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EXPORT CONTROLS AND THE ECONOMICS OF NATIONAL SECURITY

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ABSTRACT

Export controls restrict trade to limit adversaries' access to goods that contribute to military capability, but their effectiveness depends on how trade and production adjust across countries. We combine new data on U.S. export control classifications and licensing outcomes with a quantitative general equilibrium model featuring dual-use production, input-output linkages, and separate civilian and military final expenditure. We estimate large export and entry frictions from these controls. These effects are substantially smaller for U.S. exports to members of multilateral export control regimes (MECRs): the differential is equivalent to an export cost of 15 to 29 log points. Relative to a counterfactual without differential controls on adversaries, multilateral controls reduce their imports of controlled products far more than unilateral U.S. controls. Only 7% of the reduction in controlled exports under the multilateral regime is replaced by other countries, compared with 28% under unilateral U.S. policy. Multilateral controls reduce adversaries' real military expenditure by increasing their military price index. The security impact, measured as U.S. real military expenditure relative to adversaries, rises by about 1 log point under multilateral controls but only 0.14 log points under unilateral controls, with both imposing a similar civilian real cost. Even a U.S. embargo fails to reproduce the multilateral security outcome.

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1 Introduction

National security increasingly shapes trade policy across major economies, particularly through export controls. Their growing use is visible not only in the United States but also in the European Union, Japan, China, and other economies.[1] Export controls restrict international transactions, with the central objective of limiting adversaries' access to inputs that contribute to military capabilities. They can also impose large costs on domestic firms' revenue, profits, and production scale.[2] Moreover, controls may shift supply toward foreign firms unless there is international coordination, which major exporters pursue through multilateral export control regimes (MECRs). Export controls therefore create a trade-off between domestic economic costs and national security gains that depends in part on the response of other countries.

Governments recognize the trade-off but lack systematic estimates of the incidence of controls and a framework for quantifying the resulting economic costs, security effects, and dependence on international coordination.[3] We bring novel data and quantitative modeling together to develop such a framework and address the underlying research and policy questions: how do we measure, quantify and evaluate the impacts of export controls on economic and security outcomes? We proceed in three steps. First, we construct a dataset on the nature and incidence of U.S. export controls. Second, we use the variation in export control classifications to estimate their impact on export value and entry across destinations and sectors. Third, we embed these estimates in a quantitative general equilibrium model with dual-use production, input-output linkages, and endogenous entry to quantify the economic and security impacts of unilateral and multilateral control regimes.

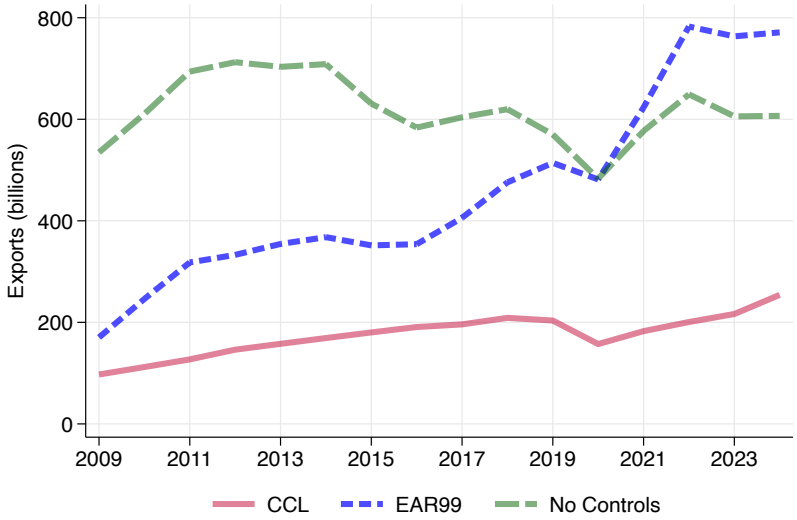
Background and new facts. We assemble a new dataset combining the control status of observed U.S. export transactions, U.S. statutory regulations (e.g. MECR status) and export licensing outcomes—approval rates and delays. MECRs coordinate controls, typically among major suppliers of sensitive, dual-use inputs: their members agree on common control lists but implement them through national systems. We use U.S. regulations to create broad mutually exclusive country

[1] The European Union substantially revised its dual-use export control regime in 2021 with a new framework that updated and consolidated EU-wide controls (see Regulation (EU) 2021/821). Japan expanded its export controls in 2023 to include new controls on advanced semiconductor-manufacturing equipment, citing the need to prevent their conversion to military applications (see Japan Ministry of Economy, Trade and Industry, "Press Conference by Minister Nishimura," March 31, 2023). China adopted a new comprehensive Export Control Law in 2020, which identifies safeguarding national security and interests among its purposes and applies controls to dual-use items (see Export Control Law of the People's Republic of China, adopted October 17, 2020).

[2] A prominent example is NVIDIA's inability to ship an additional $2.5 billion in H20 revenue in the quarter following the April 2025 U.S. license requirement on exports to China and other destinations. The company also recorded a $4.5 billion charge for excess inventory and supplier commitments associated with a chip designed to comply with earlier controls. See NVIDIA Corporation (2025).

[3] This trade-off is explicit in U.S. policy. The Bureau of Industry and Security states that its mission includes both "national security" and "economic security," and that policy should protect the "health of the U.S. economy and the competitiveness of U.S. industry" (www.bis.gov/guiding-principles). DARPA's 2026 *National Security Economic Theory* program (NASCENT) underscores the need for such a framework: it calls for "rigorous and quantitative geoeconomic theory" to support evidence-based economic statecraft (www.darpa.mil/research/programs/nascent-national-security-economic-theory).

Figure 1: U.S. Export Value by Export Control Type, 2009–2024



Notes: Nominal U.S. goods exports, in $US billions, by reported export control classification. CCL includes transactions reporting an Export Control Classification Number on the Commerce Control List; EAR99 includes transactions reported as EAR99; and No Controls includes transactions with no reported export control classification. Total controlled exports are the sum of CCL and EAR99 exports. Canada is excluded because U.S. exports to Canada are compiled from Canadian import records, which do not contain U.S. export control classifications. Authors' calculations from U.S. Census Bureau Foreign Trade Division special tabulations.

groups: MECR members (or allies) receive the most favorable licensing treatment; a subset of the remaining non-member countries face a presumption of licensing denial, and we refer to them as "adversaries".[4] We use the data to document the breadth and incidence of controls across destinations and sectors, guide the theory, and identify the policy levers for the counterfactuals.

Three of the five facts we document stand out and discipline our analysis. First, the share of U.S. exports reporting any export controls is large and growing—over 60% by 2024—as shown in Figure 1. Within this controlled share, specific items with military and civilian applications (henceforth **dual-use** inputs) are included in the Commerce Control List (CCL) and report an Export Control Classification Number (ECCN). Emerging and miscellaneous technologies still subject to control regulations are reported under a catch-all category, EAR99, which accounts for the larger share. Second, control intensity is largest in high-technology sectors, but controls are present in all NAICS-3 manufacturing industries, so a general equilibrium framework with input-output linkages and dual-use production is essential.[5] Third, MECR member licensing applications face shorter delays and higher approval rates (Figure 2), and the observed controlled exports to those destinations were twice as high as to the rest of the world by the early 2020s. These facts show that controls apply widely to allies—one way they differ from sanctions—and point to the role of favorable licensing for MECR members.

[4]The latter group includes China and Russia and several others on the U.S. D-list described in Section 2.2, some of which align with the U.S. along other dimensions.

[5]Moreover, controls are highly heterogeneous within sectors. Guided missiles are 100% CCL-classified while motor homes are 0%, which motivates the civilian vs. dual-use distinction we use later.

Export restrictiveness estimates and mechanisms. How restrictive are export controls, and through which margins do they operate? Unlike tariffs, export controls have no statutory ad valorem rate. Firms first incur classification, screening, documentation, and other compliance costs to determine how a product and transaction are treated under the regulations. Transactions requiring a license face additional application costs, approval risk, and processing delays that depend on the destination, end user, and end use. We develop a model of export entry under these regulatory frictions and use export values, shipment margins, and licensing outcomes to recover their intensive- and extensive-margin cost equivalents. The model maps export differentials across product control types and MECR status into these frictions and guides our difference-in-differences estimation.[6]

The baseline export effects imply export cost equivalents that are 28.7 log points (lp) higher for non-MECR than for MECR destinations for CCL exports and 15.2 lp for EAR99 exports.[7] Shipment margins and licensing outcomes imply corresponding export-entry cost equivalents that are 32.5 and 22.3 lp higher for non-MECR vs. MECR destinations. We further decompose these structural wedges into compliance, approval risk, and delay components, each systematically lower for MECR destinations. The larger entry effects show the importance of regulatory frictions in deterring exporters, particularly for CCL products and non-MECR destinations. The resulting loss of producer scale is central to the general equilibrium effects below.

Quantitative framework. We quantify how changes in controls on dual-use inputs reallocate trade, firm entry, and worldwide production across countries and sectors. We build a quantitative trade framework with an input-output structure similar to Caliendo and Parro (2015), but differing in three ways. First, firms within a sector operate either a civilian (C) or dual-use (D) technology, with the latter more intensive in dual-use inputs, so control shocks propagate through technology-specific as well as sectoral input-output linkages. Second, we embed the export control model used to estimate the frictions, which vary by sector and MECR status, and specify the probability that output from each technology is controlled. Third, exporting and entry are endogenous, generating external economies of scale.

