning of dual-use goods in production networks, we analyze the input-output tables for the U.S. economy. Here we borrow some material that we will describe later in more detail in Section 5. Figure 4 plots network-adjusted sales of various industries to the U.S. military and to the U.S. households. Some industries, such as missile production or tank manufacturing, sell primarily to the military. Others, like automobile manufacturing or pharmaceuticals, sell mostly to households. A range of input industries, such as semiconductors or the production of plastics, sell to both. We examine normalized military sales and household sales, with

$$\text{Military sales}_i \equiv \left[\frac{(\mathbf{I} - \mathbf{\Omega})^{-1'}\mathbf{s}^{\mathbf{M}}}{[(\mathbf{I} - \mathbf{\Omega})^{-1'}\mathbf{s}^{\mathbf{M}}]'\mathbf{1}}\right]_i, \quad \text{Household sales}_i \equiv \left[\frac{(\mathbf{I} - \mathbf{\Omega})^{-1'}\mathbf{s}^{\mathbf{C}}}{[(\mathbf{I} - \mathbf{\Omega})^{-1'}\mathbf{s}^{\mathbf{C}}]'\mathbf{1}}\right]_i$$

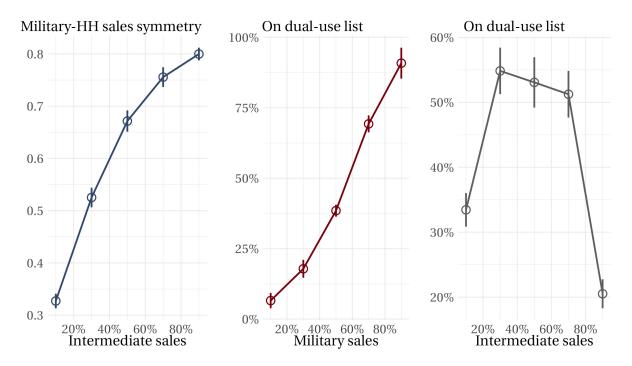
We introduce several heuristic metrics to capture relevant industry characteristics. We define *Military-HH sales symmetry* as a scaled difference between network-adjusted military and household sales of an industry (or a measure of proximity to the 45-degree line in Figure 4):

$$\label{eq:military-HH} \text{Military-HH sales symmetry}_i \equiv 1 - \frac{|\text{Military sales}_i - \text{Household sales}_i|}{\text{Military sales}_i + \text{Household sales}_i} \in [0, 1]$$

The formula follows the logic of the Grubel-Lloyd intra-industry trade index (Grubel & Lloyd, 1975). Sales symmetry takes the value of 0 when an industry sells exclusively to households or exclusively to the military, and reaches the value of 1 when an industry has equal shares in the consumption baskets of these groups groups. To measure an industry's output utilization as an input into other industries' production, we calculate the ratio of intermediate sales to total sales. We also analyze network-adjusted military sales as a share of total sales.

Figure C.2 portrays three key relationships between our measures. First, our intermediate sales share and sales symmetry measure exhibit a one-to-one relationship. The more final sales an industry has, the more it sells to a specific final agent, and vice versa. Second, the probability of being on the dual-use list correlates strongly with military sales share. If an industry sells exclusively to the military, it will be on the dual-use list, and vice versa. Finally, the relationship between the dual-use list inclusion and intermediate sales share follows an inverse U-shape. Very downstream and very upstream industries are not on the dual-use list, while industries in the middle are, which will motivate our production networks modeling treatment.<sup>34</sup>

<sup>&</sup>lt;sup>34</sup>Note that very downstream final military items are not featured on the customs dual-use lists: HS codes 93XXXX (arms and ammunition), 8710XX (tanks), and 890610 (warships) are not included. This is because those are governed by munitions lists and ITAR (International Traffic in Arms Regulations) under the U.S. De-



Notes: The figure presents bin scatters with the x-axis split into five intervals of equal length. For clarity,

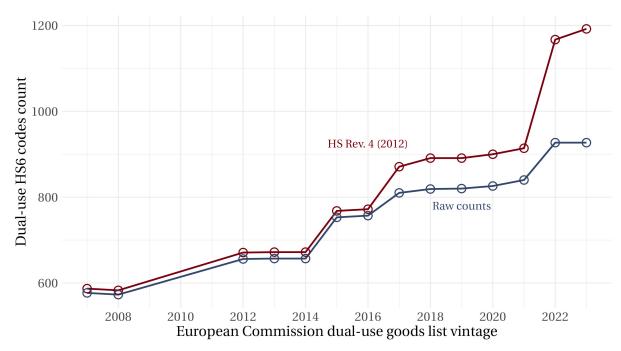
$$\text{Intermediate sales, } \%_i \equiv \frac{\text{Intermediate sales}_i}{\text{Total sales}_i}, \qquad \text{Military sales, } \%_i \equiv \frac{\text{Military sales}_i}{\text{Total sales}_i}$$

The unit of observation is an HS six-digit category. Observations are weighted by their respective trade shares. Supplementary Appendix Figure SA.B.1 presents several robustness checks.

Figure C.2: Dual-use goods in production networks

partment of State's Directorate of Defense Trade Controls (DDTC), instead of dual-use lists and EAR (Export Administration Regulations) under the Bureau of Industry Security (BIS). We add those military items manually when monotonicity in regressions for military end use becomes important, but for descriptive plots, we keep those out.

## C.1.3 Fact #2. Trade in dual-use goods is increasingly regulated: Policy scope



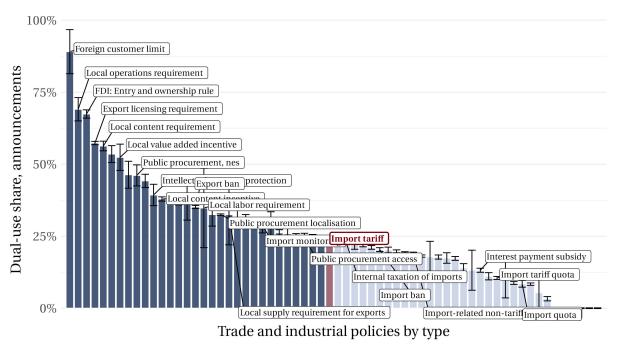
*Notes:* Data for dual-use categories are taken from the EU TARIC dual-use correlation tables. CN8 codes are converted to HS6 codes and then to Rev. 4 (2012). The blue line counts raw 6-digit stems without conversion, which is lower due to many-to-many mapping between Rev. 4 (2012) codes and Rev. 5/Rev. 6 (2017/2022) codes, with some Rev. 5/Rev. 6 categories taking pieces from many Rev. 4 categories.

Figure C.3: Dual-use goods count

### C.1.4 Fact #2. Trade in dual-use goods is increasingly regulated: Policy intensity

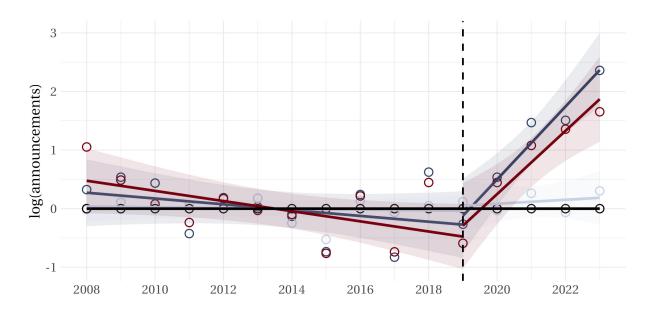
Trade policies that restrict foreign access disproportionately target goods defined as dual-use (Figure C.4). Approximately 25% of import tariff policy acts target goods from the dual-use list, close to the 21.8% number predicted by uniformly drawing HS codes. Policies that target dual-use goods at a rate higher than import tariffs tend to involve actions restricting foreign access. The top-5 such "security" policies are foreign customer limit limits (89% dual-use), local operations requirement (69%), rules regulating entry and ownership of FDI (67%), export licensing (57%), and local content requirements (56%). In contrast, dual-use goods are less targeted by standard protectionist measures such as import bans (20%) or import quotas (8.5%).

Recent years have seen a surge in security policies, especially regarding dual-use goods (Figure C.5). The emergence of this new trend can be attributed to heightened geopolitical tensions in 2020 following the pandemic, with unprecedented levels observed since 2022. The 2023 count of new security policies represents a tenfold increase compared to the prepandemic period levels.



*Notes*: The data are taken from the *Global Trade Alert* project (Evenett, 2019). Here, a unit of observation is a policy act-HS code; if the same policy act covers multiple HS codes, it is counted as multiple observations. Every policy act is classified into a text category by the *Global Trade Alert*; these categories are displayed in text labels above the bars. For every text category, the bar reflects the share of policy acts in that category directed towards dual-use goods. The dual-use goods definition is taken from the 2018 vintage of the EU customs list.

Figure C.4: Dual-use goods as targets of trade and industrial policies



Policy type O Dual-use + security O Only dual-use O Only security O Other policies

*Notes:* The data are taken from the *Global Trade Alert* project (Evenett, 2019). The individual points correspond to a double difference in new policy acts relative to the pre-trend period of 2008-2019:

$$\left[\log(\# \operatorname{acts}_{it}) - \frac{1}{13} \sum_{t=2008}^{2019} \log(\# \operatorname{acts}_{i,2008\text{-}19})\right] - \left[\log(\# \operatorname{acts}_{\operatorname{Other},t}) - \frac{1}{13} \sum_{t=2008}^{2019} \log(\# \operatorname{acts}_{\operatorname{Other},2008\text{-}19})\right]$$

Security policies are classified based on Figure C.4 with and are enumerated in Table SA.B.5.

Figure C.5: Security trade policies over time

# C.1.5 Fact #3. Dual-use trade responds to changes in security environment over time

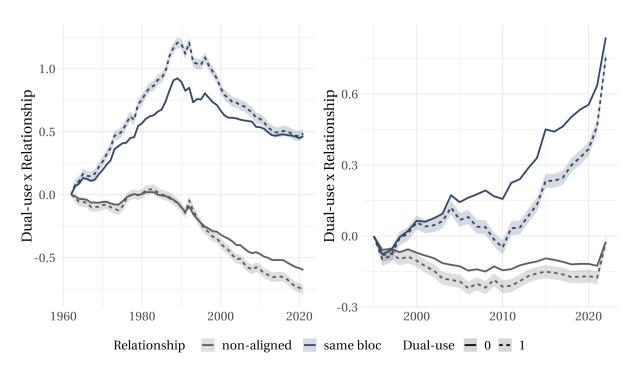
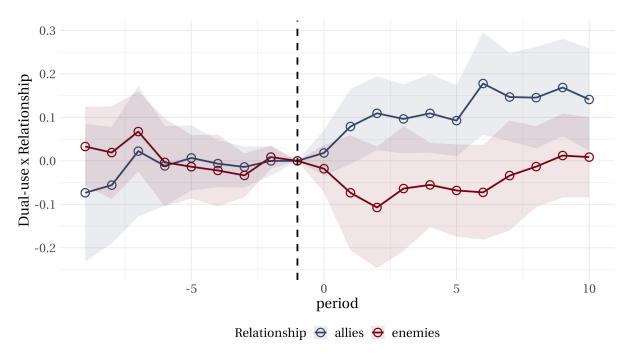


Figure C.6: Coefficient  $\gamma_{R,t}$  over time



*Notes*: The trade data for the Cold War (1962-2021) comes from the Atlas of Economic Complexity and is classified according to the SITC Rev. 2 (1975) classification. We include all inter-state and extra-state wars from the Correlates of War project that occurred from 1962 onwards (Sarkees & Wayman, 2010).

We list conflict participants who were geographically close to the main war theater. Then, we designate diplomatic alliances by manually classifying mentions of various state actors in Wikipedia articles related to the wars listed. Our approach has obvious limitations and should be considered a preliminary inquiry open for refinement in future studies. Independent of alliance classifications, Figure SA.B.6 shows that dual-use goods post-conflict experience exhibit stronger absolute changes in imports among all country pairs with a warparticipant receiver. Table SA.B.3 lists the conflicts and alliances used in our analysis. Our regression equation is

$$\log y_{wijkt} = \alpha_{wijk}^{\mathcal{T}} + \alpha_{wikt}^{\mathcal{X}} + \alpha_{wjkt}^{\mathcal{M}} + \gamma_{t,R} \times \text{Relationship}_{wij} + \beta_{t,R} \times \text{Relationship}_{wij} \times \text{Dual-use}_k + \varepsilon_{wijkt},$$

where  $\alpha_{wijk}^{\mathcal{T}}$ ,  $\alpha_{wikt}^{\mathcal{X}}$ , and  $\alpha_{wjkt}^{\mathcal{M}}$  are a set of war-exporter-importer-product, war-exporter-product-period, and war-importer-product-period fixed effects. Relationship wij is an indicator for whether countries are allies, enemies, or neither, with the first two values possible only when i is a war participant. Period t=0 marks the start of the war, and period t=-1 is used as a baseline. Standard errors are heteroskedasticity-robust, and confidence intervals are at the 95% level. Figure SA.B.5 plots  $\gamma_{t,R}$ .

Figure C.7: Trade in dual-use goods by diplomatic relationship: War studies

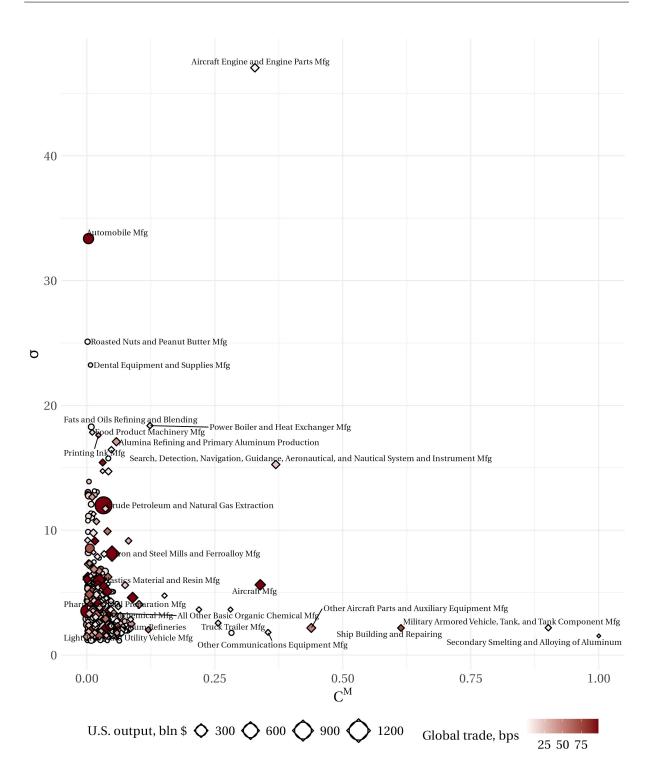
# **C.2** Empirical measurement

### C.2.1 Military use measure

$Pet C_k^N/\sigma$ $C_k^M/\sigma$ (%)NKey words in HS code descriptions[99.8, 99.9][56.42, 65.17]2vehicles, aluminium, powders, flakes, tanks, armoured, fighting, motorised, weapons[99.5, 99.6][39.24, 73.61]2boats, vessels, ships, warships, lifeboats, rowing, cruise, excursion, ferry, carge[99.3, 99.4][22.13, 27.84]2gliders, balloons, dirigibles, hang, powered, aircraft, signalling, safety, traffic, control[99.2, 99.2][16.15, 18.68]2aircraft, firearms, spring, air, gas, guns, pistols, truncheons[98.9, 99.1][14.90, 16.05]3firearms, spring, air, gas, guns, pistols, truncheons[98.9, 98.8][10.50, 12.38]4apparatus, fuses, detonating, radio, boats, floating, structures, rafts, tanks, coffer[97.5, 98.2][58.0, 7.74]4apparatus, steel, elactical, wire, barbed, iron, steel, witsted, instruments, elements[94.1, 97.4][3.30, 5.00]40tubes, steel, plates, iron, graphite, carbon, concentrates, metal, electrical, rods[94.1, 97.4][2.14, 2.48]40apparatus, steel, machines, iron, wire, recording, electrical, metal, copper, hand[87.4, 90.1][1.70, 1.88]40tron., steel, aluminium, waste, machines, dolomite, wire, electrically, scrap, devices[84.1, 87.4][2.11, 2.48]40toron., steel, plates, chemically, sugar, ignition, cut, hair, rods[87.4, 70.6][1.25, 1.37]40torantural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods[87.3, 60.6][0.88, 0.97]40textile, polymers, primary, forms, materials, watches, metal, compounds				
99.7, 99.7    39.87, 46.25  2   boats, vessels, ships, warships, lifeboats, rowing, cruise, excursion, ferry, cargo   199.5, 99.6    32.27, 36.17  2   10ating, vessels, light, fire, floats, dredgers, cranes, navigability, subsidiary, docks   199.2, 99.2    16.15, 18.66  2   aircraft, firearms, spring, air, gas, guns, pistols, truncheons   198.9, 99.1    14.90, 16.05  3   4   aircraft, firearms, spring, air, gas, guns, pistols, truncheons   198.2, 98.8    10.50, 12.38  4   apparatus, fuses, detonating, radio, boats, floating, structures, rafts, tanks, coffer   4   apparatus, stesels, plates, iron, graphite, carbon, concentrates, metal, electrical, rods   apparatus, steel, plates, iron, graphite, carbon, concentrates, metal, electrical, rods   apparatus, steel, machines, iron, wire, recording, electrically, scrap, devices   4   40   antural, ores, concentrates, mechanically, propelled, aircraft, launching, deck   apparatus, steel, machines, iron, wire, recording, electrical, rods   apparatus, steel, machines, iron, wire, recording, electrically, scrap, devices   4   40   antural, ores, concentrates, mechanically, sugar, ignition, cut, hair, rods   170, 188  40   antural, ores, concentrates, mechanically, sugar, ignition, cut, hair, rods   antural, ores, concentrates, hechanically, sugar, ignition, cut, hair, rods   antural, ores, concentrates, hechanically, sugar, ignition, cut, hair, rods   antural, ores, concentrates, hechanically, sugar, ignition, cut, hair, rods   antural, ores, concentrates, hechanically, sugar, ignition, cut, hair, rods   antural, ores, concentrates, hemetals, sead, copper, rubber, water, liquid   antural, ores, concentrates, head, copper, rubber, water, liquid   antural, ores, concentrates, hemetals, sead, copper, rubber, water, liquid   antural, ores, concentrates, hemetals, sead, copper, rubber, water, liquid   antural, ores, concentrates, hemetals, sead, copper, rubber, water, gas   antural, ores, concentrates, dead, copper, rubber, water, gas   antural, ores, concentrates, hemetal, h	$\operatorname{Pct} \mathcal{C}_k^M/\sigma$	$\mathcal{C}_k^M/\sigma$ (%)	N	Key words in HS code descriptions
99.5, 99.6   32.27, 36.17   2   floating, vessels, light, fire, floats, dredgers, cranes, navigability, subsidiary, docks   993.99.4   22.13, 27.84   2   gliders, balloons, dirigibles, hang, powered, aircraft, signalling, safety, traffic, control aircraft, 992.99.5   16.15, 18.68   2   3   6   6   7   7   7   7   7   7   7   7	[99.8, 99.9]	[56.42, 65.17]	2	vehicles, aluminium, powders, flakes, tanks, armoured, fighting, motorised, weapons
99.3, 99.4   12.13, 27.84   2   gliders, balloons, dirigibles, hang, powered, aircraft, signalling, safety, traffic, control aircraft, firearms, spring, air, gas, guns, pistols, truncheons     98.9, 99.1   14.90, 16.05   3   4   4   4   4   4   4   4   4   4	[99.7, 99.7]	[39.87, 46.25]	2	boats, vessels, ships, warships, lifeboats, rowing, cruise, excursion, ferry, cargo
99.2, 99.2   16.15, 18.68   2   aircraft, firearms, spring, air, gas, guns, pistols, truncheons   198.9, 99.1   14.90, 16.05   3   4   apparatus, fuses, detonating, radio, boats, floating, structures, rafts, tanks, coffer   198.2, 98.5   8.16, 10.16   4   trailers, gear, turbo, semi, vehicles, mechanically, propelled, aircraft, launching, deck   397.5, 98.2   5.80, 7.74   9   941.1, 97.4   33.0, 5.00   40   40   40   40   40   40   40	[99.5, 99.6]	[32.27, 36.17]	2	floating, vessels, light, fire, floats, dredgers, cranes, navigability, subsidiary, docks
98.9, 99.1   14.90, 16.05   3   firearms, devices, pistols, mechanical, sporting, shotguns, rifles, muzzle, loading, firing apparatus, fuses, detonating, radio, boats, floating, structures, rafts, tanks, coffer trailers, gear, turbo, semi, vehicles, mechanically, propelled, aircraft, launching, deck apparatus, vessels, optical, wire, barbed, iron, steel, twisted, instruments, elements tubes, steel, plates, iron, graphite, carbon, concentrates, metal, electrical, rods apparatus, steel, machines, iron, wire, recording, electrical, metal, copper, hand iron, steel, aluminium, waste, machines, dolomite, wire, electrically, scrap, devices steel, plates, iron, graphite, carbon, concentrates, metal, electrical, rods apparatus, steel, machines, iron, wire, recording, electrical, metal, copper, hand iron, steel, aluminium, waste, machines, dolomite, wire, electrically, scrap, devices steel, plates, chemically, spaparatus, alloy, photographic, film, sensitised natural, ores, concentrates, mechanical, iron, steel, nimal, instruments, waste, gas paparatus, waste, gas metal, slag, apparatus, alloy, photographic, film, sensitised natural, ores, concentrates, lead, copper, rubber, water, liquid natural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods oron, electrical, sead, copper, rubber, water, liquid natural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods oron, electrical, sead, copper, rubber, water, liquid natural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods oron, call, oils, plastics, optical, material, skins, feathers, compounds, filtings worked, iron, clad, oils, plastics, optical, material, skins, feathers, compounds, filtings oron, clad, oils, plastics, optical, materials, watches, metal, compounds, alloy forms, acids, halogenated, sulphonated, nitrated, nitrosated, starches, fabrics, lamps, steel form, secil, sale, machines, synthetic, natural, primary, compounds textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens of pab	[99.3, 99.4]	[22.13, 27.84]	2	gliders, balloons, dirigibles, hang, powered, aircraft, signalling, safety, traffic, control
98.6, 98.8   10.50, 12.38   4   apparatus, fuses, detonating, radio, boats, floating, structures, rafts, tanks, coffer   198.2, 98.5   [8.16, 10.16]   4   trailers, gear, turbo, semi, vehicles, mechanically, propelled, aircraft, launching, deck   197.5, 98.2   [5.80, 7.74]   9   apparatus, vessels, optical, wire, barbed, iron, steel, twisted, instruments, elements   194.1, 97.4   [3.30, 5.00]   40   tubes, steel, plates, iron, graphite, carbon, concentrates, metal, electrical, rods   apparatus, steel, machines, iron, wire, recording, electrical, metal, copper, hand   iron, steel, aluminium, waste, machines, dolomite, wire, electrically, scrap, devices   steel, bars, rods, cement, slag, apparatus, alloy, photographic, film, sensitised   natural, ores, concentrates, mechanical, iron, steel, animal, instruments, waste, gas   metal, wax, umbrellas, ores, concentrates, lead, copper, rubber, water, liquid   natural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods   iron, metal, precious, metals, steel, vegetable, petroleum, oils, matter, glues   watches, tools, tubes, plastics, optical, material, skins, feathers, compounds, fittings   worked, iron, clad, oils, plastics, materials, watches, metal, coppounds, alloy   forms, acids, halogenated, sulphonated, nitrated, nitrosated, starches, fabrics, lamps, steel   artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds   textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens   dabrics, x, ray, apparatus, textile, eher, peroxides, instruments, materials, alpha   wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets   ceramic, wood, preparations, fluit, absorbent   paper, fabrics, cork, plates, sheets, peetric, data, vinegar, paper   oils, wood, printed, slate, stone, fractions, paper, forms, machines, machines, machines, machines, machines, oil, matterial, swood, fabrics, reagents   glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, abso	[99.2, 99.2]	[16.15, 18.68]	2	aircraft, firearms, spring, air, gas, guns, pistols, truncheons
98.2, 98.5   [8.16, 10.16]   4   Taillers, gear, turbo, semi, vehicles, mechanically, propelled, aircraft, launching, deck   97.5, 98.2   [5.80, 7.74]   9   40   40   40   40   40   40   40	[98.9, 99.1]	[14.90, 16.05]	3	firearms, devices, pistols, mechanical, sporting, shotguns, rifles, muzzle, loading, firing
97.5, 98.2   [5.80, 7.74   9   apparatus, vessels, optical, wire, barbed, iron, steel, twisted, instruments, elements   94.1, 97.4   (3.30, 5.00)   40   40   40   40   40   40   40	[98.6, 98.8]	[10.50, 12.38]	4	apparatus, fuses, detonating, radio, boats, floating, structures, rafts, tanks, coffer
[94.1, 97.4] [3.30, 5.00] 40 tubes, steel, plates, iron, graphite, carbon, concentrates, metal, electrical, rods [90.8, 94.1] [2.78, 3.29] 40 apparatus, steel, machines, iron, wire, recording, electrical, metal, copper, hand [87.4, 90.7] [2.48, 2.76] 40 iron, steel, aluminium, waste, machines, dolomite, wire, electrically, scrap, devices [84.1, 87.4] [2.14, 2.48] 40 steel, bars, rods, cement, slag, apparatus, alloy, photographic, film, sensitised [80.9, 84.0] [1.89, 2.14] 40 natural, ores, concentrates, mechanical, iron, steel, animal, instruments, waste, gas [77.4, 80.7] [1.70, 1.88] 40 metal, wax, umbrellas, ores, concentrates, lead, copper, rubber, water, liquid [74.1, 77.3] [1.54, 1.70] 40 natural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods [70.7, 74.0] [1.37, 1.53] 40 worked, iron, clad, oils, plastics, optical, material, skins, feathers, compounds, fittings [64.0, 67.2] [1.08, 1.25] 40 worked, iron, clad, oils, plastics, materials, watches, metal, compounds, alloy forms, acids, halogenated, sulphonated, nitrated, nitrosated, starches, fabrics, lamps, steel [57.3, 60.6] [0.88, 0.97] 40 artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds [54.0, 57.2] [0.55, 0.62] 40 textile, polymers, primary, forms, materials, awa, natural, chemical, metal, pens [43.9, 47.2] [0.55, 0.62] 40 textile, polymers, primary, forms, materials, ava, natural, chemical, metal, pens [40.6, 43.8] [0.47, 0.54] 40 wood, ceramic, laminated, forms, plates, vegetable, extile, gas, rubber, sheets ceramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper [37.2, 40.5] [0.42, 0.47] 40 upaper, fabrics, cork, plates, sheets, papers, forms, machines, apparatus, wool, fabrics, reagents [30.3, 33.8] [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparatius, fruit, absorbent paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool fractions, p	[98.2, 98.5]	[8.16, 10.16]	4	trailers, gear, turbo, semi, vehicles, mechanically, propelled, aircraft, launching, deck
90.8, 94.1   2.78, 3.29   40 apparatus, steel, machines, iron, wire, recording, electrical, metal, copper, hand   87.4, 90.7   2.48, 2.76   40 iron, steel, aluminium, waste, machines, dolomite, wire, electrically, scrap, devices   84.1, 87.4   2.14, 2.48   40 steel, bars, rods, cement, slag, apparatus, alloy, photographic, film, sensitised   80.9, 84.0   1.89, 2.14   40 natural, ores, concentrates, mechanical, iron, steel, animal, instruments, waste, gas   metal, wax, umbrellas, ores, concentrates, lead, copper, rubber, water, liquid   174.1, 77.3   1.54, 1.70   40 natural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods   170.7, 74.0   13.7, 1.53   40 iron, metal, precious, metals, steel, vegetable, petroleum, oils, matter, glues   40.6, 67.2   10.8, 1.25   40 worked, iron, clad, oils, plastics, optical, material, skins, feathers, compounds, fittings   164.0, 67.2   10.8, 1.25   40 worked, iron, clad, oils, plastics, materials, watches, metal, compounds, alloy   60.7, 63.9   10.98, 1.08   40 forms, acids, halogenated, sulphonated, nitrated, nitrosated, starches, fabrics, lamps, steel   57.3, 60.6   10.88, 0.97   40 artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds   154.0, 57.2   10.55, 0.62   40 textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens   150.6, 53.8   10.68, 0.75   40 textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens   150.6, 53.8   10.4, 0.5, 0.62   40 textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens   150.5, 0.62   40 textile, polymers, primary, forms, plates, vegetable, textile, gas, rubber, sheets   43.9, 47.2   10.55, 0.62   40 textile, polymers, primary, forms, plates, vegetable, textile, gas, rubber, sheets   43.9, 47.2   10.55, 0.62   40 textile, polymers, primary, forms, plates, vegetable, textile, gas, rubber, sheets   43.9, 47.2   10.37, 0.42   40 textile, polymers, primary, forms, plates, seeds, paper, forms, materials, avan, natural	[97.5, 98.2]	[5.80, 7.74]	9	apparatus, vessels, optical, wire, barbed, iron, steel, twisted, instruments, elements
[87.4, 90.7] [2.48, 2.76] 40 iron, steel, aluminium, waste, machines, dolomite, wire, electrically, scrap, devices steel, 184.1, 87.4] [2.14, 2.48] 40 steel, bars, rods, cement, slag, apparatus, alloy, photographic, film, sensitised natural, ores, concentrates, mechanical, iron, steel, animal, instruments, waste, gas [77.4, 80.7] [1.70, 1.88] 40 metal, wax, umbrellas, ores, concentrates, lead, copper, rubber, water, liquid [74.1, 77.3] [1.54, 1.70] 40 natural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods iron, metal, precious, metals, steel, vegetable, petroleum, oils, matter, glues watches, tools, tubes, plastics, optical, material, skins, feathers, compounds, fittings worked, iron, clad, oils, plastics, optical, materials, watches, metal, compounds, alloy forms, acids, halogenated, sulphonated, nitrated, nitrosated, starches, fabrics, lamps, steel artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens fabrics, x, ray, apparatus, textile, ether, peroxides, instruments, materials, alpha wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets ceramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent paper, fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted leather, dried, meat, fish, metals, knitted, crocheted, dried, yarn, animal, put, retail, sale dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs machines, oil, machinery, extraction, meat, ground	[94.1, 97.4]	[3.30, 5.00]	40	tubes, steel, plates, iron, graphite, carbon, concentrates, metal, electrical, rods
84.1, 87.4   2.14, 2.48   40   steel, bars, rods, cement, slag, apparatus, alloy, photographic, film, sensitised   80.9, 84.0   1.89, 2.14   40   natural, ores, concentrates, mechanical, iron, steel, animal, instruments, waste, gas metal, wax, umbrellas, ores, concentrates, lead, copper, rubber, water, liquid   74.1, 77.3   1.54, 1.70   40   natural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods   70.7, 74.0   1.37, 1.53   40   iron, metal, precious, metals, steel, vegetable, petroleum, oils, matter, glues   watches, tools, tubes, plastics, optical, material, skins, feathers, compounds, fittings   worked, iron, clad, oils, plastics, optical, material, skins, feathers, compounds, fittings   worked, iron, clad, oils, plastics, optical, material, skins, feathers, compounds, alloy   forms, acids, halogenated, sulphonated, nitrated, nitrosated, starches, fabrics, lamps, steel   artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds   textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens   40.6, 43.8   60.68, 0.75   40   fabrics, x, ray, apparatus, textile, ether, peroxides, instruments, materials, alpha   wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets   ceramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines   yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper   oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus   yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents   glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent   paper, fabrics, cork, plates, sheets, papers, rolls, wood, haited, crocheted   trace, 20.4   10.17, 0.21   40   trace, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres   fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted   dried, frozen, fresh, leather, nuts, cocoa, prepared, chi	[90.8, 94.1]	[2.78, 3.29]	40	apparatus, steel, machines, iron, wire, recording, electrical, metal, copper, hand
[80.9, 84.0] [1.89, 2.14] 40 natural, ores, concentrates, mechanical, iron, steel, animal, instruments, waste, gas [77.4, 80.7] [1.70, 1.88] 40 metal, wax, umbrellas, ores, concentrates, lead, copper, rubber, water, liquid [74.1, 77.3] [1.54, 1.70] 40 natural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods iron, metal, precious, metals, steel, vegetable, petroleum, oils, matter, glues [67.4, 70.6] [1.25, 1.37] 40 watches, tools, tubes, plastics, optical, material, skins, feathers, compounds, fittings [64.0, 67.2] [1.08, 1.25] 40 worked, iron, clad, oils, plastics, materials, watches, metal, compounds, alloy [60.7, 63.9] [0.98, 1.08] 40 forms, acids, halogenated, sulphonated, nitrated, nitrosated, starches, fabrics, lamps, steel artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds [54.0, 57.2] [0.75, 0.87] 40 textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens [50.6, 53.8] [0.68, 0.75] 40 textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens [50.6, 53.8] [0.62, 0.67] 40 wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets (ceramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines [40.6, 43.8] [0.47, 0.54] 40 yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus [33.9, 37.2] [0.37, 0.42] 40 yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents [27.2, 30.3] [0.31, 0.35] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 fabrics, pulp, silk, woven, leather, nuts, cocoa, prepared, chilled, waters,	[87.4, 90.7]	[2.48, 2.76]	40	iron, steel, aluminium, waste, machines, dolomite, wire, electrically, scrap, devices