This framework allows us to track trade, production, and prices across countries, sectors, producer types, and final user types. We classify an industry within a sector as dual-use if its exports are sufficiently control-intensive and civilian otherwise. We model two final users, civilian and military, and we measure the effects of controls on their real expenditures. Controls affect real expenditures by changing a country's nominal income and the price indices relevant for civilian and military users.[8]

[6]The estimates are robust to sample composition, unobserved country-industry heterogeneity, and differential military expenditure on controlled goods. A stacked-cohort design exploiting destination-specific changes in U.S. regulatory treatment provides similar results.

[7]The differential export effects are largest for control codes applied to electronics, aerospace, navionics and computers but extend to others, reflecting the broad range of inputs classified as dual-use.

[8]Civilian and military aggregate nominal expenditures are constant shares of national income and thus change at the same rate within a country, so any differential real expenditure changes are driven by the price changes.

The distinction between production technologies and final user types is what allows us to quantify the economic and security effects of controls. First, dual-use inputs are more likely to be controlled and thus increase costs for dual-use producers that use them more intensively. Second, military final demand is concentrated in dual-use-intensive sectors. As a result of these two features of the data, export controls generally raise a destination's military price index by more than its civilian price index. A standard quantitative trade model without these distinctions would largely capture the civilian outcomes in our setting but not the differential effect on military users, which is the target of controls and what we use to compare security outcomes across control regimes.

Global economic and security impacts of control regimes. We compare three regimes to a benchmark counterfactual with no U.S. or other MECR members' differential controls on adversaries: the baseline multilateral, with the frictions estimated on 2016–2024 data; the 2024 multilateral (MECR24 henceforth), which adds the recent tightening in controls and is the scenario we focus on; and the unilateral, in which only the U.S. applies those 2024 frictions to adversaries. We present the results for the 2024 regime in three steps: the effects on controlled trade, their transmission to the prices faced by military users in adversary countries, and the resulting real expenditure and security outcomes.

First, coordination by MECR countries sharply amplifies the effect of export controls on trade. Under the baseline regime, U.S. exports of controlled products to adversaries fall by 80 lp for CCL and 35 lp for EAR99 products, with similar rates for other MECR members, which apply the same controls as the U.S. to the same adversaries. The 2024 CCL tightening roughly doubles the export reduction in that category. In both scenarios the other MECR members account for about four-fifths of the value of the export reduction, a contribution that is absent under unilateral U.S. controls. Coordination also limits leakage: about 7% of the reduction in MECR members' controlled exports to adversaries is replaced by other suppliers, but the leakage rate would be 28% if the U.S. used unilateral controls. As a result, adversaries' imports of controlled products fall by 5.7 times as much in value under MECR24 as they do under the unilateral scenario.

Second, these trade reductions raise the prices faced by military users in adversary countries. We deflate each user's nominal expenditure by a model-consistent price index that weights sector prices using final-use shares from observed input-output use tables, separately for civilian and military (i.e. government defense) users. Under MECR24 the adversary military price index rises 2.6 lp on average. Price increases are larger in control-intensive sectors—aerospace and other transport (18.7 lp), motor vehicles (6.8 lp), and computers and electronics (2.8 lp)—but these sectors account for only about 20% of military expenditure; the remainder goes to sectors such as services, where prices rise by less than 1 lp. The aggregate price effect is thus mitigated by limited exposure of military users to sectors with high control intensity. That exposure is even lower for civilian users.

Third, controls increase adversaries' nominal income relative to the U.S., which halves the security impact of controls in the MECR24 regime. We measure the security impact of controls by the increase in U.S. real military expenditure relative to that of its adversaries, as implied by a

contest model.[9] Under MECR24 the security impact is about 1 lp. The military price index of adversaries rises by about 2 lp in aggregate relative to the U.S., but about half of the impact on real expenditure is offset by the increase in their relative nominal income, which arises because controls shift production of controlled goods away from the U.S. toward adversaries and lower U.S. relative income. In the unilateral scenario the security impact is only 0.14 lp. Moreover, we find that tighter unilateral controls backfire: they increase the economic cost *and* reduce security. Even a unilateral U.S. embargo on adversaries cannot reproduce the multilateral security outcome.

Our final contribution is to provide a metric for ranking alternative control regimes. MECR24 dominates the unilateral regime for the U.S. in terms of national security at a similar civilian cost, but this need not hold for other alternatives. We therefore propose a price of security that summarizes the trade-off between these margins for a government that values both: the log points of real civilian expenditure forgone per log point of relative real military expenditure gained. Under MECR24, aggregate U.S. exports are 5.7 lp lower than under the no-control counterfactual, and the resulting decline in aggregate U.S. real civilian expenditure is 0.05 lp. With a security gain of about 1 lp, the price of security is roughly 0.05. Under the model's objective, the U.S. choice to remain in MECR24 is consistent with a security valuation of at least 0.05, and we show how to use this benchmark and the quantitative framework to rank the most valuable MECR members and sectors for further tightening.

Related literature. Our paper contributes to a growing literature on the use of international economic policy for national security and geopolitical objectives. The systematic analysis of trade as a source of strategic leverage begins with Hirschman (1945). Trade and trade agreements affect incentives for military conflict by changing bilateral dependence and the opportunity cost of war (Martin, Mayer, and Thoenig 2008, 2012). Formal economic analyses of sanctions include Eaton and Engers (1992), with a growing recent literature studying their design and effectiveness, particularly following Russia's invasion of Ukraine (Ahn and Ludema 2020; Becko 2024; Itskhoki and Ribakova 2024; Mayer, Méjean, and Thoenig 2026). Recent work that is closer to our analysis studies how trade and financial relationships themselves create geoeconomic power and can be used for coercion (Becko and O'Connor 2025; Clayton, Maggiori, and Schreger 2026). International relations research emphasizes the tension between the economic benefits of trade and its contribution to an adversary's military capabilities (Farrell and Newman 2023; Grinberg 2021; Miller 2022). Our paper contributes to this literature by providing an empirically disciplined framework that connects the regulatory frictions generated by a major instrument of economic and security policy to both domestic and foreign measures of civilian and military outcomes.

We also build on and contribute to research defining and measuring defense output. A useful distinction in this literature is between defense outputs, such as military capability, and outcomes, such as security; both are difficult to operationalize but increase with inputs such as personnel and

[9]The adversary military aggregate effect is dominated by the countries with the largest real expenditures: China and Russia. The security impacts and prices can be recomputed for any ally country and desired combination of potential adversaries using the current quantification.

equipment (cf. Hartley 2012; Smith 2024). Defense output has no observable market price, and input-specific prices are difficult to construct, so national accounts typically measure it as nominal expenditure deflated by an aggregate index. Like the national accounts, we measure real input expenditure rather than output; unlike them, we deflate by a model-consistent price index specific to military users and focus on changes rather than levels. Because only export controls vary across our counterfactuals, changes in this measure plausibly capture changes in defense output within each country, which the contest model maps into the corresponding security outcomes.[10]

Economic evidence on export controls themselves remains more limited. Existing work documents several margins that are central to our analysis: export shortfalls from U.S. high-technology controls (Sundaram and Richardson 2013); trade diversion following Japanese and U.S. dual-use restrictions (Hayakawa et al. 2023); and costs to U.S. suppliers and substitution toward alternative suppliers by targeted Chinese firms (Crosignani et al. 2026). Using public ECCN export data together with confidential Census firm-level data, Basker and Kamal (2026) study the 2014 U.S. export controls on Russia and find that affected firms reduce not only targeted exports to Russia but also exports of other products and to other destinations, with accompanying declines in payroll. Related work studies controls on dual-use trade with Russia (Alekseev and Lin 2026). We differ by measuring export control frictions across destinations and control classifications and by embedding those estimates in a framework that quantifies how domestic and security effects depend on international coordination.[11]

2 Export Control Regimes: Background and Stylized Facts

We provide institutional background for the U.S. and the multilateral export control regimes (MECRs) and use novel data to establish five stylized facts that guide our subsequent modeling.

2.1 Institutional Background

Export control regimes are legal frameworks that restrict the international transfer of sensitive goods, technologies, and technical information. Governments impose export controls to prevent the proliferation of military capabilities and other technologies with national security implications. These controls operate primarily through export licensing requirements. Firms must obtain government approval before exporting certain products to particular destinations, end-users and end-uses. Failure to comply carries substantial financial penalties and, in the United States, potential denial of any export privileges.

[10] Robertson (2022) shows that country real military expenditure rankings change when using input cost deflators (for personnel, operations, and equipment) but notes that this is still insufficient to rank capabilities because countries can differ in their military production efficiency.

[11] Fan, Handley, and Limão (2026) find that aggregate bilateral trade is higher between MECR members upon accession in 1965–2010, as described in Section 2.

Export controls apply to military items and "dual-use" goods. Military items cover goods such as weapons systems, munitions, and defense services. Dual-use goods have both civilian and military applications and thus include a wide range of advanced manufacturing inputs and technologies, such as sensors, machine tools, semiconductors, and aerospace components, but also other basic inputs, as we show below.

U.S. export control regime. In the U.S., export controls on dual-use goods are administered by the Bureau of Industry and Security (BIS) under the Export Administration Regulations (EAR). Products are assigned Export Control Classification Numbers (ECCNs) that determine the conditions under which exports require a license. Licensing requirements depend on the product classification, the destination country, the end-use, and the end user. Therefore licensing decisions by the BIS are made on a case-by-case basis.