[77.4, 80.7][1.70, 1.88]40metal, wax, umbrellas, ores, concentrates, lead, copper, rubber, water, liquid[74.1, 77.3][1.54, 1.70]40natural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods[70.7, 74.0][1.37, 1.53]40iron, metal, precious, metals, steel, vegetable, petroleum, oils, matter, glues[67.4, 70.6][1.25, 1.37]40watches, tools, tubes, plastics, optical, material, skins, feathers, compounds, fittings[64.0, 67.2][1.08, 1.25]40worked, iron, clad, oils, plastics, materials, watches, metal, compounds, alloy[67.7, 63.9][0.98, 1.08]40forms, acids, halogenated, sulphonated, nitrosated, starches, fabrics, lamps, steel[57.3, 60.6][0.88, 0.97]40artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds[54.0, 57.2][0.75, 0.87]40textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens[50.6, 53.8][0.68, 0.75]40fabrics, x, ray, apparatus, textile, ether, peroxides, instruments, materials, alpha[47.3, 50.5][0.62, 0.67]40wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets[43.9, 47.2][0.55, 0.62]40ceramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines[40.6, 43.8][0.47, 0.45]40oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus[33.9, 37.2][0.37, 0.42]40silas, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent[27.2, 30.3][0.31, 0.35] <td>[84.1, 87.4]</td> <td>[2.14, 2.48]</td> <td>40</td> <td>steel, bars, rods, cement, slag, apparatus, alloy, photographic, film, sensitised</td>	[84.1, 87.4]	[2.14, 2.48]	40	steel, bars, rods, cement, slag, apparatus, alloy, photographic, film, sensitised
[74.1, 77.3][1.54, 1.70]40natural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods[70.7, 74.0][1.37, 1.53]40iron, metal, precious, metals, steel, vegetable, petroleum, oils, matter, glues[67.4, 70.6][1.25, 1.37]40watches, tools, tubes, plastics, optical, material, skins, feathers, compounds, fittings[64.0, 67.2][1.08, 1.25]40worked, iron, clad, oils, plastics, materials, watches, metal, compounds, alloy[60.7, 63.9][0.98, 1.08]40forms, acids, halogenated, sulphonated, nitrated, nitrosated, starches, fabrics, lamps, steel[57.3, 60.6][0.88, 0.97]40artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds[54.0, 57.2][0.75, 0.87]40textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens[50.6, 53.8][0.68, 0.75]40wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets[43.9, 47.2][0.55, 0.62]40wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines[40.6, 43.8][0.47, 0.54]40yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper[37.2, 40.5][0.42, 0.47]40oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus[33.9, 37.2][0.37, 0.42]40yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents[30.3, 33.8][0.35, 0.37]40paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool[27.2, 30.3][0.31, 0.35]40	[80.9, 84.0]	[1.89, 2.14]	40	natural, ores, concentrates, mechanical, iron, steel, animal, instruments, waste, gas
[70.7, 74.0] [1.37, 1.53] 40 iron, metal, precious, metals, steel, vegetable, petroleum, oils, matter, glues [67.4, 70.6] [1.25, 1.37] 40 watches, tools, tubes, plastics, optical, material, skins, feathers, compounds, fittings [64.0, 67.2] [1.08, 1.25] 40 worked, iron, clad, oils, plastics, materials, watches, metal, compounds, alloy [60.7, 63.9] [0.98, 1.08] 40 forms, acids, halogenated, sulphonated, nitrosated, starches, fabrics, lamps, steel artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds [54.0, 57.2] [0.75, 0.87] 40 textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens [50.6, 53.8] [0.68, 0.75] 40 fabrics, x, ray, apparatus, textile, ether, peroxides, instruments, materials, alpha wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets (eramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines (eramic, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents [30.3, 33.8] [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent [27.2, 30.3] [0.31, 0.35] 40 paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres [20.5, 23.8] [0.21, 0.24] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs machines, oil, machinery, extraction, meat, ground	[77.4, 80.7]	[1.70, 1.88]	40	metal, wax, umbrellas, ores, concentrates, lead, copper, rubber, water, liquid
[67.4, 70.6] [1.25, 1.37] 40 watches, tools, tubes, plastics, optical, material, skins, feathers, compounds, fittings [64.0, 67.2] [1.08, 1.25] 40 worked, iron, clad, oils, plastics, materials, watches, metal, compounds, alloy [60.7, 63.9] [0.98, 1.08] 40 forms, acids, halogenated, sulphonated, nitrated, nitrosated, starches, fabrics, lamps, steel [57.3, 60.6] [0.88, 0.97] 40 artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens [50.6, 53.8] [0.68, 0.75] 40 fabrics, x, ray, apparatus, textile, ether, peroxides, instruments, materials, alpha wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets ceramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper [37.2, 40.5] [0.42, 0.47] 40 oils, wood, printed, slate, stone, fractions, paper, forms, machinery, apparatus yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents [30.3, 33.8] [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs fresh, chilled, knitted, crocheted, machinery, extraction, meat, ground	[74.1, 77.3]	[1.54, 1.70]	40	natural, copper, steel, plates, chemically, sugar, ignition, cut, hair, rods
[64.0, 67.2] [1.08, 1.25] 40 worked, iron, clad, oils, plastics, materials, watches, metal, compounds, alloy [60.7, 63.9] [0.98, 1.08] 40 forms, acids, halogenated, sulphonated, nitrosated, starches, fabrics, lamps, steel [57.3, 60.6] [0.88, 0.97] 40 artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds [54.0, 57.2] [0.75, 0.87] 40 textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens [50.6, 53.8] [0.68, 0.75] 40 fabrics, x, ray, apparatus, textile, ether, peroxides, instruments, materials, alpha wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets (43.9, 47.2] [0.55, 0.62] 40 ceramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines (40.6, 43.8] [0.47, 0.54] 40 yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper (37.2, 40.5] [0.42, 0.47] 40 oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus (33.9, 37.2) [0.37, 0.42] 40 yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents (30.3, 33.8) [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent (27.2, 30.3) [0.31, 0.35] 40 paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool (23.8, 27.1] [0.24, 0.31] 40 fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres (abrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted (17.2, 20.4) [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing (13.8, 17.1) [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale (10.5, 13.7) [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs (17.1, 10.4) [0.06, 0.09] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[70.7, 74.0]	[1.37, 1.53]	40	iron, metal, precious, metals, steel, vegetable, petroleum, oils, matter, glues
[60.7, 63.9] [0.98, 1.08] 40 forms, acids, halogenated, sulphonated, nitrated, nitrosated, starches, fabrics, lamps, steel [57.3, 60.6] [0.88, 0.97] 40 artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds [54.0, 57.2] [0.75, 0.87] 40 textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens [60.6, 53.8] [0.68, 0.75] 40 fabrics, x, ray, apparatus, textile, ether, peroxides, instruments, materials, alpha wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets (eramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper (oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[67.4, 70.6]	[1.25, 1.37]	40	watches, tools, tubes, plastics, optical, material, skins, feathers, compounds, fittings
[57.3, 60.6] [0.88, 0.97] 40 artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds [54.0, 57.2] [0.75, 0.87] 40 textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens [50.6, 53.8] [0.68, 0.75] 40 fabrics, x, ray, apparatus, textile, ether, peroxides, instruments, materials, alpha wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets (eramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents [30.3, 33.8] [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent [27.2, 30.3] [0.31, 0.35] 40 paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres [20.5, 23.8] [0.21, 0.24] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[64.0, 67.2]	[1.08, 1.25]	40	worked, iron, clad, oils, plastics, materials, watches, metal, compounds, alloy
[54.0, 57.2] [0.75, 0.87] 40 textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens [50.6, 53.8] [0.68, 0.75] 40 fabrics, x, ray, apparatus, textile, ether, peroxides, instruments, materials, alpha [47.3, 50.5] [0.62, 0.67] 40 wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets [43.9, 47.2] [0.55, 0.62] 40 ceramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines [40.6, 43.8] [0.47, 0.54] 40 yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper [37.2, 40.5] [0.42, 0.47] 40 oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents [30.3, 33.8] [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres [20.5, 23.8] [0.21, 0.24] 40 fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[60.7, 63.9]	[0.98, 1.08]	40	forms, acids, halogenated, sulphonated, nitrated, nitrosated, starches, fabrics, lamps, steel
[50.6, 53.8] [0.68, 0.75] 40 fabrics, x, ray, apparatus, textile, ether, peroxides, instruments, materials, alpha [47.3, 50.5] [0.62, 0.67] 40 wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets (43.9, 47.2] [0.55, 0.62] 40 ceramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines [40.6, 43.8] [0.47, 0.54] 40 yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper [37.2, 40.5] [0.42, 0.47] 40 oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus [33.9, 37.2] [0.37, 0.42] 40 yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents [30.3, 33.8] [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent [27.2, 30.3] [0.31, 0.35] 40 paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool [23.8, 27.1] [0.24, 0.31] 40 fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres [20.5, 23.8] [0.21, 0.24] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing [13.8, 17.1] [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale [10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[57.3, 60.6]	[0.88, 0.97]	40	artificial, stone, forms, retail, sale, machines, synthetic, natural, primary, compounds
[47.3, 50.5] [0.62, 0.67] 40 wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets [43.9, 47.2] [0.55, 0.62] 40 ceramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines [40.6, 43.8] [0.47, 0.54] 40 yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper [37.2, 40.5] [0.42, 0.47] 40 oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus [33.9, 37.2] [0.37, 0.42] 40 yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents [30.3, 33.8] [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent [27.2, 30.3] [0.31, 0.35] 40 paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool [23.8, 27.1] [0.24, 0.31] 40 fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres [20.5, 23.8] [0.21, 0.24] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing [13.8, 17.1] [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale [10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [7.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[54.0, 57.2]	[0.75, 0.87]	40	textile, polymers, primary, forms, materials, raw, natural, chemical, metal, pens
[43.9, 47.2] [0.55, 0.62] 40 ceramic, wood, preparations, tiles, goods, siliceous, tanning, soap, organic, machines [40.6, 43.8] [0.47, 0.54] 40 yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper [37.2, 40.5] [0.42, 0.47] 40 oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus [33.9, 37.2] [0.37, 0.42] 40 yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents [30.3, 33.8] [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent [27.2, 30.3] [0.31, 0.35] 40 paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool [23.8, 27.1] [0.24, 0.31] 40 fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres [20.5, 23.8] [0.21, 0.24] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing [13.8, 17.1] [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale [10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[50.6, 53.8]	[0.68, 0.75]	40	fabrics, x, ray, apparatus, textile, ether, peroxides, instruments, materials, alpha
[40.6, 43.8] [0.47, 0.54] 40 yarn, waste, wood, hair, textile, fibres, electric, data, vinegar, paper [37.2, 40.5] [0.42, 0.47] 40 oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus [33.9, 37.2] [0.37, 0.42] 40 yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents [30.3, 33.8] [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent [27.2, 30.3] [0.31, 0.35] 40 paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool [23.8, 27.1] [0.24, 0.31] 40 fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres [20.5, 23.8] [0.21, 0.24] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing [13.8, 17.1] [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale [10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[47.3, 50.5]		40	wood, ceramic, laminated, forms, plates, vegetable, textile, gas, rubber, sheets
[37.2, 40.5] [0.42, 0.47] 40 oils, wood, printed, slate, stone, fractions, paper, forms, machines, apparatus [33.9, 37.2] [0.37, 0.42] 40 yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents [30.3, 33.8] [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent [27.2, 30.3] [0.31, 0.35] 40 paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool [23.8, 27.1] [0.24, 0.31] 40 fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres [20.5, 23.8] [0.21, 0.24] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing [13.8, 17.1] [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale [10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	-		40	
[33.9, 37.2] [0.37, 0.42] 40 yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents [30.3, 33.8] [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent [27.2, 30.3] [0.31, 0.35] 40 paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool [23.8, 27.1] [0.24, 0.31] 40 fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres [20.5, 23.8] [0.21, 0.24] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing [13.8, 17.1] [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale [10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[40.6, 43.8]		40	
[30.3, 33.8] [0.35, 0.37] 40 glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent [27.2, 30.3] [0.31, 0.35] 40 paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool [23.8, 27.1] [0.24, 0.31] 40 fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres [20.5, 23.8] [0.21, 0.24] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing [13.8, 17.1] [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale [10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[37.2, 40.5]		40	
[27.2, 30.3] [0.31, 0.35] 40 paper, fabrics, cork, plates, sheets, papers, rolls, wood, materials, wool [23.8, 27.1] [0.24, 0.31] 40 fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres [20.5, 23.8] [0.21, 0.24] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing [13.8, 17.1] [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale [10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[33.9, 37.2]	[0.37, 0.42]	40	yarn, paper, paperboard, sewing, machines, machinery, apparatus, wool, fabrics, reagents
[23.8, 27.1] [0.24, 0.31] 40 fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres [20.5, 23.8] [0.21, 0.24] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing [13.8, 17.1] [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale [10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[30.3, 33.8]	[0.35, 0.37]	40	glass, worked, paper, sheets, reflecting, cellulose, wood, preparations, fruit, absorbent
[20.5, 23.8] [0.21, 0.24] 40 fabrics, pulp, silk, woven, leather, yarn, waste, wood, knitted, crocheted [17.2, 20.4] [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing [13.8, 17.1] [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale [10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[27.2, 30.3]	[0.31, 0.35]	40	
[17.2, 20.4] [0.17, 0.21] 40 leather, dried, meat, fish, metals, knitted, crocheted, fabrics, genus, printing [13.8, 17.1] [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale [10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[23.8, 27.1]	[0.24, 0.31]	40	fractions, paper, modified, cotton, mixed, animal, refined, chemically, woven, fibres
[13.8, 17.1] [0.13, 0.16] 40 fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale [10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[20.5, 23.8]	[0.21, 0.24]	40	
[10.5, 13.7] [0.09, 0.13] 40 dried, frozen, fresh, leather, nuts, cocoa, prepared, chilled, waters, molluscs [7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[17.2, 20.4]	[0.17, 0.21]	40	9 . 9
[7.1, 10.4] [0.06, 0.09] 40 machines, fresh, fish, prepared, chilled, yarn, coffee, vinyl, organs, vegetables [3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground	[13.8, 17.1]	[0.13, 0.16]	40	fish, coaches, knitted, crocheted, dried, yarn, animal, put, retail, sale
[3.8, 7.0] [0.04, 0.06] 40 fresh, chilled, knitted, crocheted, machines, oil, machinery, extraction, meat, ground			40	
			40	
[0.0, 3.7] [0.00, 0.04] 45 precious, metal, fresh, prepared, tobacco, preparations, cars, rubber, jackets, chilled			40	,
	[0.0, 3.7]	[0.00, 0.04]	45	precious, metal, fresh, prepared, tobacco, preparations, cars, rubber, jackets, chilled

*Notes*: The table is generated utilizing military use for HS 4-digit codes for expositional purposes. The reason is that 4-digit text descriptions are concise and bundle 6-digit codes that are linguistically similar together. The first column contains the percentile of military use. The second column contains military use, expressed in percent. The third column is the number of 4-digit categories within the defined bucket. The last column details 10 most common words, in decreasing order, from the associated HS code descriptions.

Table C.2: HS codes: Keywords



*Notes:* Industries that produce at least one dual-use good are depicted with a diamond; all other industries are depicted with a circle.

Figure C.8: Military centrality and trade elasticities: NAICS 6-digit level

Variable	$C^M/\sigma$	$\operatorname{pct} \mathcal{C}^M/\sigma$	$\mathcal{C}^{M}$	$\operatorname{pct} \mathcal{C}^M$	$\mathcal{S}^{M}$	$\operatorname{pct} \mathcal{S}^M$	$s^M$	$\operatorname{pct} s^M$	$\Psi's^M$	$\operatorname{pct} \Psi' s^M$	$s^C$	$\operatorname{pct} s^C$	$\Psi's^C$	$\operatorname{pct} \Psi' s^C$
$\mathcal{C}^{M}/\sigma$	1.00	0.48	0.90	0.44	0.62	0.35	0.48	0.26	0.30	0.30	-0.07	-0.08	-0.03	-0.08
$\operatorname{pct} \mathcal{C}^M/\sigma$		1.00	0.45	0.83	0.32	0.55	0.21	0.36	0.32	0.61	-0.21	-0.21	0.07	0.01
$\mathcal{C}^{M}$			1.00	0.52	0.68	0.40	0.59	0.31	0.39	0.37	-0.08	-0.08	-0.01	-0.07
$\operatorname{pct} \mathcal{C}^M$				1.00	0.36	0.62	0.23	0.41	0.44	0.74	-0.23	-0.23	0.14	0.05
$\mathcal{S}^M$					1.00	0.45	0.45	0.35	0.18	0.22	-0.06	-0.17	-0.10	-0.10
$\operatorname{pct} \mathcal{S}^M$						1.00	0.26	0.73	0.11	0.36	-0.12	-0.19	-0.13	-0.17
$s^M$							1.00	0.30	0.56	0.24	0.28	0.14	0.21	0.07
$\operatorname{pct} s^M$								1.00	0.25	0.53	0.26	0.46	0.22	0.32
$\Psi's^M$									1.00	0.60	0.20	0.25	0.74	0.48
pct $\Psi's^M$										1.00	0.07	0.26	0.53	0.65
$s^C$											1.00	0.50	0.63	0.40
$\operatorname{pct} s^C$												1.00	0.47	0.69
$\Psi's^C$													1.00	0.70
$\det \Psi' s^C$														1.00

Table C.3: Key variables: Correlation table

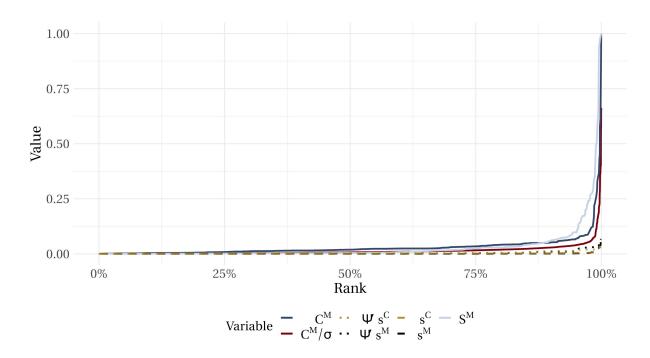


Figure C.9: Cumulative distribution function of key variables

### **C.2.2** Policy targeting

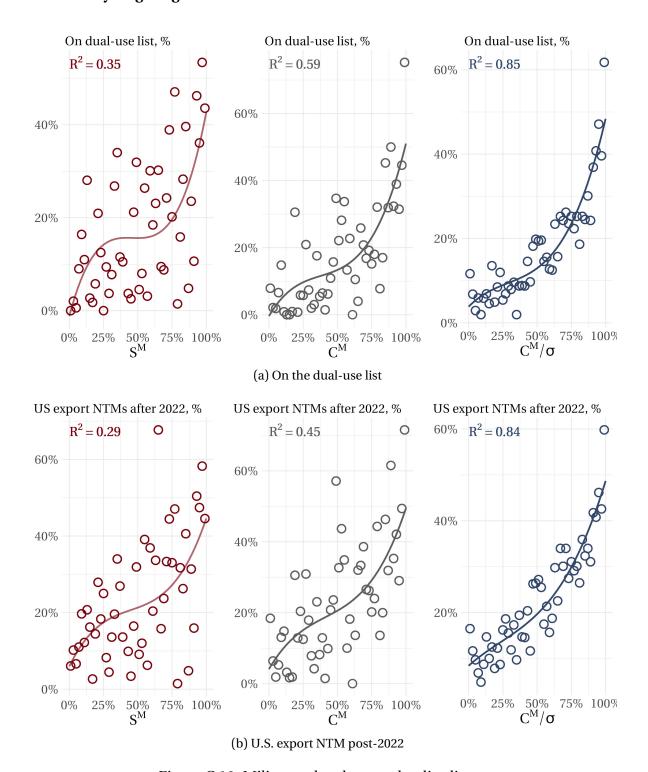


Figure C.10: Military sales share and policy lists

Dependent Variable:			On d	ual-use list	: Yes		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
$S_{\mathrm{US}}^{M}$	0.6027***		-0.0230				
	(0.0933)		(0.0752)				
$\mathcal{C}_{ ext{US}}^{M}/\sigma$		3.020***	3.063***	2.733***	2.796***	2.653***	1.987***
		(0.3266)	(0.3767)	(0.3126)	(0.3151)	(0.2818)	(0.2324)
Fixed-effects							
Polynomial $S_{\mathrm{US}}^{M}$				Yes			
Piecewise $S_{\mathrm{US}}^{M}$					Yes	Yes	Yes
Goods controls (trade, sales,)						Yes	Yes
HS 2-digit							Yes
Fit statistics							
Observations	5,135	5,135	5,135	5,135	5,135	5,134	5,134
$\mathbb{R}^2$	0.02127	0.05871	0.05872	0.07982	0.08109	0.12487	0.32321
Within R <sup>2</sup>				0.07982	0.04179	0.04849	0.02454