These institutional features generate substantial compliance costs for U.S. exporters. Exporters must determine product classifications and licensing requirements and screen counterparties' identities and end-use, sometimes even after the transaction. In a survey of aerospace firms, 58% identified export controls as the primary barrier to entry, with compliance costs of 1–8% of sales and lost sales exceeding 15% of exports (AFRL and DOC 2007). Government surveys of the U.S. space industrial base report that 15.2% of firms avoided exporting products subject to controls and 8.3% abandoned or altered business lines (BIS 2014). Similarly, over 40% of printed circuit board manufacturers identify export controls as a source of competitive disadvantage (BIS 2017).

Another export control friction identified across these surveys is uncertainty over licensing requirements and outcomes, which discourages export activity. Firms report avoiding transactions when licensing is likely or unclear, and foreign buyers often substitute toward non-U.S. suppliers. New chip controls, for example, add compliance burdens, delays, and business uncertainty even though "most respondents did not have products that are immediately controlled" and, as one respondent explained, "a lot of foreign firms will ask first, and if there is a license requirement, they tend to go elsewhere" (BIS 2023).[12]

These frictions are reinforced by ongoing costly enforcement and non-compliance penalties, which are severe and include export bans, criminal liability, and large administrative fines.[13] If these frictions applied to a well-identified and narrow set of products, their impact could be limited, but that is not the case, as the stylized facts will show.

Multilateral export control regimes (MECRs). MECRs help members coordinate. They require information-sharing, harmonize restriction lists, and disseminate best practices across member states. These activities can reduce regulatory uncertainty and duplicated compliance effort

[12]Compliance requirements translate into substantial and uneven organizational burdens. Survey evidence shows that while many firms maintain dedicated compliance teams, with a majority of effort devoted to transaction-level processing, 25% lack formal compliance programs and 44% report inadequate internal understanding of export control requirements (KPMG 2021).

[13]Seagate paid a $300 million penalty for shipping foreign-produced hard disk drives, designated EAR99 but produced with CCL controlled U.S. equipment, to Huawei without a license. Numerous similar cases appear in BIS reports (www.bis.gov/press-release/bis-releases-new-edition-dont-let-happen-you).

without weakening restrictions on outside destinations.

The first such modern regime, the Coordinating Committee on Multilateral Export Controls (COCOM), was formed after World War II by the U.S. and its European allies to restrict exports to the Soviet bloc. COCOM developed common control lists and let any member block another's export of a controlled item to a restricted destination.

COCOM dissolved after the collapse of the USSR and was replaced by the Wassenaar Arrangement (WA) in 1996. This arrangement remains the primary MECR governing dual-use goods. It maintains and updates dual-use and military control lists, requires members to report license denials so partners can condition their own decisions on that information, and conducts outreach to non-members. Unlike COCOM it does not target a single country and there is no veto power over member exports.[14] Three narrower regimes—the Missile Technology Control Regime (MTCR), the Nuclear Suppliers Group (NSG), and the Australia Group (AG)—apply the same coordination logic to missile, nuclear, and chemical/biological technologies, respectively.

There is no systematic evidence on the impact of MECRs on exports with the exception of Fan, Handley, and Limão (2026). There we find long-run gravity evidence that aggregate bilateral trade is about 30 lp higher following MECR accessions. That paper does not identify the frictions or how they vary across products and countries. Here we do both, starting with the following stylized facts.

2.2 Stylized Facts on U.S. Export Controls

We use a novel dataset to document five stylized facts about the incidence of export controls, their distribution across destinations and sectors, and the licensing frictions associated with them. The data we assemble combine special tabulations of U.S. export transactions from the U.S. Census Bureau Foreign Trade Division (FTD) with newly digitized information on export licensing outcomes and statutory country classifications from the Export Administration Regulations. The export data cover 2009–2024 at the Schedule B product-country-quarter level and report the value of exports and number of transactions by control code and license type. U.S. exports to Canada are omitted because, under U.S.-Canada data-sharing arrangements, they are compiled from Canadian import records, which do not contain U.S. export control classifications.[15]

This information is complemented with data we digitized on: (1) BIS annual and country reports on license approvals and processing times, which are available for a subset of countries from 2012-2022 (world aggregates from 2010), and (2) EAR yearly classifications of MECR members and other destinations receiving more or less favorable licensing treatment.

We establish five stylized facts. First, export controls cover a large and rapidly growing share of

[14] www.wassenaar.org/about-us/, accessed December 23, 2025.

[15] The remaining sample covers about 80% of total U.S. exports. Exports to Canada are nonetheless subject to the same U.S. export controls and licensing process as those to other MECR members.

Table 1: Exports by Level of Control Group

	2016			2024			Growth
	Exports ($bil)	Share of Total Exports	As Share of Controlled	Exports ($bil)	Share of Total Exports	As Share of Controlled	Rate (%)
No Controls	$584	51%	0%	$607	37%	0%	4%
Any Controls	$546	47%	100%	$1,027	62%	100%	88%
Of which:							
EAR99	$354	31%	65%	$771	46%	75%	118%
CCL NLR	$164	14%	30%	$223	13%	22%	36%
CCL Lic. Exc.	$20	2%	4%	$23	1%	2%	12%
CCL Licensed	$7	0.6%	1%	$9	0.5%	1%	18%
Lic. Exc. Other	$0.4	0.04%	0.08%	$0.4	0.02%	0.04%	-3%
Other Agency Lic.	$25.81	2%	–	$28.56	2%	–	11%
Total (ex-CAN)	$1,155			$1,662			44%

Notes: Authors' calculations using Census FTD special tabulations. Exports listed on the CCL can be No License Required (NLR), exported under a license exception, or exported under license. Exports licensed by other U.S. government agencies that are not classified as EAR99 or CCL are reported separately as Other Agency License, but excluded from the analysis sample. Growth rates differ from values in table due to rounding.

U.S. exports. Second, they are concentrated in high-technology sectors but are broad and highly heterogeneous within sectors. Third, controlled exports are characterized by fewer transactions and larger average shipment values, consistent with fixed regulatory costs and selection. Fourth, licensing outcomes vary systematically across destinations, with MECR members facing higher approval rates and shorter processing times. Fifth, control intensity differs sharply across countries, while the value and growth of controlled exports are more concentrated in MECR destinations.

Fact 1: Controls cover a large and growing share of U.S. exports

We aggregate exports into three groups by control classification. CCL products face the most stringent controls because they are explicitly classified under the Commerce Control List and may require a license depending on the destination, end use, or end user. EAR99 products are not listed on the CCL but remain subject to the Export Administration Regulations, and may require a license. The remaining transactions form the no reported control group.

Figure 1 shows the composition of U.S. goods exports to countries other than Canada by control classification in billions of U.S. dollars. From 2016 to 2024, the period of our baseline regressions, U.S. nominal exports with any reported control classification grew by 88%, whereas exports with no reported control classification grew by only 4%. As we show in Table 1, by 2024, 62% of exports in our sample had some reported control classification, with about 15% listed on the CCL and the remainder reported as EAR99. While the share of CCL export value under license or license exception is small, this is not evidence of low licensing frictions. It is an equilibrium outcome of observed trade after licensing determinations and selection.

Table 2: 2016 Export Value by Category and License Type ($ Billion)

Product Tech Category	BIS Licensed	Lic. Exception	NLR	Total
Aerospace & Propulsion	5.19	1.59	103.37	**110.15**
Telecommunications & Information Security	0.14	15.68	22.90	**38.72**
Electronics	0.65	2.00	16.81	**19.47**
Computers	0.00	0.01	11.62	**11.64**
Materials, Chem, Microorg. & Toxins	0.34	0.05	2.67	**3.06**
Navigation & Avionics	0.20	0.12	2.53	**2.85**
Materials Processing	0.22	0.07	1.80	**2.09**
Lasers and Sensors	0.17	0.12	1.00	**1.29**
Marine	0.05	0.04	0.76	**0.85**
Nuclear Materials, Facilities and Equip. & Misc	0.37	0.08	0.18	**0.62**

Notes: Authors' calculations using Census FTD special tabulations. The 10 product technology categories are obtained from the first digit of the ECCN as defined in the CCL.

Fact 2: Controls are broad across sectors, heterogeneous within them and concentrated in high-tech

CCL exports are concentrated in high-technology sectors, but control exposure varies sharply within sectors. This variation reflects how export controls target inputs with specific uses, not sectors or industries.

Table 2 reports CCL export values in 2016 by technology category and license type.[16] The largest CCL export categories are aerospace and propulsion, telecommunications and information security, electronics, and computers. The nuclear materials and equipment category, for example, accounts for a much smaller share of observed CCL trade (and is the only category where the value that is licensed exceeds that with no license required). This pattern underscores that export controls apply to dual-use technologies embedded in ordinary commercial trade, not only to products that are exclusively military or nuclear.

Table 2 is useful for showing where CCL export value is concentrated and this information is available in official reports. But it does not measure control intensity at disaggregated industry and product levels or for export destinations. The main reason is that BIS technology categories are defined only for CCL listed goods and thus do not report the corresponding value of non-controlled exports. One advantage of our transaction-level export data is that they allow us to measure control intensity directly. We observe export values by control classification within product, industry, and destination cells, with which we calculate the controlled share of trade in each cell.

[16] Products listed on the CCL receive an alphanumeric ECCN code that assigns the export to one of ten broad BIS technology categories.