Heteroskedasticity-robust standard-errors in parentheses

Signif. Codes: \*\*\*: 0.001, \*\*: 0.01, \*: 0.05

Table C.4: Dual-use goods: A regression analysis

Dependent Variable:		I	Had a US e	xport NTM	after 2022		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
$S_{\mathrm{US}}^{M}$	0.5773***		0.0783				
	(0.0926)		(0.0915)				
$\mathcal{C}_{ ext{US}}^{M}/\sigma$		2.589***	2.443***	2.179***	2.166***	1.947***	$0.7805^{*}$
		(0.3339)	(0.3825)	(0.3200)	(0.3249)	(0.2984)	(0.3037)
Fixed-effects							
Polynomial $S_{\mathrm{US}}^{M}$				Yes			
Piecewise $S_{\mathrm{US}}^{M}$					Yes	Yes	Yes
Goods controls (trade, sales,)						Yes	Yes
HS 2-digit							Yes
Fit statistics							
Observations	5,135	5,135	5,135	5,135	5,135	5,134	5,134
$\mathbb{R}^2$	0.01597	0.03529	0.03547	0.05602	0.06666	0.16382	0.38737
Within R <sup>2</sup>				0.05602	0.02950	0.03845	0.01941

Heteroskedasticity-robust standard-errors in parentheses

Signif. Codes: \*\*\*: 0.001, \*\*: 0.01, \*: 0.05

Table C.5: Export NTMs: A regression analysis

Dependent Variable:				On dual	-use list: Ye	s		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
$\mathcal{C}_{ ext{US}}^{M}/\sigma$	1.948***	2.438***	2.410***	2.355***				
	(0.2803)	(0.2796)	(0.2844)	(0.2575)				
rank $\mathcal{C}_{ ext{US}}^{M}/\sigma$					0.2948***	0.3206***	0.2872***	0.2970***
					(0.0190)	(0.0213)	(0.0193)	(0.0232)
Fixed-effects								
Polynomial $s_{\mathrm{US}}^{M}$	Yes				Yes			
Polynomial $\Psi's^M_{ t US}$		Yes				Yes		
Polynomial rank $s_{\mathrm{US}}^{M}$			Yes				Yes	
Polynomial rank $\Psi's^M_{\mathrm{US}}$				Yes				Yes
Fit statistics								
Observations	5,135	5,135	5,135	5,135	5,135	5,135	5,135	5,135
$\mathbb{R}^2$	0.07464	0.07758	0.08517	0.08686	0.10329	0.08843	0.09592	0.08643
Within R <sup>2</sup>	0.07464	0.07758	0.08517	0.08686	0.10329	0.08843	0.09592	0.08643

Heteroskedasticity-robust standard-errors in parentheses

Signif. Codes: \*\*\*: 0.001, \*\*: 0.01, \*: 0.05

Table C.6: Dual-use goods: More robustness

Dependent Variable:			Нас	l a US expo	ort NTM aft	er 2022		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
$\mathcal{C}_{ ext{US}}^{M}/\sigma$	1.520***	2.109***	1.938***	1.993***				
	(0.2960)	(0.3018)	(0.2919)	(0.2748)				
rank $\mathcal{C}_{ ext{US}}^{M}/\sigma$					0.2908***	0.3275***	0.2674***	0.2859***
					(0.0208)	(0.0231)	(0.0210)	(0.0256)
Fixed-effects								
Polynomial $s_{\mathrm{US}}^{M}$	Yes				Yes			
Polynomial $\Psi's^M_{ extsf{US}}$		Yes				Yes		
Polynomial rank $s_{\mathrm{US}}^{M}$			Yes				Yes	
Polynomial rank $\Psi's^M_{\mathrm{US}}$				Yes				Yes
Fit statistics								
Observations	5,135	5,135	5,135	5,135	5,135	5,135	5,135	5,135
$\mathbb{R}^2$	0.05141	0.04688	0.07284	0.06029	0.07901	0.06444	0.08586	0.06546
Within R <sup>2</sup>	0.05141	0.04688	0.07284	0.06029	0.07901	0.06444	0.08586	0.06546

 $Heterosked a sticity-robust\ standard-errors\ in\ parentheses$ 

Signif. Codes: \*\*\*: 0.001, \*\*: 0.01, \*: 0.05

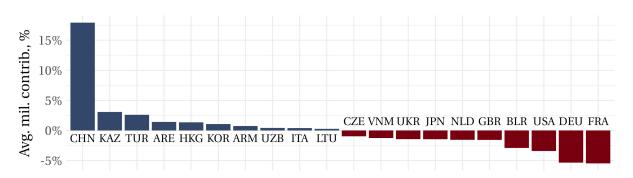
 ${\it Note:} \ {\it Supplementary} \ {\it Appendix} \ {\it Tables} \ {\it SA.B.7-SA.B.54} \ provide \ additional \ robustness.$ 

Table C.7: Export NTMs: More robustness

### **C.2.3** Trade flows: Events

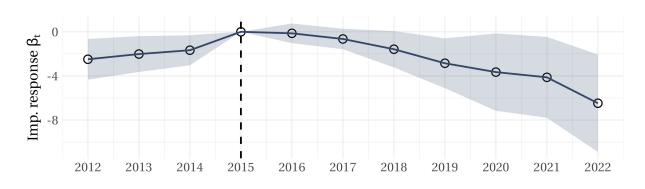


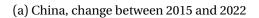
#### (a) Russia, change between 2021 and 2022

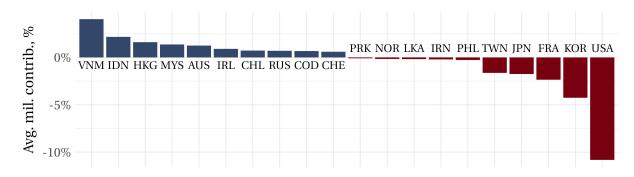


(b) Russia, 2022 War

Figure C.11: Trade responses following geopolitical shocks: Russia-2022







(b) China, 2015-2022

Figure C.12: Trade responses following geopolitical shocks: China-2016

# C.2.4 Trade flows: Decomposition by good

HS code	Description	ISO	chg (%)
930690	Ammunition; n.e.c. in chapter 93	POL	8.22
930110	Military weapons; artillery weapons (e.g. guns, howitzers, and mortars)	POL	5.05
871000	Tanks and other armoured fighting vehicles; motorised, whether or not fitted with weapons, and parts of such vehicles	CAN	2.68
871000	Tanks and other armoured fighting vehicles; motorised, whether or not fitted with weapons, and parts of such vehicles	POL	2.04
930690	Ammunition; n.e.c. in chapter 93	SVK	1.83
890610	Vessels; warships	USA	1.41
871000	Tanks and other armoured fighting vehicles; motorised, whether or not fitted with weapons, and parts of such vehicles	BEL	1.38
871000	Tanks and other armoured fighting vehicles; motorised, whether or not fitted with weapons, and parts of such vehicles	ROU	1.18
930110	Military weapons; artillery weapons (e.g. guns, howitzers, and mortars)	SVK	1.12
271000	Waste Oils; of petroleum or obtained from bituminous minerals, not crude; and preparations n.e.c., weight 70% or preparations of the same, containing polychlorinated biphenyls (PCBs), polychorinated terphenyls (PCTs) or polybrominated biphenyls (PBBs)	POL	0.94
930690	Ammunition; n.e.c. in chapter 93	NOR	0.89
930630	Ammunition; cartridges and parts thereof n.e.c. in heading no. 9306	USA	0.78
880212	Helicopters; of an unladen weight exceeding 2000kg	ROU	0.57
850220	Electric generating sets; with spark-ignition internal combustion piston engines	CHN	0.49
880212	Helicopters; of an unladen weight exceeding 2000kg	SVK	0.47
871639	Trailers and semi-trailers; (other than tanker type)	POL	0.42
271000	Waste Oils; of petroleum or obtained from bituminous minerals, not crude; and preparations n.e.c., weight 70% or preparations of the same, containing polychlorinated biphenyls (PCBs), polychorinated terphenyls (PCTs) or polybrominated biphenyls (PBBs)	BGR	0.40
930630	Ammunition; cartridges and parts thereof n.e.c. in heading no. 9306	SVK	0.38
271000	Waste Oils; of petroleum or obtained from bituminous minerals, not crude; and preparations n.e.c., weight 70% or preparations of the same, containing polychlorinated biphenyls (PCBs), polychorinated terphenyls (PCTs) or polybrominated biphenyls (PBBs)	IND	0.38
871631	Tanker trailers and tanker semi-trailers	TUR	0.36

Table C.8: Ukraine: country-goods

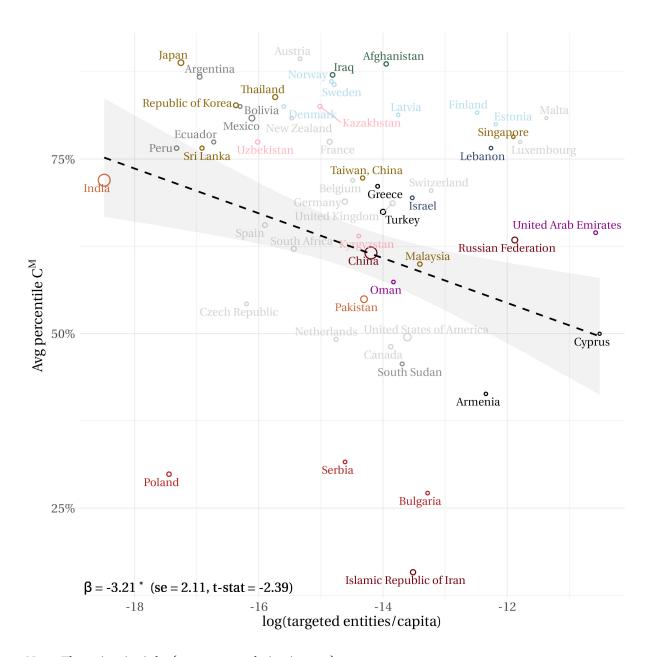
HS code	Description	ISO	chg (%)
880240	Aeroplanes and other aircraft; of an unladen weight exceeding	FRA	-4.16
	15,000kg		
880240	Aeroplanes and other aircraft; of an unladen weight exceeding	DEU	-2.12
	15,000kg		
841112	Turbo-jets; of a thrust exceeding 25kN	USA	-1.92
890510	Dredgers	CHN	-1.78
852990	Reception and transmission apparatus; for use with the apparatus	CHN	-0.94
	of heading no. 8525 to 8528, excluding aerials and aerial reflectors		
841112	Turbo-jets; of a thrust exceeding 25kN	GBR	-0.64
851712	Telephones for cellular networks or for other wireless networks	VNM	-0.59
890190	Vessels; n.e.c. in heading no. 8901, for the transport of goods and	NLD	-0.58
	other vessels for the transport of both persons and goods		
871639	Trailers and semi-trailers; (other than tanker type)	DEU	-0.50
890120	Tankers	CHN	-0.49
890399	Yachts and other vessels; for pleasure or sports, rowing boats and	NLD	-0.47
	canoes, n.e.c. in heading no. 8903, other than inflatable		
852990	Reception and transmission apparatus; for use with the apparatus	VNM	-0.40
	of heading no. 8525 to 8528, excluding aerials and aerial reflectors		
841112	Turbo-jets; of a thrust exceeding 25kN	POL	-0.39
890190	Vessels; n.e.c. in heading no. 8901, for the transport of goods and	DEU	-0.34
	other vessels for the transport of both persons and goods		
281820	Aluminium oxide; other than artificial corundum	UKR	-0.31
901380	Optical devices, appliances and instruments; n.e.c. in heading no.	CHN	-0.30
	9013 (including liquid crystal devices)		
281820	Aluminium oxide; other than artificial corundum	AUS	-0.29
890590	Vessels; light, fire-floats, floating cranes and other vessels, the navi-	TUR	-0.27
	gability of which is subsidiary to their main function, floating docks		
890130	Vessels, refrigerated; other than tankers	JPN	-0.25
841112	Turbo-jets; of a thrust exceeding 25kN	FRA	-0.24

Table C.9: Russia: country-goods

HS code	Description	ISO	chg (%)
880240	Aeroplanes and other aircraft; of an unladen weight exceeding 15,000kg	USA	-9.89
901380	Optical devices, appliances and instruments; n.e.c. in heading no. 9013 (including liquid crystal devices)	KOR	-4.28
901380	Optical devices, appliances and instruments; n.e.c. in heading no. 9013 (including liquid crystal devices)	TWN	-2.77
880240	Aeroplanes and other aircraft; of an unladen weight exceeding 15,000kg	FRA	-2.10
851770	Telephone sets and other apparatus for the transmission or reception of voice, images or other data, via a wired or wireless network; parts	KOR	-1.33
901380	Optical devices, appliances and instruments; n.e.c. in heading no. 9013 (including liquid crystal devices)	JPN	-1.14
890190	Vessels; n.e.c. in heading no. 8901, for the transport of goods and other vessels for the transport of both persons and goods	TWN	-0.69
890120	Tankers	KOR	-0.68
880240	Aeroplanes and other aircraft; of an unladen weight exceeding 15,000kg	DEU	-0.64
841112	Turbo-jets; of a thrust exceeding 25kN	RUS	-0.63
851770	Telephone sets and other apparatus for the transmission or reception of voice, images or other data, via a wired or wireless network; parts	JPN	-0.50
841191	Turbines; parts of turbo-jets and turbo-propellers	USA	-0.49
890590	Vessels; light, fire-floats, floating cranes and other vessels, the navigability of which is subsidiary to their main function, floating docks	JPN	-0.32
901390	Optical appliances and instruments; parts and accessories for articles of heading no. 9013	THA	-0.31
841112	Turbo-jets; of a thrust exceeding 25kN	USA	-0.29
270112	Coal; bituminous, whether or not pulverised, but not agglomerated	AUS	-0.28
852990	Reception and transmission apparatus; for use with the apparatus of heading no. 8525 to 8528, excluding aerials and aerial reflectors	JPN	-0.24
901390	Optical appliances and instruments; parts and accessories for articles of heading no. 9013	JPN	-0.22
901390	Optical appliances and instruments; parts and accessories for articles of heading no. 9013	TWN	-0.19
890690	Vessels; other, including lifeboats other than rowing boats, other than warships	SGP	-0.19

Table C.10: China: country-goods

# **C.3** Policy evaluation



*Notes:* The point size is log(country population in 2023).

Figure C.13: Centrality by country: Targeted entities per capita

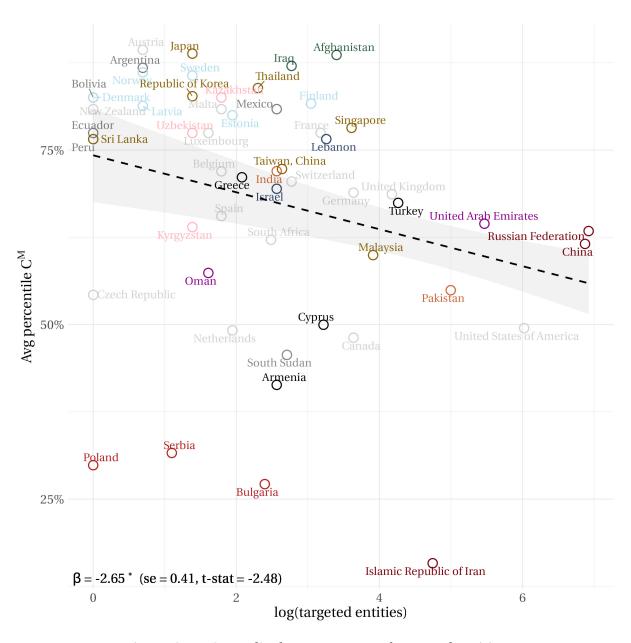


Figure C.14: Centrality by country: Total targeted entities

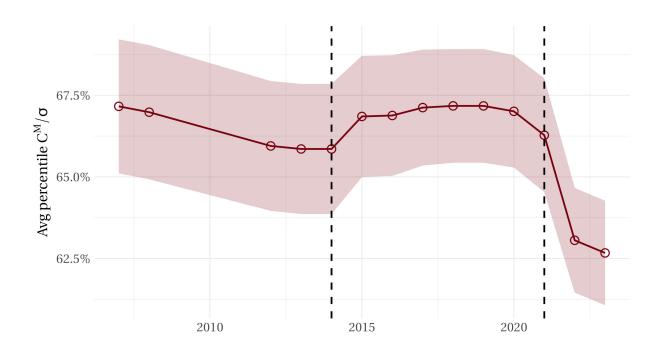


Figure C.15: EU dual-use lists: Military use over time

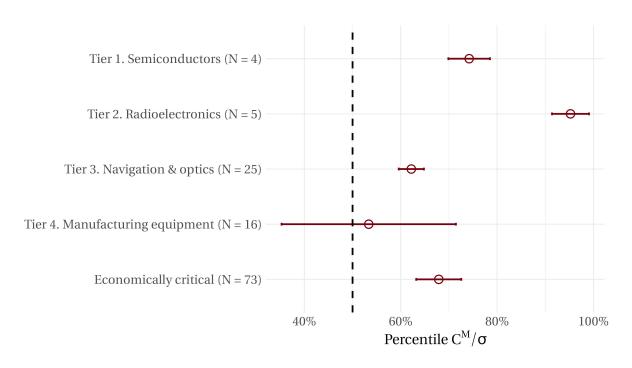
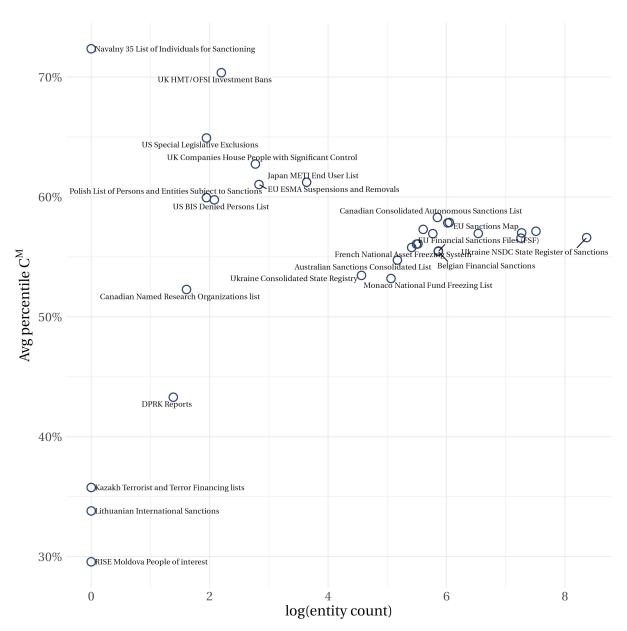


Figure C.16: EU Commission critical goods



*Notes:* The database of sanctions is taken from the OpenSanctions project. The Russian enterprises are matched to the Russian tax registry EGRUL, and the provided OKVED industries are then crosswalked into NAICS (Rev. 2012) codes. The centrality rank is then taken for the resulting industries. When an entity is linked to multiple industries, we treat those probabilistically, so one entity can have several weighted observations. Supplementary Appendix Figure SA.B.33 reports confidence intervals on the estimates.

Figure C.17: Sanctions against Russia

# C.4 Trade statistics

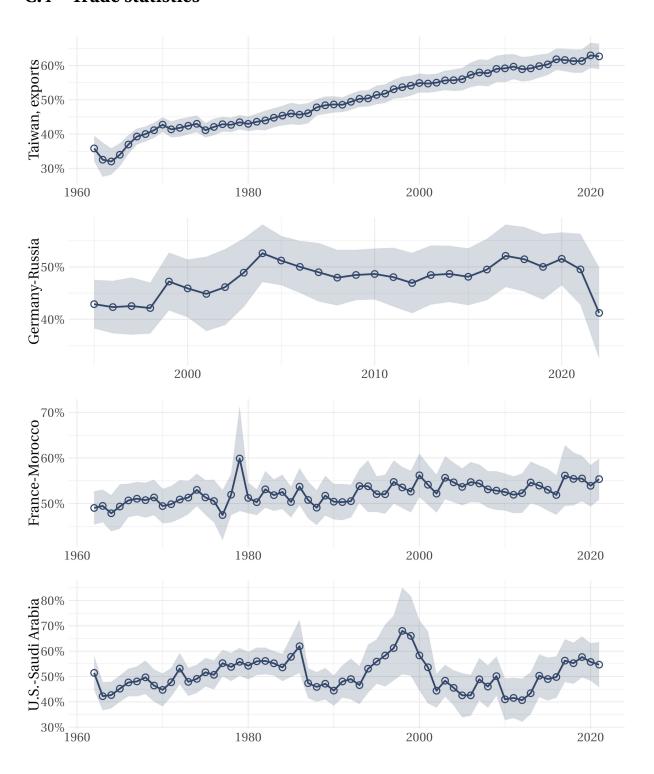


Figure C.18: Trade flow military intensity (average military use)

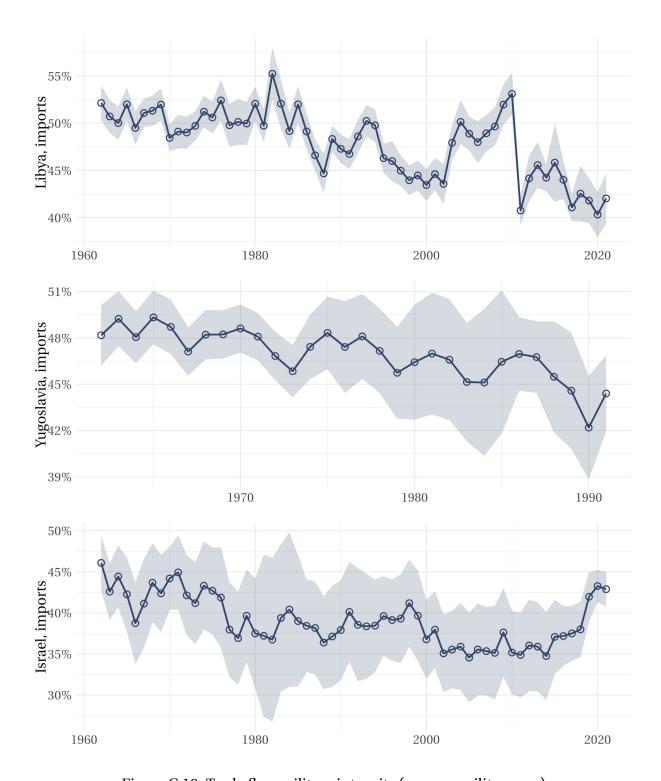
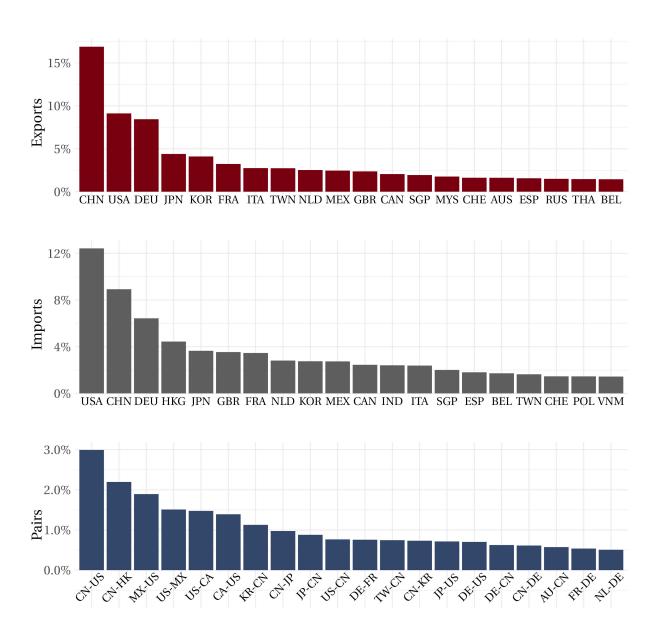


Figure C.18: Trade flow military intensity (average military use)

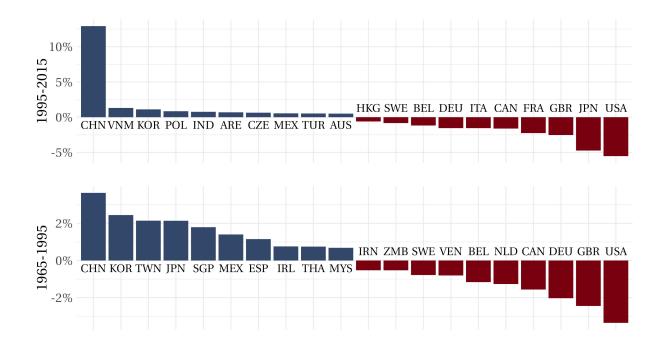


Notes: The definition for military contribution is

$$\text{contribution}_{ijkt} = \frac{\sum_{k} y_{ijk} \% \left[\mathcal{C}_{\text{US},k}^{M}/\sigma_{k}\right]}{\sum_{l} \sum_{k} y_{ilk} \% \left[\mathcal{C}_{\text{US},k}^{M}/\sigma_{k}\right]}.$$

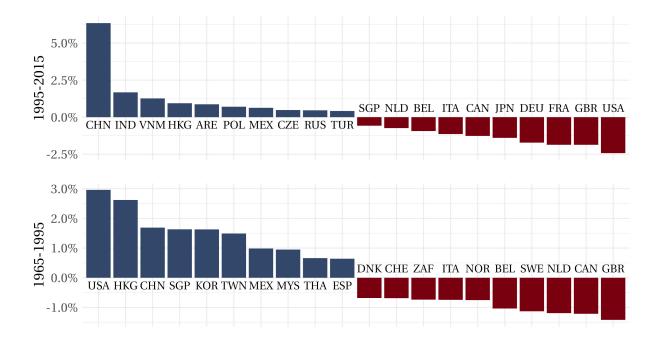
The figure plots changes in military usage shares between two initial years. By considering military use percentiles instead of absolute military use, we make product distribution uniform, implicitly down-weighting military-only goods at the right tail and maintaining focus on the overall industrial mix.