Table 3: Export Controls Are Widespread across Sectors but Heterogeneous within Them, 2016

	Sector		**Within 6-digit**	**Most CCL controlled 6-digit industry**		**Least CCL controlled 6-digit industry**	
Sector	**CCL %**	**EAR99 %**	**CCL mean (SD)**	Industry	%	Industry	%
Transportation Equip.	49.9	19.1	22.7 (33.2)	*Guided Missiles & Space Vehicles*	100.0	*Motor Homes*	0.0
Computer & Elec. Prod.	36.3	27.6	22.9 (19.0)	*Elec. Computer*	60.0	*Electromedical Apparatus*	0.1
Machinery	15.9	36.8	8.0 (13.5)	*Semiconductor Machinery*	70.8	*Lawn & Garden Equip.*	0.0
Elec. Equip. & Comp.	10.6	37.5	8.4 (11.7)	*Carbon & Graphite Prod.*	53.5	*Household Laundry Equip.*	0.1
Nonmetallic Mineral	10.4	37.4	4.3 (7.3)	*Pressed/Blown Glassware*	26.5	*Lime*	0.0
Fabricated Metal	9.1	35.1	10.9 (18.2)	*Ammunition, ex. Small Arms*	75.3	*Metal Window & Door*	0.1
Textile Prod.	8.5	26.0	4.9 (9.6)	*Other Misc. Textiles*	22.1	*Carpet & Rug Mills*	0.2
Furniture & Related	3.0	25.5	1.1 (2.6)	*Showcases, Shelving & Lockers*	8.7	*Wood Kitchen Cabinets*	0.0
Printing & Support	2.2	23.0	1.4 (2.0)	*Commercial Printing*	3.7	*Support Activities for Printing*	0.1
Plastics & Rubber	1.5	30.4	1.1 (1.3)	*Plastics Pipe & Pipe Fitting*	4.4	*Tire Retreading*	0.0
Primary Metals	1.4	32.3	2.8 (5.3)	*Nonfer. Metal Die-Casting Foundries*	19.5	*Iron & Steel Pipes/Tubes*	0.0
Textile Mills	1.1	23.5	1.3 (1.5)	*Narrow Fabric Mills*	4.0	*Knit Fabric Mills*	0.0
Misc.	1.0	33.9	2.3 (3.5)	*Doll, Toy, & Game*	10.4	*Dental Laboratories*	0.0
Chemical	0.9	47.7	3.3 (11.6)	*Explosives*	60.9	*Ethyl Alcohol*	0.0
Apparel	0.8	18.6	1.2 (2.2)	*Apparel Accessories*	5.6	*Hosiery & Sock Mills*	0.0
Leather & Allied	0.2	22.6	0.2 (0.3)	*Women's Handbags & Purses*	0.6	*Leather Tanning & Finishing*	0.0
Paper	0.1	30.6	0.1 (0.1)	*Paper Bags & Coated/Treated Paper*	0.3	*Pulp Mills*	0.0
Wood	0.0	9.2	0.0 (0.1)	*Other Millwork (inc. Flooring)*	0.3	*Engineered Wood*	0.0
Food	0.0	12.3	0.0 (0.0)	*Nonchoc. Confectionery*	0.0	*Chocolate & Confectionery*	0.0
Petroleum & Coal	0.0	76.3	0.0 (0.0)	*Other Petro & Coal Prod.*	0.0	*Asphalt Shingles & Coatings*	0.0
Beverage & Tobacco	0.0	14.6	0.0 (0.0)	*Bottled Water*	0.0	*Tobacco*	0.0

Notes: Each row is a NAICS-3 manufacturing sector, sorted by the sector's value-weighted CCL value share. "Within 6-digit CCL mean (SD)" is the unweighted mean and standard deviation of the CCL value share across the sector's constituent NAICS-6 industries. The most-/least-controlled columns name the NAICS-6 industry with the highest and lowest CCL value share in each sector. All figures are percentages.

We define control intensity for control type $k \in \{\text{CCL}, \text{EAR99}, \text{Any}\}$ in cell c as

$$s_c^k = \frac{\text{Exports}_c^k}{\text{Exports}_c^{\text{CCL}} + \text{Exports}_c^{\text{EAR99}} + \text{Exports}_c^{\text{NC}}},$$

where c can denote a sector, industry, destination, or sector–destination cell and NC refers to no control. We define $s_c^{\text{Any}} = s_c^{\text{CCL}} + s_c^{\text{EAR99}}$.

Control intensity varies sharply across and within broader manufacturing sectors. Table 3 reports, for each NAICS-3 sector, the share of export value listed on the CCL and reported as EAR99, together with the mean and standard deviation of CCL shares across the sector's constituent NAICS-6 industries. CCL intensity is highest in transportation equipment (50%), computers and electronics (36%), and machinery (16%), but nontrivial CCL shares extend beyond these high-technology sectors into chemicals, fabricated metals, nonmetallic minerals, and textiles. At the same time, sectors with relatively low CCL shares can still have high aggregate control intensity because much of their export value is reported as EAR99. This distinction can be important empirically if the CCL controls are more stringent, as we will test. The more remarkable pattern for CCL products is the dispersion within sectors. The contrast between the most- and least-controlled industries inside a single sector is stark. Transportation equipment spans guided missiles (100%) and motor homes (0%); computers and electronics span electronic computers (60%) and electromedical apparatus (0.1%); and chemicals, despite a low average CCL share of 0.9%, contains explosives (61%) alongside ethyl alcohol (0%). In all but one sector, the within-sector standard deviation of NAICS-6 CCL shares is comparable to or larger than the mean.

This within-sector dispersion motivates the civilian/dual-use distinction used in the quantitative model. In Section 6.2, we classify NAICS-6 industries as dual-use when their CCL export share exceeds 15 percent. This threshold is approximately the aggregate CCL share of U.S. exports to MECR destinations in 2016.

Fact 3: Controlled exports have fewer transactions and larger average shipments

The differences between controlled and non-controlled exports are not limited to aggregate export values or sectoral composition. They also appear in the transaction structure of trade. Most importantly, the average shipment value is larger for controlled products.

Table 4 reports mean log values across countries by control type for each export margin.[17] Mean export values rise as we move from CCL to EAR99 to exports with no reported control classification, and the same pattern holds for the number of transactions. The pattern reverses, however, for average shipment size. The mean average shipment value for exports with no reported control classification is 27 lp lower than for CCL exports and 22 lp lower than for EAR99.

[17] We define the transaction margin as the number of recorded shipments in U.S. export data, which is referred to as the "card count" in U.S. Census foreign trade data.

Table 4: Average Exports, Shipments, and Exports per Shipment by Control Type

Control Type	Exports (ln)	Number of Shipments (ln)	Exports per Shipment (ln)	Obs.
CCL	17.32	6.52	10.80	1,732
EAR99	18.70	7.94	10.75	1,737
None	19.13	8.59	10.53	1,737

Notes: Authors' calculations using Census FTD special tabulations. Averages by destination, control type and year for 2016–2024.

These patterns are consistent with export licensing operating as a fixed regulatory cost. If exporters face fixed compliance costs, approval risk, or licensing delays, then only sufficiently profitable transactions will be observed, reducing the number of transactions while raising average shipment size. This motivates the modeling approach in Section 3, where export controls affect trade through compliance costs, approval probabilities, and licensing delays that alter the productivity cutoff for exporting. In Section 4, we estimate the combined effect of these frictions.

Fact 4: Licensing frictions are lower for MECR destinations

Export controls do not impose a uniform licensing burden across destinations. Under the EAR, licensing requirements and the availability of license exceptions depend on country-group designations codified in the regulations and implemented by BIS. These designations create a hierarchy of destination treatment: countries participating in MECRs generally receive more favorable treatment, while destinations associated with various national security concerns face greater scrutiny and, in some cases, a presumption of denial.

Countries appearing on the EAR-A lists (A1–A4) participate in one or more MECRs and typically receive more favorable licensing treatment. The EAR-B list contains countries that are not members of these regimes but are generally eligible for case-by-case licensing decisions and certain license exceptions. The EAR-D list (D1–D5) destinations are associated with national security concerns, including arms embargoes and nuclear, chemical, biological, or missile proliferation risks. Export license applications to these destinations face heightened scrutiny and a presumption of denial. The EAR-STA list (A6) includes destinations that have a Strategic Trade Authorization (STA) and also receive favorable treatment.

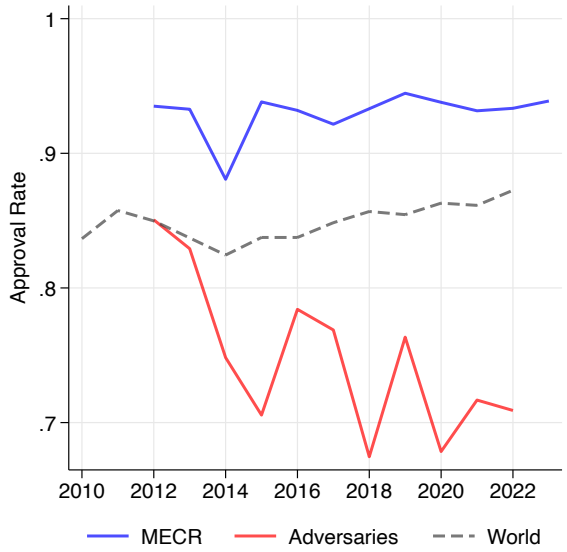
Countries may appear on multiple lists, so we define and focus on three mutually exclusive empirical groups.[18]

- **MECR** destinations: countries appearing on at least one U.S. EAR-A list under any MECR

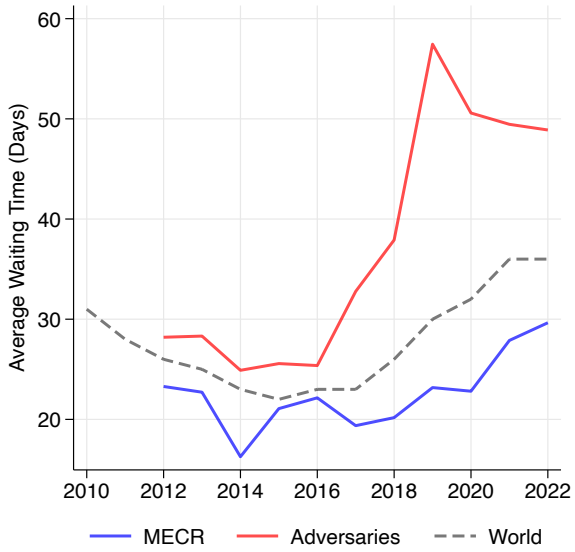
[18] We provide more details and a country list in Appendix B.1. A fourth set of destinations are those in the EAR-A6 list and not any other EAR-A or EAR-D list. It is a separate category in the empirical analysis, but we do not report the results because it includes only Albania and Singapore. Two others, Iran and North Korea, are in the E-list and excluded from the analysis.

Figure 2: Export Licensing Outcomes by Destination Group (MECR, Adversary, World)

(a) License Approval Rates



(b) Average Licensing Waiting Times



Notes: The data are digitized from available BIS annual and country reports that include approval rates and licensing waiting times. Country-level detail is only available for 18 countries in the MECR or A6 group and 12 countries from the adversary group. Panel (a) reports approval rates for BIS export license applications. Approval rates are available in annual reports for each control regime for most years. MECR is the annual mean of approval shares reported for the four multilateral regimes: the Australia Group (AG), Nuclear Suppliers Group (NSG), Wassenaar Arrangement (WA), and Missile Technology Control Regime (MTCR); missing application and approval totals are linearly interpolated before computing approval shares. The adversary series is the simple mean approval rate reported for the subset of available countries. Panel (b) reports simple mean processing times across the available country reports. Reports on world aggregates are available from 2010–2022 and more disaggregated data from 2012–2022.

but not on any EAR-D list. These countries are labeled "Allies" in the quantitative model counterfactuals.

- **Adversary** destinations: countries appearing on any EAR-D list.
- **Neutral** destinations: countries on the EAR-B list and not on any EAR-A or EAR-D list.

These statutory differences map into observed licensing outcomes in predictable ways. We use newly digitized BIS reports on licensing outcomes. Country reports provide approval rates and processing times for a subset of destinations, while annual reports include approval shares tabulated by regime: AG, NSG, WA, and MTCR.[19] Figure 2a plots the mean of these four regime-level approval series as our MECR benchmark, together with the BIS world approval rate and average for adversary destinations where data are available. Over 2016–2022, the average approval rates are highest for MECR members at about 93 percent, lower for the world average (86 percent), and lowest for adversary destinations (72 percent).[20]

[19]BIS does not provide comprehensive country-by-year reporting on licensing approvals and processing times. We digitize all available annual world and country reports from 2010–2022 and construct a new panel of licensing outcomes for the countries and years BIS reports.

[20]The BIS world aggregate includes MECR members receiving favorable treatment. When we adjust the aggregate

Figure 2b shows a similar ranking for processing times. This figure uses the country reports because the regime tabulations do not report processing times. Applications for MECR destinations are resolved most quickly (23 days on average over 2016–2022), while those for adversary destinations face the longest delays (43 days). Average times have increased for all groups as the number of applications has expanded.

These differences provide direct evidence that export licensing imposes economically meaningful regulatory frictions, which vary systematically with the destination's export control status. This pattern motivates the mechanism we formalize in Section 3; helps explain the allocation of controlled exports across destinations documented in the next fact; and will be used to quantify the impact of observed increased frictions on China and Russia in the quantitative section.

Fact 5: Control intensity varies across destinations, and values are highest to MECR destinations

Table 5 reports CCL and EAR99 shares and controlled export values for the top 10 MECR and non-MECR destinations in 2016, ranked within each group by CCL share. The table shows substantial heterogeneity among large destinations. Among MECR destinations, 41.4 percent of U.S. exports to France are listed on the CCL, compared with 3.2 percent for Belgium. Other major allied destinations like Mexico lie between these extremes. Among non-MECR destinations, CCL intensity is also dispersed: Malaysia and the U.A.E. have CCL shares above 30 percent, while Thailand, Chile, and Colombia are much lower. About half of all exports to China reported some control in 2016, and at $57.6 billion they accounted for about one half of all U.S. controlled exports to the adversary group, which will be important for the quantification exercises.

Figure 1 and Table 1 show that controlled exports grew sharply over this period, rising from 47 percent of U.S. exports in 2016 to 62 percent in 2024. Decomposing this growth by destination group, the share of total U.S. exports accounted for by controlled exports to MECR members rose steadily through 2024, reaching 41 percent of all exports, while the corresponding share for non-MECR destinations remained comparatively flat at about 20 percent. Thus, the aggregate expansion of controlled trade was concentrated in MECR markets.

3 Firm Entry and Transactions under Export Control Risk

The evidence in the previous section highlights three features of export controls: compliance is costly, licensing outcomes are uncertain, and the resulting frictions vary across transactions. We incorporate these features into a heterogeneous firm model of export entry under licensing risk. The partial equilibrium framework isolates the central mechanisms and serves two purposes. First, it

by subtracting the applications and approvals reported separately for MECR destinations, the approval rate averages approximately 84 percent over 2016–2022.

Table 5: Control Intensity and Values Across Destinations, 2016

	Share (%)		Value		Share (%)		Value
MECR Destination	**CCL**	**EAR99**	**($ bil)**	**Non-MECR Destination**	**CCL**	**EAR99**	**($ bil)**
Top 10				*Top 10*			
France	41.4	26.1	20.0	Malaysia[b]	39.4	31.9	8.3
United Kingdom	26.3	26.4	27.4	U.A.E.[d]	34.0	22.6	11.2
Brazil	22.3	43.6	19.5	Taiwan[d]	28.5	28.3	13.8
South Korea	19.3	28.1	18.5	Vietnam[d]	27.7	18.3	4.6
Japan	18.8	32.7	31.3	Saudi Arabia[d]	24.8	27.1	7.6
Germany	17.1	44.1	28.9	China[d]	21.1	29.3	57.6
Netherlands	16.6	48.4	25.5	Israel[d]	18.7	24.6	5.1
Switzerland	9.4	30.1	8.7	Thailand[b]	17.6	39.4	5.9
Mexico	7.5	23.3	68.6	Chile[b]	11.0	34.5	5.7
Belgium	3.2	47.2	15.9	Colombia[b]	7.4	42.4	6.3
All other	16.3	34.2	66.5	*All other*	12.3	33.5	55.8
MECR overall	**15.2**	**31.6**	**330.8**	**Non-MECR overall**	**19.3**	**30.8**	**181.9**
				of which Neutrals[b]	12.1	35.3	63.2
				of which Adversaries[d]	23.4	28.1	118.6

Notes: Top ten countries by total exports within each MECR group, sorted by CCL export share. All other categories aggregate destinations outside the top ten. CCL and EAR99 are shares of total export value to the destination. Value is the dollar value (in billions) of exports subject to CCL or EAR99 controls. Superscripts [b] and [d] denote destinations on the mutually exclusive lists we construct from all non-MECR destinations, as described in Section 2, Fact 4 and Appendix B.1. Overall rows aggregate all destinations in the indicated group. Totals do not match Table 1 because the table does not include Group A6 or destinations not in our main regression sample.

guides the empirical specification by showing how variation in licensing treatment across products and destinations identifies differences in aggregate export control frictions, which in turn discipline the general equilibrium counterfactuals in Section 7. Second, it uses the distinct responses of export values, transaction counts, and value per transaction to decompose these frictions into economically interpretable components, including average approval risk and fixed compliance costs.

3.1 Environment and Timing

We denote the firm's origin by o, the destination by d, and defer sector subscripts until Section 5.

Demand. Demand for a firm's product comes from downstream buyers of two types, $b \in \{C, D\}$: civilian-oriented firms and consumers (C), or military-oriented and dual-use downstream firms (D). Each buyer type generates demand with absorption $X_{d,b}$ and a composite price index $P_{d,b}$.

Export controls. We model policy using two distinct components.

i. *Classification*: each product is assigned to a control regime $k \in \{\text{NC}, \text{EAR99}, \text{CCL}\}$, ranging from no control to the most stringent. The classification reflects features of the product—its technological sensitivity, potential military applications, and its production process. In Section 5 we formalize this through a probabilistic classification function. Here we assume that, after entry, a firm knows its product's classification and, given k, the applicable export

control regime.[21,22]

ii. *Control frictions*: these capture distinct costs and vary by regime and destination:

- $\rho_{od,k} \in [0,1]$: the *approval probability* of a shipment.
- $Q_{od,k} \in (0,1]$: the *quality shifter*—delays reduce the effective quality of the good at arrival, entering demand as $Q_{od,k} \equiv e^{-\chi T_{od,k}} \leq 1$, where $\chi > 0$ is the depreciation rate and $T_{od,k}$ is the observed processing delay in days.
- $f_{od,k} \geq 0$: the *compliance fixed cost*—this includes the standard export costs (in labor units), which in the case of controlled categories also reflect licensing applications, legal review, end-use certifications, etc.

Exporting firms also face standard bilateral iceberg trade costs $\tau_{od} \geq 1$, which differ only across destinations (and later sectors).

Timing. The following are the two stages for any potential exporting firm.

i. The firm observes its classification k, the control frictions and any other parameters and decides whether to pay the compliance cost $f_{od,k}$.

ii. If the firm pays and the license is approved, which occurs with probability $\rho_{od,k}$, it exports; otherwise it does not.