Figure C.19: Cross-section of military contributions to trade flows: 2015-2019



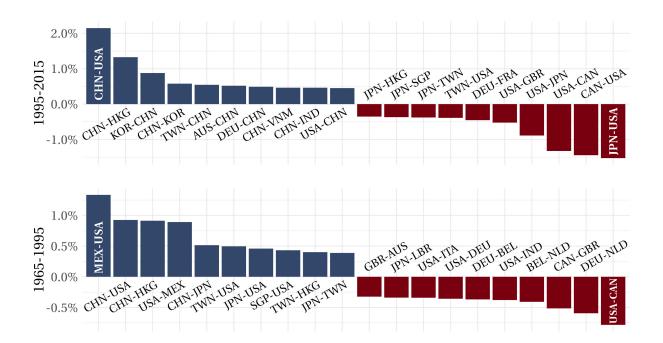
*Notes*: Base years are 1965-1969, 1995-1999, and 2015-2019. The figure plots changes in military contributions between the two time periods specified by the y-axis label. The change between 1995 and 2015 is computed using the HS Rev. 0 (1992); the change between 1965 and 1995 is computed using the SITC Rev. 2 (1975).

Figure C.20: Export decompositions



*Notes*: Base years are 1965-1969, 1995-1999, and 2015-2019. The figure plots changes in military contributions between the two time periods specified by the y-axis label. The change between 1995 and 2015 is computed using the HS Rev. 0 (1992); the change between 1965 and 1995 is computed using the SITC Rev. 2 (1975).

Figure C.21: Import decompositions



*Notes*: Base years are 1965-1969, 1995-1999, and 2015-2019. The figure plots changes in military contributions between the two time periods specified by the y-axis label. The change between 1995 and 2015 is computed using the HS Rev. 0 (1992); the change between 1965 and 1995 is computed using the SITC Rev. 2 (1975).

Figure C.22: Trade pair decompositions

#### C.5 Calibration

The effect for the U.S. increases from 180% to 250%, while the effect for China drops from 225% to 140%. This occurs because military spending affects demand for factors across countries, which affects final goods' prices. An increase in Chinese military demand lowers home wages ( $d \log w_{\rm CHN}/dM_{\rm CHN}=-0.025$ ) because military sectors depend more on the Rest of the World than consumer sectors do (38% and 25.8% of the basket respectively; Table C.11). The opposite occurs in the U.S. ( $d \log w_{\rm CHN}/dM_{\rm CHN}=0.017$ , 31% and 19% of the basket). This results in the value of the prize being lower compared to the partial equilibrium in China and higher in the U.S..

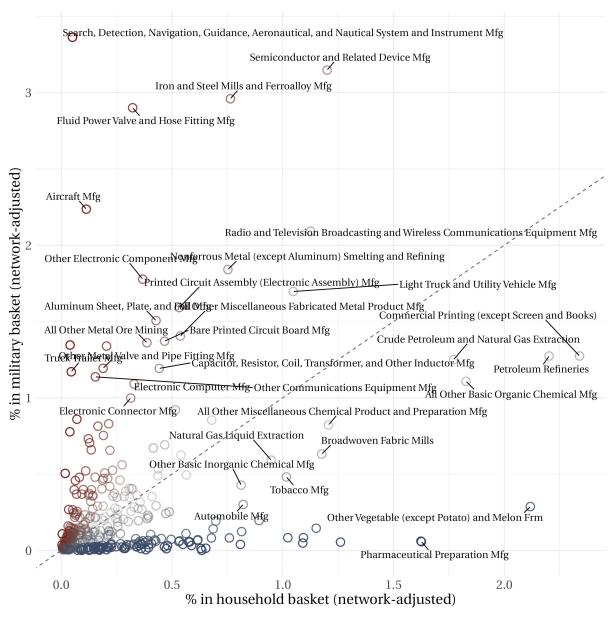
		CHN			USA			ROW			
	w	$P^C$	$P^{M}$	w	$P^C$	$P^{M}$	w	$P^C$	$P^{M}$		
CHN	-2.4847	-1.8049	-1.4985	0.0615	0.0740	0.0635	-0.8000	-0.5867	-0.4875		
USA	-0.2051	-0.2245	-0.2136	1.6931	1.1047	1.3337	-0.3901	-0.2833	-0.3238		
ROW	0.0000	-0.0951	0.0000	0.0000	0.0473	0.0000	0.0000	-0.0392	0.0000		

*Notes:* The rows indicate the countries that increase its military spending. The columns report price reactions in respective countries. The rest-of-the-world wage is normalized.

	CF	ΗN		USA			ROW		
	C	C $M$		C	M		C	M	
CHN	72.498	60.181		3.659	2.101		3.608	0.000	
USA	1.739	1.565		65.115	78.693		2.662	0.000	
ROW	25.763	38.254		31.226	19.206		93.730	100.000	

*Notes:* The rows report the network-adjusted purchase share of the labor factor across various countries by consumers and military.

Table C.11: Decomposition of general equilibrium effects behind military spending



Notes: Data for the Chinese input-output table are taken for 2018 from the National Bureau of Economic Statistics. Data for the final military demand come from the revenue of military firms accessed via CSMAR. We convert the NBES industry classifications to NAICS (Rev. 2012). The consumer and military network-adjusted sales are calculated using Leontief inverses as  $\left[\frac{(\mathbf{I}-\Omega)^{-1'}\mathbf{s}^{\mathbf{C}}}{[(\mathbf{I}-\Omega)^{-1'}\mathbf{s}^{\mathbf{C}}]'\mathbf{1}}\right]$  and  $\left[\frac{(\mathbf{I}-\Omega)^{-1'}\mathbf{s}^{\mathbf{M}}}{[(\mathbf{I}-\Omega)^{-1'}\mathbf{s}^{\mathbf{M}}]'\mathbf{1}}\right]$ , where  $\Omega$  is an input-output expenditure matrix and  $\mathbf{s}^{\mathbf{C}}$ ,  $\mathbf{s}^{\mathbf{M}}$  are expenditure shares of final agents.

Figure C.23: 2018 input-output table for China

	USA	(% chan	ige)	CHN	N (% chan	ge)		baseline	
	CHN	USA	ROW	CHN	USA	ROW	CHN	USA	ROW
$U^I$	-1.000	0.166	0.019	1.506	-1.583	0.270	19.436	53.941	41.553
$U^C$	-1.182	0.245	0.016	1.748	-2.846	0.254	16.144	29.162	41.993
$U^M$	-0.068	0.065		0.082	-0.079		3.994	25.348	
$\overline{c}$	-1.241	0.256	0.019	1.874	-2.917	0.270	63.222	28.592	41.553
C	-0.582	-1.105	0.000	-4.655	-0.654	0.000	15.442	28.592	41.553
$P^C$	0.668	-1.358	-0.019	-6.408	2.330	-0.269	0.244	1.000	1.000
$\nu$	-0.033	0.033		0.040	-0.040		0.489	0.511	
m	-1.104	0.572		0.743	-1.369		0.707	0.678	
M	-0.582	-1.105		-4.655	-0.654		0.233	0.682	
$P^{M}$	0.528	-1.668		-5.358	0.725		0.329	1.006	
wL	-0.656	-2.141	0.000	-8.793	-0.933	0.000	13.895	20.533	52.074
R/wL	0.000	0.578		3.883	0.000		0.000	0.000	
$mp_{\mathrm{CHN,\cdot}}$	-0.730	-2.450	-0.748	-9.955	-41.796	2.596	63.561	1.883	2.477
$mp_{\mathrm{USA},\cdot}$	-50.105	-2.078	1.105	-11.102	-0.942	-3.833	0.549	70.238	1.678
$mp_{\mathrm{ROW,.}}$	3.764	-2.317	0.000	-11.837	7.285	0.000	5.591	9.085	4.155

Table C.12: Baseline welfare

	US	A (% chan	ge)	CHI	N (% cha	nge)		baseline	
	CHN	USA	ROW	CHN	USA	ROW	CHN	USA	ROW
$U^I$	-0.090	-0.158	-0.015	-0.218	-0.097	0.037	18.879	54.522	41.553
$U^C$	-0.235	-0.235	-0.235	-0.034	-0.034	-0.034	85.587	85.587	85.587
$U^M$	-0.427	0.410		0.230	-0.220		3.437	25.929	
c	-0.015	-0.673	-0.015	-0.318	0.015	0.037	63.222	28.592	41.553
C	0.147	-0.232	0.000	0.107	-0.050	0.000	15.442	28.592	41.553
$P^C$	0.161	0.444	0.015	0.426	-0.065	-0.037	0.244	1.000	1.000
$\overline{\nu}$	-0.209	0.209		0.113	-0.113		0.489	0.511	
m	-0.004	11.604		5.518	0.036		0.707	0.678	
M	0.147	-0.232		0.107	-0.050		0.233	0.682	
$P^{M}$	0.151	-10.605		-5.128	-0.086		0.329	1.006	
wL	0.166	-0.148	0.000	0.142	-0.071	0.000	13.895	20.533	52.074
R/wL	0.000	-0.183		-0.021	0.000		0.000	0.000	
$mp_{\mathrm{CHN},\cdot}$	0.111	-0.388	0.431	0.156	0.341	0.314	63.561	1.883	2.477
$mp_{ ext{USA},\cdot}$	-3.090	-0.246	-0.636	0.255	-0.060	-0.464	0.549	70.238	1.678
$mp_{\mathrm{ROW,.}}$	0.364	-0.224	0.000	0.228	-0.141	0.000	5.591	9.085	4.155

Table C.13: Industrial policy results

# **D** Theory

#### MODEL STRUCTURE

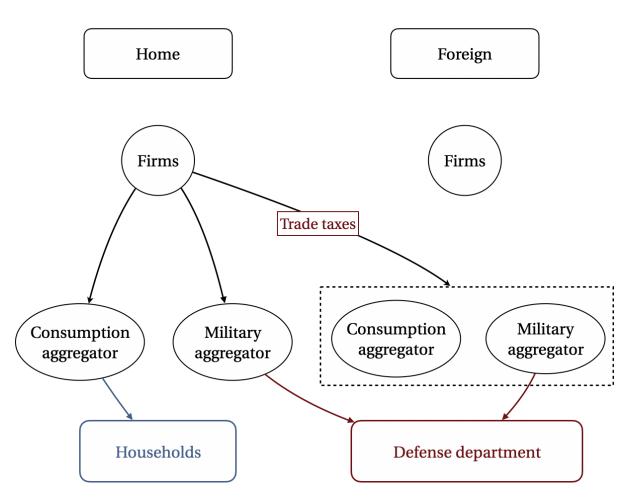


Figure D.1: Horizontal model structure

## D.1 Proof of Proposition 1

*Proof.* We first characterize the best response policies. After that, we describe the Nash equilibrium. The best response for defense spending was established in (18) and is given by

$$M_i = \beta_i^{\zeta_i} \left( M_{-i} \frac{P_i^M}{P_{-i}^M} \right)^{1-\zeta_i}. \tag{69}$$

For trade policy, consider small changes in taxes imposed by government i. The result-

ing change in welfare is given by

$$dW_{i} = \underbrace{dR_{i}}_{\text{revenue}} + \underbrace{M_{i}d\log P_{-i}^{M}}_{\text{foreign military}} - \underbrace{\left(C_{i}d\log P_{i}^{C} + M_{i}d\log P_{i}^{M}\right)}_{\text{domestic distortion}} \tag{70}$$

It is a sum of revenue and price effects. By Shephard's lemma, the changes in prices are

$$d\log P_{i}^{C} = \sum_{k \in \{H,F\}} s_{ik}^{C} d\log \tau_{ik}^{\mathcal{M}}, \qquad d\log P_{i}^{M} = \sum_{k \in \{H,F\}} s_{ik}^{M} d\log \tau_{ik}^{\mathcal{M}}, \tag{71}$$

$$d\log P^M_{-i} = s^M_{-i,i} d\log \tau^{\mathcal{X}}_{-i,i}$$

The revenue changes can be expanded as

$$dR_{i} = \frac{E_{-i,i}}{\tau_{-i,i}^{\mathcal{M}}} \left[ \frac{\tau_{-i,i}^{\mathcal{X}} - 1}{\tau_{-i,i}^{\mathcal{X}}} (\mathcal{E}_{-i,i}^{-i,i} - 1) + \underbrace{1}_{\text{unit revenue}} \right] d \log \tau_{-i,i}^{\mathcal{X}}$$

$$+ \sum_{k \in \{H,F\}} \left[ \frac{\tau_{ik}^{\mathcal{M}} - 1}{\tau_{ik}^{\mathcal{M}}} E_{ik} (\mathcal{E}_{ik}^{ik} - 1) + \underbrace{\sum_{l \neq k} \frac{\tau_{il}^{\mathcal{M}} - 1}{\tau_{il}^{\mathcal{M}}} E_{il} \mathcal{E}_{ik}^{il}}_{\text{unit revenue}} \right] d \log \tau_{ik}^{\mathcal{M}}$$

$$(72)$$

An increase in the export tax increases the revenue earned from one unit exported but loses revenue due to decreased foreign demand. An increase in the import tariff has a similar effect for the home country but additionally generates revenue spillovers due to the shifting of home spending toward other imported goods. Further details about these elasticities are provided in Supplementary Appendix A.1.