3.2 Pricing, Demand, and Profits

A firm at o with productivity z has unit cost A_o/z, where A_o is the cost of the production input bundle. Under CES demand and monopolistic competition, the markup is $\mu \equiv \sigma/(\sigma-1)$ and the delivered price is $p_{od}(z) = \mu\, A_o\, \tau_{od}/z$, which is common across classifications. This arises naturally because the licensing process entails delays that operate through the demand shifter and fixed costs, both of which will affect selection but not the price of an entrant. Demand from type-b buyers at d for a product under classification k is:

$$q_{od,b,k}(z) = Q_{od,k} \left(\frac{p_{od}(z)}{P_{d,b}} \right)^{-\sigma} \frac{X_{d,b}}{P_{d,b}}, \tag{1}$$

[21] In practice, firms must invest to determine their classification, but we do not observe those that do and choose not to export, so we simplify by treating the classification as known. Relaxing this simplification could provide another motive for reduced EAR99 exports since if firms believe there is some probability of higher frictions, e.g. CCL, there will be less export entry. In the general equilibrium model, firm entry into production under uncertain regime classification captures this mechanism.

[22] In principle, classification could also vary by destination, end-user, or even transaction. In practice, BIS assigns export control classification numbers (ECCNs) based on technical product characteristics; destination-specific variation enters through licensing requirements conditional on classification—precisely our second component. Moreover, the data do not allow us to distinguish classification changes across transactions for the same product. These considerations motivate our two-component structure.

which captures quality depreciation from any licensing delays but is otherwise standard.
Using the optimal price and quantity we obtain the revenue and operating profit:

$$r_{od,b,k}(z) = Q_{od,k}(\frac{p_{od}(z)}{P_{d,b}})^{1-\sigma} X_{d,b}\,, \qquad \pi_{od,b,k}(z) = \frac{r_{od,b,k}(z)}{\sigma}. \tag{2}$$

3.3 Market Entry Decision

The firm pays the compliance cost if and only if it does not exceed the expected operating profit, which is (2) conditional on approval:

$$\rho_{od,k}\pi_{od,b,k}(z) \geq w_o\, f_{od,k}, \tag{3}$$

where w_o is the wage. The equality in (3) defines the productivity cutoff such that firms with $z \geq z^*_{od,b,k}$ find it profitable to enter the licensing process to potentially export a product k to (d,b). That **productivity cutoff** increases with the licensing frictions as follows:

$$(z^*_{od,b,k})^{\sigma-1} = (\mu\, A_o\, \tau_{od})^{\sigma-1} \frac{\sigma\, w_o\, f_{od,k}}{\rho_{od,k} Q_{od,k} X_{d,b} P_{d,b}^{\sigma-1}}. \tag{4}$$

Aggregating exports under classification k from o to (d,b) requires two additional objects, assumed to be independent of buyer type. First, the measure of potential exporters at o of product category k, $M_{o,k}$. Second, their productivity distribution, which we assume is Pareto:

$$G(x) \equiv \Pr(z \leq x) = 1 - x^{-\kappa} \text{ for x} \geq 1; \theta \equiv \kappa - (\sigma - 1) > 0. \tag{5}$$

The parameter θ governs the responsiveness of exporter entry to trade costs and export control frictions and has the standard restriction to ensure finite mean. The **expected aggregate exports** of k from o to d buyers (of type-b) is then

$$M_{o,k} \int_{z^*_{od,b,k}}^{\infty} \rho_{od,k} r_{od,b,k}(z)\, dG(z), \tag{6}$$

which aggregates the expected revenues of all entrants. The corresponding **expected number of transactions** is the product of the approval probability and the mass of entrants:

$$\rho_{od,k} M_{o,k} (1 - G(z^*_{od,b,k})). \tag{7}$$

Increases in *any* export control friction reduce entry, export values, and transactions. But higher compliance costs and lower approval rates increase exports per transaction, as we show below.

3.4 Aggregate Expressions and Predictions

The data aggregate export values and transactions by product-destination-classification, but do not include buyer identity. Thus, we derive aggregate predictions by summing (6) over buyer types and substituting the cutoff (4) into it. This yields the exports in k from o to d:

$$\text{Exports}_{od,k} = \Phi_{od,k}(\tau_{od}^{-\kappa} S_{o,k} B_d \frac{\kappa}{\theta}), \tag{8}$$

where $\Phi_{od,k}$, which we term the **selection factor**, summarizes all control-specific frictions:

$$\Phi_{od,k} \equiv (\rho_{od,k} Q_{od,k})^{\kappa/(\sigma-1)} (\sigma\, f_{od,k})^{-\theta/(\sigma-1)}. \tag{9}$$

The selection factor falls as controls tighten: it decreases in the compliance cost $f_{od,k}$ and increases in the approval probability $\rho_{od,k}$ and the quality shifter $Q_{od,k}$. In (8) the terms in parentheses include the iceberg cost and the supply and demand potentials. Specifically, $S_{o,k} \equiv M_{o,k}\,(\mu\, A_o)^{-\kappa}\, w_o^{-\theta/(\sigma-1)}$ collects origin supply conditions for products classified as k and is common across destinations, whereas $B_d \equiv \sum_b (X_{d,b}\, P_{d,b}^{\sigma-1})^{\kappa/(\sigma-1)}$ aggregates demand across buyers in a destination and is independent of classification. These supply and demand potential terms are endogenous and modeled in Section 5, but in the reduced form estimation they are controlled via fixed effects.

Therefore, after controlling for supply and demand shifters, the selection factor $\Phi_{od,k}$ **is a sufficient statistic for the bilateral direct export effect of the control regime**. In Section 4, we identify Φ from variation across country groups and product classifications. The specification and identification are also valid in the general equilibrium model. In Section 6, we combine the Φ estimate with a probabilistic control classification to capture both components in the quantification.

The data also report the average transaction value. In Appendix C.1 we derive the closed-form prediction for this observable:

$$\frac{\text{Exports}_{od,k}}{\text{Transactions}_{od,k}} \equiv v_{od,k} = \frac{w_o f_{od,k}}{\rho_{od,k}} \frac{\kappa}{\theta} \sigma. \tag{10}$$

For a given origin wage w_o, average transaction value depends on control frictions only through the compliance-cost-to-approval ratio $f_{od,k}/\rho_{od,k}$. The result follows from the entry decision. At the productivity cutoff, (3) holds with equality, so revenue at the cutoff equals $\sigma w_o f_{od,k}/\rho_{od,k}$; under Pareto, mean revenue among firms above the cutoff is κ/θ times the revenue at the cutoff. Delays, iceberg costs τ_{od}, and destination demand move the cutoff, as (4) shows, but change neither revenue at the cutoff nor the multiple κ/θ, so average transaction value is unaffected. The data pool buyer types, but because the type-specific average is the same for every b, aggregating across types leaves the average transaction value (10) unchanged. We use this restriction to identify differences in $f_{od,k}/\rho_{od,k}$ across destinations and classifications.

In sum, the model predicts that, *all else constant*, more stringent controls in the form of lower

approval rates or higher compliance fixed costs imply lower export values but higher average transaction values. The predictions apply across classifications for a given destination, e.g. CCL vs. EAR99. They also apply across destinations for a given control type, e.g. non-MECR destinations with lower approval rates than MECR members. The model also identifies the supply and demand potential terms that the empirical specification in Section 4 absorbs through classification and destination fixed effects.

4 Trade Effects of U.S. Export Controls

4.1 Identifying Control Frictions

Our main goal is to identify differential export control costs from the aggregate and average value equations (8) and (10). Since $o = \text{U.S.}$ throughout, we drop the o subscript. Taking logs of (8):

$$\ln \text{Exports}_{d,k} = \ln \Phi_{d,k} + \underbrace{\ln S_k}_{\text{control-type specific}} + \underbrace{\ln\left[\tau_d^{-\kappa} B_d(\kappa/\theta)\right]}_{\text{destination specific}}. \tag{11}$$

For identification, we rely on a cross-sectional double difference: across control classifications within a destination, and across destinations facing different licensing requirements. We first write the within-destination ratio of controlled to uncontrolled exports using a *hat to denote values relative to non-controlled*, e.g. $\hat{\Phi}_{d,k} \equiv \frac{\Phi_{d,k}}{\Phi_{d,NC}}$:

$$\ln \widehat{\text{Exports}}_{d,k} = \ln \widehat{\Phi}_{d,k} + \ln \widehat{M}_k. \tag{12}$$

This within-destination difference cancels the terms that do not vary by classification: the iceberg costs τ_d, the demand potential B_d, and the components of origin supply common to all products. What survives is the control-specific component of S_k, namely the mass of potential exporters under classification k. Further differencing across destinations eliminates it and isolates the differential selection factor. In practice, export control regimes operate at the country-group level: MECR membership and the EAR lists define groups $g \in \{A, N, V\}$, denoting allies, neutrals, and adversaries, and control stringency is approximately common within each group. We use "allies" as shorthand for countries participating in an MECR; the label does not imply a formal mutual defense alliance. Denoting by Δ_d the difference between MECR members ($d \in A$) and non-members ($d \notin A$), and using the definition of Φ in (9), we have:

$$\Delta_d \ln \widehat{\text{Exports}}_{d,k} = \underbrace{\frac{\kappa}{\sigma - 1} \Delta_d \left(\ln \widehat{\rho}_{d,k} + \ln \widehat{Q}_{d,k}\right) - \frac{\theta}{\sigma - 1} \Delta_d \ln \widehat{f}_{d,k}}_{\Delta_d \ln \widehat{\Phi}_{d,k}} \tag{13}$$

For the average transaction value, since the supply shifter does not appear in (10), differencing