Combining changes in revenue and changes in trade taxes, we obtain

$$dW_{i} = \frac{E_{-i,i}}{\tau_{-i,i}^{\mathcal{M}}} \left[ \frac{\tau_{-i,i}^{\mathcal{X}} - 1}{\tau_{-i,i}^{\mathcal{X}}} (\mathcal{E}_{-i,i}^{-i,i} - 1) + 1 + \tau_{-i,i}^{\mathcal{M}} \frac{M_{i}}{M_{-i}} S_{-i,i}^{\mathcal{M}} \right] d \log \tau_{-i,i}^{\mathcal{X}}$$

$$+ \sum_{k \in \{H,F\}} \left[ \frac{\tau_{ik}^{\mathcal{M}} - 1}{\tau_{ik}^{\mathcal{M}}} E_{ik} (\mathcal{E}_{ik}^{il} - 1) + \sum_{l \neq k} \frac{\tau_{il}^{\mathcal{M}} - 1}{\tau_{il}^{\mathcal{M}}} E_{il} \mathcal{E}_{ik}^{il} \right] d \log \tau_{ik}^{\mathcal{M}}$$
(73)

Under the best response policies, small changes in trade taxes should not lead to changes in welfare. The rearranging of the terms in brackets generates the following matrix expression:

$$\underbrace{\begin{bmatrix} \frac{\tau_{-i,i}^{\mathcal{X}} - 1}{\tau_{-i,i}^{\mathcal{X}}} \\ \frac{\tau_{-i,i}^{\mathcal{X}} - 1}{\tau_{-i,i}^{\mathcal{X}}} \\ \frac{\tau_{-i,i}^{\mathcal{X}} - 1}{\tau_{-i,i}^{\mathcal{X}}} \end{bmatrix}}_{\text{evenue responses}} = - \underbrace{\begin{bmatrix} \frac{E_{-i,i}}{\tau_{-i,i}^{\mathcal{X}}} (\mathcal{E}_{-i,i}^{-i,i} - 1) & 0 & 0 \\ 0 & E_{ii}(\mathcal{E}_{ii}^{ii} - 1) & E_{i,-i}\mathcal{E}_{ii}^{i,-i} \\ 0 & E_{ii}\mathcal{E}_{i,-i}^{i,-i} & E_{i,-i}(\mathcal{E}_{i,-i}^{i,-i} - 1) \end{bmatrix}^{-1} \begin{bmatrix} \frac{E_{-i,i}}{\tau_{-i,i}^{\mathcal{X}}} \left(1 + \tau_{-i,i}^{\mathcal{X}} \frac{M_{i}}{M_{-i}} S_{-i,i}^{\mathcal{X}} \right) \\ 0 & 0 & 0 \end{bmatrix}}_{\text{formula security vector}}$$

$$(74)$$

Thus, we obtain the best response tax policy:

$$\frac{\tau_{-i,i}^{\mathcal{X}} - 1}{\tau_{-i,i}^{\mathcal{X}}} = -\frac{1}{1 + \underbrace{\tau_{-i,i}^{\mathcal{M}}(M_i/M_{-i})S_{-i,i}^{M}}^{\text{national security externality}}}{\mathcal{E}_{-i,i}^{-i,i} - 1}, \qquad \tau_{ik}^{\mathcal{M}} = 1.$$
 (75)

For a civilian good with  $S_{-i,i}^M=0$ , the export tax follows the standard inverse elasticity rule  $( au_{-i,i}^X-1)/ au_{-i,i}^X=-1/(\mathcal{E}_{ii}^{-i,i}-1)$ . The presence of an additional term  $au_{-i,i}^{\mathcal{M}}(M_i/M_{-i})S_{-i,i}^{\mathcal{M}}$  in the numerator represents a Pigouvian correction for a national security externality by internalizing the cost that every unit sold to a foreign defense sector has on domestic welfare. This term grows with the sales share of a variety to the foreign defense sector  $S_{-i,i}^{\mathcal{M}}$ . The best response policy for the import tariff is  $au_{ik}^{\mathcal{M}}=1$ . Any domestic price manipulation results in a deadweight loss.

Equations (69) and (75) characterize the best response policies. To solve for the Nash equilibrium, we assume that those expressions hold simultaneously for both countries. Taking the logarithm of both sides in (69), we obtain

$$\log M_i = -\zeta_i \log \beta_i + (1 - \zeta_i)(\log M_{-i} + \log P_i^M - \log P_{-i}^M)$$
(76)

Solving the system of equations for  $i \in \{H, F\}$  yields

$$M_{i} = \beta_{i}^{\zeta_{-i,i}} \beta_{-i}^{(1-\zeta_{i})\zeta_{i,-i}} \left(\frac{P_{i}^{M}}{P_{-i}^{M}}\right)^{(1-\zeta_{i})\zeta_{i,-i}}, \quad \zeta_{i,-i} \equiv \frac{\zeta_{-i}}{\zeta_{i} + \zeta_{-i} - \zeta_{i}\zeta_{-i}}$$
(77)

Here  $\zeta_{i,-i}$ , which we will call *conflict elasticity*, is a measure of how responsive home welfare is to changes in the relative military price ratio  $(P_i^M/P_{-i}^M)$ . Since the import tariffs are zero for both countries,  $\tau_{ik}^{\mathcal{M}}=1$ . Subsequently, we plug the zero import tariffs into (75) to obtain (21). The derivation is complete.

More broadly, the best response trade taxes (75) apply to any game in which the home government takes foreign defense spending  $M_{-i}$  as given. These are one-shot games in which the foreign government picks its policies  $\mathcal{P}^{(-i)}$  before or simultaneously with the home trade policy  $\mathcal{P}_{\tau}^{i}$ .

#### **D.2** Calibration: Jacobian calculation

The goods market clearing can be written as

$$\mathbf{X} = \tilde{\mathbf{\Psi}}'(\mathbf{s}^{\mathbf{C}}(\mathbf{w}\mathbf{L} + \mathbf{R} + \mathbf{D} - \mathbf{M}) + \mathbf{s}^{\mathbf{M}}\mathbf{M})$$
(78)

Note that

$$R_{i} = \sum_{k \in \mathcal{K}_{-i}} \frac{\tau_{ki}^{\mathcal{X}} - 1}{\tau_{ki}^{\mathcal{X}}} \frac{\Omega_{ki}^{M}}{\tau_{ki}^{\mathcal{M}}} X_{k} + \sum_{k \in \mathcal{K}} \frac{\tau_{k,-j}^{\mathcal{M}} - 1}{\tau_{k,-j}^{\mathcal{M}}} \Omega_{k,-j}^{M} X_{k}, \tag{79}$$

which can be recast in matrix form as  $\mathbf{R} = \mathbf{\Lambda}^{\mathbf{R}} \mathbf{X}$ . After accounting for revenue amplification, the goods market clearing can be recast as

$$\mathbf{X} = \mathbf{\Lambda}^{\mathbf{X}} \mathbf{\tilde{\Psi}}' (\mathbf{s}^{\mathbf{C}} (\mathbf{w} \mathbf{L} + \mathbf{D} - \mathbf{M}) + \mathbf{s}^{\mathbf{M}} \mathbf{M}), \quad \mathbf{\Lambda}^{\mathbf{X}} \equiv (\mathbf{I} - \mathbf{\tilde{\Psi}}' \mathbf{s}^{\mathbf{C}} \mathbf{\Lambda}^{\mathbf{R}})^{-1}.$$
(80)

The factor market clearing is

$$wL = \Omega^{L'}X. \tag{81}$$

Plugging in an expression for X yields

$$\Lambda^{L}wL = \Omega^{L'}\Lambda^{X}\tilde{\Psi}'(s^{C}(D-M) + s^{M}M), \quad \Lambda^{L} \equiv I - \Omega^{L'}\Lambda^{X}\tilde{\Psi}'s^{C}.$$
 (82)

Solving for that equation allows us to solve for factor prices.

To find a wage jacobian, we now consider an equation that results from small policy changes:

$$(d\mathbf{\Lambda}^{\mathbf{L}})\mathbf{w}\mathbf{L} + \mathbf{\Lambda}^{\mathbf{L}}\mathbf{w}\mathbf{L}d\log\mathbf{w} = d\mathbf{\Omega}^{\mathbf{L}'}\mathbf{\Lambda}^{\mathbf{X}}\tilde{\mathbf{\Psi}}'(\mathbf{s}^{\mathbf{C}}(-\mathbf{D} - \mathbf{M}) + \mathbf{s}^{\mathbf{M}}\mathbf{M})$$

$$+ \mathbf{\Omega}^{\mathbf{L}'}(d\mathbf{\Lambda}^{\mathbf{X}})\tilde{\mathbf{\Psi}}'(\mathbf{s}^{\mathbf{C}}(-\mathbf{D} - \mathbf{M}) + \mathbf{s}^{\mathbf{M}}\mathbf{M})$$

$$+ \mathbf{\Omega}^{\mathbf{L}'}\mathbf{\Lambda}^{\mathbf{X}}(d\tilde{\mathbf{\Psi}}')(\mathbf{s}^{\mathbf{C}}(-\mathbf{D} - \mathbf{M}) + \mathbf{s}^{\mathbf{M}}\mathbf{M})$$

$$+ \mathbf{\Omega}^{\mathbf{L}'}\mathbf{\Lambda}^{\mathbf{X}}\tilde{\mathbf{\Psi}}'d(\mathbf{s}^{\mathbf{C}}(-\mathbf{D} - \mathbf{M}) + \mathbf{s}^{\mathbf{M}}\mathbf{M})$$

$$+ \mathbf{\Omega}^{\mathbf{L}'}\mathbf{\Lambda}^{\mathbf{X}}\tilde{\mathbf{\Psi}}'d(\mathbf{s}^{\mathbf{C}}(-\mathbf{D} - \mathbf{M}) + \mathbf{s}^{\mathbf{M}}\mathbf{M})$$

$$(83)$$

One can further expand changes in each matrix:

$$d\tilde{\Psi}' = -\tilde{\Psi}'(d\tilde{\Omega}')\tilde{\Psi}', \qquad d\Lambda^{X} = \Lambda^{X}d(\tilde{\Psi}'s^{C}\Lambda^{R})\Lambda^{X}.$$
 (84)

Expressing the primitive  $d\Omega$  as a function of  $d \log w$  and  $d \log P$  for taxes and military changes allows to recast the expression as

$$\mathbf{A}d\log\mathbf{w} = d\log\mathbf{P},\tag{85}$$

which allows us to recover a relevant jacobian.

## **D.3** Calibration: Stockpiling

The utility contest function is

$$U_i(\{c_j\}_{i=1}^N, \{m_j\}_{i=1}^N) = c_i + \sum_{j \neq i} \alpha_{ij} c_j + \beta_i \frac{g(m_i)}{g(m_i) + \sum_{j \neq i} g(m_j)}.$$
 (86)

Taking the first-order condition with two players yields

$$\frac{\beta_i}{P_i^M} \frac{g'(m_i)(g(m_i) + \sum_{j \neq i} g(m_j)) - g(m_i)g'(m_i)}{(g(m_i) + \sum_{j \neq i} g(m_j))^2} = \frac{1}{P_i^C}$$
(87)

or

$$\beta_i \frac{g'(m_i)}{g(m_i)} \frac{\nu_i (1 - \nu_i)}{P_i^M} = \frac{1}{P_i^C}.$$
 (88)

The derivative with respect to  $m_i$  is

$$\beta_i \frac{g'(m_j)}{g(m_j)} \frac{\nu_i \nu_j}{P_j^M}.$$
 (89)

If  $g(m_i)=m_i^\gamma$ , then  $g'/g=\gamma m_i^{-1}$ . If there is a stockpile of goods  $m_{0i}$  and  $g(m_i)=(m_{0i}+m_i)^\gamma$ , then  $g'/g=\gamma (m_{0i}+m_i)^{-1}$ . We introduce  $g'/g=\gamma \kappa_i m_i^{-1}$ , where  $\kappa_i=m_i/(m_{0i}+m_i)$  is the ratio of military goods to the total goods, including the stockpile. Note that in this case

$$\nu_i = \frac{(m_{0i} + m_i)^{\gamma}}{(m_{0i} + m_i)^{\gamma} + (m_{0,-i} + m_{-i})^{\gamma}} = \frac{\kappa_i^{-\gamma} m_i^{\gamma}}{\kappa_i^{-\gamma} m_i^{\gamma} + \kappa_{-i}^{-\gamma} m_{-i}^{\gamma}}.$$
 (90)

For the purpose of  $\gamma$  estimation we assume that  $\kappa_i = \kappa_{-i}$ , simplifying the expression to

$$\nu_i = \frac{m_i^{\gamma}}{m_i^{\gamma} + m_{-i}^{\gamma}}.\tag{91}$$

From that,

$$\gamma \beta_i \kappa_i m_i^{-1} \frac{\nu_i (1 - \nu_i)}{P_i^M} = \frac{1}{P_i^C}, \qquad \kappa_i \equiv \frac{m_i}{m_{0i} + m_i}, \tag{92}$$

naturally follows.