Table 6: Mapping Regression Outcomes to Structural Objects

Outcome $Y_{d,k}$	Structural Object Identified by $\delta_{M,k}$	Sign of $\delta_{M,k}$
Exports	$\delta_{M,k}^{\text{Exports}} = \ln \widehat{\Phi}_{A,k} - \ln \widehat{\Phi}_{\bar{A},k}$	+
$\frac{\text{Exports}}{\text{Transactions}}$	$\delta_{M,k}^{v} = \ln \frac{\widehat{f}_{A,k}}{\widehat{\rho}_{A,k}} - \ln \frac{\widehat{f}_{\bar{A},k}}{\widehat{\rho}_{\bar{A},k}}$	−
Transactions	$\delta_{M,k}^{n} = \delta_{M,k}^{\text{Exports}} - \delta_{M,k}^{v}$	+

Notes: $\widehat{x}_{.,k} \equiv x_{.,k}/x_{.,NC}$ and k=CCL, EAR99; $\bar{A}$ denotes non-MECR destinations ($N \cup V$); Φ is defined in (9).

across classifications within a destination already isolates the relative compliance-cost-to-approval ratio:

$$\ln \widehat{v}_{d,k} = \ln \widehat{f}_{d,k} - \ln \widehat{\rho}_{d,k}. \tag{14}$$

4.2 Baseline: Differentials across Destinations and Control Classifications

We implement this identification by estimating:

$$\ln Y_{d,k} = \delta_{M,k}\, \mathbf{1}(\text{MECR}_d) \times \mathbf{1}(\text{Ctrl}_k) + \alpha_d + \alpha_k + \mathbf{Z}'_{d,k}\zeta + \varepsilon_{d,k}, \tag{15}$$

where the outcome $Y_{d,k}$ is, in turn, export values, the number of transactions, or the average transaction value. Destination fixed effects α_d absorb the destination-specific demand aggregate B_d, and classification fixed effects α_k absorb the supply composition S_k. The key coefficient $\delta_{M,k}$ identifies the differential control friction between controlled and other products in MECR member countries (A) vs. non-members (N or V). Table 6 summarizes how each regression margin maps to structural parameters and the predicted sign of the MECR differential. The coefficient $\delta_{M,k}^{\text{Exports}}$ identifies the average difference in Φ for controlled relative to uncontrolled products between MECR members and non-members as shown in (13).

For the average value margin, the coefficient $\delta_{M,k}^{v}$ identifies the differential compliance-cost-to-approval ratio across country groups as shown by differencing (14). We can also identify the compliance-cost-to-approval ratio for MECR and non-MECR groups separately—both predicted to be positive. The transaction margin coefficient is the difference of coefficients of the export and average export by construction and is predicted to be positive.

We observe multiple years and so *we estimate* (15) *on the pooled sample* of destination-by-classification cells across years, restricting the differential parameters to be constant so that $\delta_{M,k}$ is a precision-weighted average of the year-specific differentials. We include country–year fixed effects and cluster standard errors at that level.

4.3 Identification Threats and Interpretation

Our identifying assumption is that, absent differences in export control frictions across destination groups, the within-destination ratio of controlled to uncontrolled outcomes would be the same for MECR and non-MECR destinations, conditional on the fixed effects and covariates in (15). The remaining difference identifies the friction differential in (13).

The principal threat to this assumption is that control stringency differs across sectors, and countries' demand composition across sectors also differs. When estimating at the aggregate level, the MECR differential could partly reflect the fact that some countries demand more goods from sectors that are subject to stricter controls on average—for instance, because of high military spending—for reasons independent of their MECR membership. To address this, the controls $\mathbf{Z}_{d,k}$ include country characteristics that proxy for demand composition across control types—such as military and government expenditure shares interacted with control-type indicators. We do this in the robustness section where we also (i) split the sample by GDP and GDP per capita to verify that market size or development level does not drive the differential, and (ii) estimate the specification at the sector level to fully account for sector heterogeneity.

4.4 Data

We use a special tabulation by the U.S. Census Bureau. It includes export data from 2009–2024 on a quarterly basis, disaggregated by 10-digit Schedule B export codes, country, and reported export control classification (CCL, EAR99, or none). After excluding countries subject to embargo, countries that switch into or out of the MECR or A6 groups in the period 2016–2024, and territories, we have data on 191 countries. U.S. exports to Canada are compiled from Canadian imports, which omit U.S. export control classifications, so Canada is excluded from the regression analysis.

In the baseline we aggregate the data to the yearly level and focus on 2016–2024. This avoids substantial changes in country list classifications. In Section 4.9 we exploit the full time period and quarterly information in a different identification strategy. There, we identify the effects of a country being upgraded or downgraded in terms of U.S. export control lists, which we construct using the Federal Register.

We also use the USITC Dynamic Gravity Dataset (Gurevich and Herman 2018) for heterogeneity by GDP and population measures, which we supplement with World Development Indicators (World Bank 2025) and World Economic Outlook (International Monetary Fund 2025). We also use World Development Indicators for measures of military and government share of GDP.

For additional details on data sourcing and construction of measures used in the regression and quantitative model see Appendix B.5 and Appendix Table B2.

4.5 Baseline Estimates: Aggregate Exports

We start with baseline estimates for export values and examine the other outcomes in Section 4.7.

Table 7 presents the results from estimating (15). Throughout, we use a tilde to denote an estimated object. We find positive estimates of $\delta_{M,k}^{\text{Exports}}$, as predicted. In column 1, we aggregate EAR99 and CCL export values into an "any control" group. The U.S. exports relatively more to MECR countries: $\tilde{\delta}_{M,ctrl} = 0.54$, which is statistically significant.[23] In column 2, we add control type-year fixed effects, which changes only the standard errors. In columns 3 and 4 we disaggregate the EAR99 and CCL products, hence the increase in sample size. Each of the controls has the predicted sign. Moreover, $\tilde{\delta}_{M,CCL} = 1.08 > 0.52 = \tilde{\delta}_{M,EAR99}$, so the stricter CCL controls have more than double the impact of the catch-all EAR99. Adding control type-year effects in column 4 does not change the estimates, and this is the baseline for subsequent robustness.

The ordering of the estimates provides additional support for the model's mechanism. EAR99 goods ordinarily do not require a license, but firms must still incur the initial compliance costs of classification under the EAR and screening the destination, end-user, and end-use before determining no license is required. This process also involves uncertainty and enforcement risk if the determination later proves incorrect. CCL transactions face these same preliminary costs and may additionally require a formal license application, with further application costs, approval risk, and processing delays. The larger CCL coefficient is therefore consistent with MECR membership mitigating a broader and more stringent set of frictions than for EAR99 transactions.

Our baseline estimates cluster standard errors at the country-year level to allow for arbitrary correlation across control categories within a country-year. In Table A1 we find that alternative standard error assumptions (robust, jackknife, bootstrap) leave our inference unchanged. Moreover, the jackknife estimation shows that leaving any one country out does not affect the results.

4.6 Robustness and Heterogeneity

We test robustness to various sample splits, disaggregation, and additional country heterogeneity.

Country composition. We investigate whether the estimated effects are robust to alternative samples and heterogeneous across comparison groups. Column 1 of Table A2 replicates column 4 of Table 7. We then change the comparison non-MECR group. In column 2 we drop the countries in the adversaries group (EAR-D list) so that the estimated differential is only relative to the neutral country group. The results remain similar to the baseline. In column 3 we instead drop the neutral countries so that the differential is estimated relative only to adversaries. The estimated coefficients remain positive and statistically significant, and they are smaller for both CCL and EAR99 exports relative to the baseline. Across specifications, the differential point estimate for CCL remains larger

[23] Throughout we also include an indicator for A6 countries, which are not in MECRs but have strategic trade authorizations. Controlled exports to them are generally also relatively higher than for non-MECR, but the estimate is imprecise since there are only two countries in the sample.

Table 7: U.S. Export Differentials by Agreement and Control Status

Sample:	No Controls vs Any Control		vs EAR99 and CCL controls	
Dependent Variable:	exports (ln)			
	1	2	3	4
MECR*Any Control	0.537	0.537		
	(0.045)	(0.043)		
A6*Any Control	0.028	0.028		
	(0.304)	(0.307)		
Any Control	-0.165	-0.165		
	(0.030)	(0.030)		
MECR*CCL			1.075	1.075
			(0.068)	(0.067)
MECR*EAR99			0.521	0.521
			(0.044)	(0.042)
CCL (binary)			-2.071	-2.071
			(0.047)	(0.047)
EAR99 (binary)			-0.547	-0.547
			(0.029)	(0.029)
Country-Year Fixed Effects	Yes	Yes	Yes	Yes
Control Type by Year Effects	No	Yes	No	Yes
Observations	3,438	3,438	5,152	5,152
R-squared	0.966	0.967	0.932	0.934
adjusted R-squared	0.932	0.934	0.898	0.900

Notes: Standard errors clustered by country-year in parentheses. Columns 1-2 have fewer observations because we aggregate EAR99 and CCL exports together. Columns 3-4 split "Any Control" into EAR99 and CCL subsets. Any Control, EAR99 and CCL coefficients in columns 2 and 4 are the mean of control type by year effects. A6 group interactions with Any Control, CCL and EAR99 indicators included in regression but omitted from table.

than for EAR99. In sum, the basic estimates are robust and the magnitudes are heterogeneous with respect to the comparison group.

Our sample includes a number of small island economies and micro-states, some of which exhibit very low or very high shares of controlled exports. In columns 4 and 5 of Table A2 we drop countries with population below 500,000, mostly neutral group countries, and repeat the estimation. The estimated differentials only fall materially in column 4 relative to 2, suggesting small countries inflated the neutral group estimates. The structural decomposition estimates will use this sample.

Country size and demand heterogeneity. Our results could be affected by demand size and composition. For example, large or high income countries may purchase more controlled exports but also be MECR members. In Table A4, we first split the sample by above and below median GDP. We continue to find a positive MECR differential and large effect for CCL exports in each subsample. We do find smaller effects for larger markets. In columns 3 and 4 we split countries by median GDP per capita and again find a positive differential for both EAR99 and CCL. The CCL

differential is larger than EAR99 above the median (94 vs 24 lp) but not below it (68 vs 78 lp).

Government and military expenditure heterogeneity. Our results could also reflect differential government expenditures in controlled products. Both U.S. allies, e.g. NATO, and adversaries may have high government expenditure on controlled products. The country-year fixed effects in our baseline already control for unobserved government or military expenditure overall, but this assumes a common effect across control types. To allow for differential effects we interact control type with either government or military expenditure (sourced from the World Bank), which are available for a subset of countries and years (2016–2022). In Table A5 the expenditure shares in GDP of either government (column 1) or military (column 4) do have a differential positive and significant effect on controlled exports. But, importantly, the baseline coefficients of interest, the differential for MECR members in CCL and EAR99 exports, remain positive and significant with CCL twice as large as EAR99.

Unobserved country-industry heterogeneity. Our results may be driven by composition effects for particular country-industry pairs. Therefore, we return to the HS10 data and aggregate to the country-*industry*-control type by year. We can thus re-estimate the average differential effects while including country-*industry*-year fixed effects (we also retain the control-year fixed effects). In Table A6 we provide these results for alternative industry classifications. In column 1 we use the 21 broad sections of the HS. This expands the sample to over 70,000 observations with positive trade. We find a positive and significant differential for MECR members for both EAR99 and CCL. The results are similar when we use NAICS 3-digit industries (about 91,000 observations) in column 2 or ISIC division groupings—roughly the level of disaggregation in our quantification exercise.[24]

Heterogeneity by CCL technology categories. Using the HS10 data and the associated ECCN code we can aggregate into each of the CCL technology categories reported in Table 2. We do two exercises with these data.

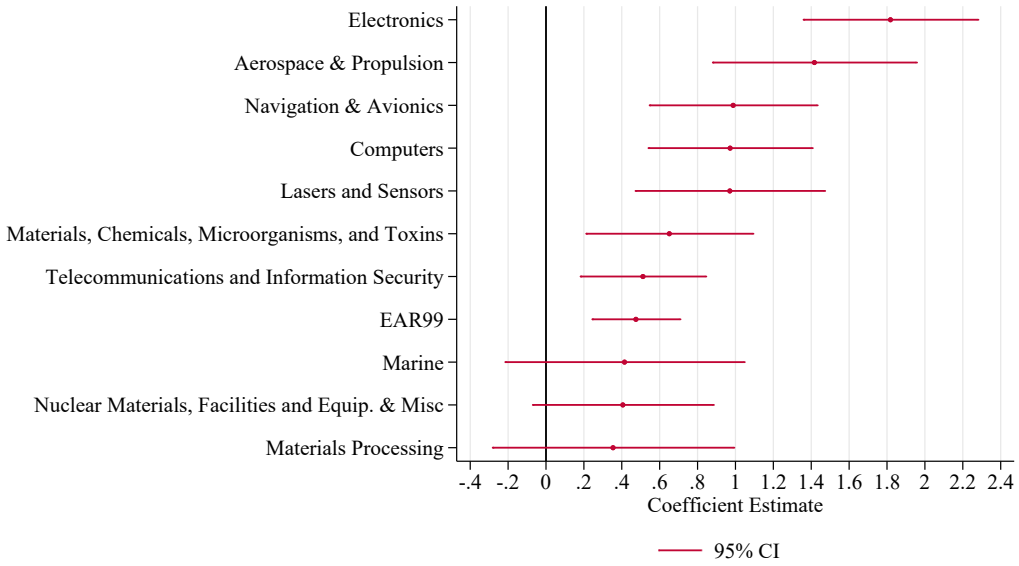
First, we re-run our baseline in (15), but instead of having a single CCL category we now have ten. In Table A6, column 4 we show the estimates, including fixed effects for country-year and each category of control-year. The average differential for the CCL categories is nearly the same as the aggregate one in the baseline.[25]

Second, we re-estimate (15) and compare each controlled category separately with the same non-controlled aggregate used in the baseline. Figure 3 reports the point estimates, ordered by magnitude, with the 95% confidence interval. The estimated differential is positive for all categories. The largest effects are for electronics, aerospace, navigation and computers, and the smallest for EAR99, marine, nuclear materials and materials processing. These patterns are robust to other sample restrictions such as dropping the neutral or adversary groups and low population countries

[24]The average magnitudes of the differentials are smaller because all industry observations have equal weight even though in some of them exports are much smaller in controlled and/or non-controlled products. We confirm this heterogeneity when we estimate the effects separately by industry. Appendix Table A7 reports the sector-specific differentials used in the quantification.

[25]The EAR99 observations are unchanged and thus the differential matches the baseline value.

Figure 3: U.S. Export Differentials by Agreement and Control Status—Category Heterogeneity



Notes: Point estimates with 95% confidence intervals from estimating (15) by product category. Estimates are ordered from highest to lowest by the difference-in-differences coefficient in (15) estimated by product category. Standard errors clustered by country-year.

similarly to the baseline results.

4.7 Mechanism Evidence

We now examine the predictions for the number of transactions and the average transaction value summarized in Table 6. Higher compliance costs or lower licensing approval probabilities raise the productivity cutoff for exporting, so only larger transactions are observed. Conversely, if export licensing frictions are lower toward MECR members, the productivity cutoff for exporting falls and smaller shipments become viable. The model therefore predicts that average shipment values should be lower toward MECR destinations for controlled exports, which we now test.

Transactions and controlled product entry. In Table 8, we report regression results for the baseline along all the margins. Column 1 reproduces the export value baseline for comparison. In column 3, we find a positive differential in the number of recorded shipment transactions toward MECR members for both CCL and EAR99 trade. We interpret this as evidence that lower expected licensing frictions increase entry into controlled exports, as the model predicts. Consistent with export controls affecting the extensive margin, we also find a positive and precisely estimated MECR differential in the number of traded HS10 products in column 4.

Average transaction and entry thresholds. Column 2 examines exports/transactions. The CCL and EAR99 fixed effects are positive and significant—approximately 30 lp each—which is consistent with the model prediction that shipment sizes are larger on average for controlled exports.

Table 8: U.S. Export Margin Differentials by Agreement and Control Status

Dependent Variable:	Exports (ln)	Exports per Shipment (ln)	Number of Shipments (ln)	Number of traded HS10s (ln)	Exports (ln)	Exports per Shipment (ln)
	1	2	3	4	5	6
MECR*CCL	1.075	-0.163	1.239	0.586	0.863	-0.227
	(0.067)	(0.049)	(0.050)	(0.029)	(0.068)	(0.049)
MECR*EAR99	0.521	-0.379	0.900	0.246	0.454	-0.325
	(0.042)	(0.036)	(0.038)	(0.019)	(0.042)	(0.036)
CCL FE Mean	-2.071	0.296	-2.368	-2.019	-1.869	0.331
	(0.0468)	(0.0314)	(0.0393)	(0.0252)	(0.049)	(0.034)
EAR99 FE Mean	-0.547	0.305	-0.853	-0.395	-0.495	0.232
	(0.0289)	(0.0277)	(0.0294)	(0.0170)	(0.031)	(0.028)
Observations	5,152	5,152	5,152	5,152	4,346	4,346
R-squared	0.934	0.480	0.953	0.957	0.936	0.462
adjusted R-squared	0.900	0.215	0.929	0.936	0.904	0.187

Notes: Standard errors clustered by country-year in parentheses. All regressions include country-year and control type-year fixed effects. A6 group interactions with CCL and EAR99 indicators included in regression but omitted from table. Reported EAR99 and CCL effects are mean over 2016–2024. Columns 5 and 6 drop the countries with population below 0.5 million and are used to compute the structural parameters.

However, average shipment values decline toward MECR destinations: the MECR differential is −16 lp for CCL exports and −38 lp for EAR99 exports. These results are consistent with the prediction of the model that lower expected export licensing frictions reduce average shipment size by allowing smaller shipments to enter.

Country composition and quantification sample. Columns 5 and 6 exclude low population countries, yielding qualitatively similar but more conservative estimates. We use these results for the structural estimates below since they more closely match the quantification sample. The corresponding sample estimates using either the adversary or neutral group are in columns 4 and 5 of Tables A2 (exports) and A3 (average shipment).

In sum, the margins display the pattern predicted by the model for CCL and EAR99 control categories: MECR destinations have more shipment transactions and traded products, but lower average shipment values, consistent with lower regulatory frictions relaxing the export cutoff. The average shipment estimates isolate the compliance-cost-to-approval component, while the export estimates capture the combined effect of all regulatory frictions. We use both margins in the structural decomposition below.

4.8 Structural Interpretation of Export Control Costs

The model in Section 3 provides a structural interpretation of the estimated coefficients. We use them to decompose the export differential into its underlying frictions, check whether the implied

magnitudes are consistent with observable licensing outcomes, and compute ad-valorem equivalents costs of licensing for export controls. Throughout we set κ and σ values consistent with the literature and with median values used in the GE quantification.

Decomposing export and entry frictions. The three fundamental friction parameters are ρ, Q, and f, which combine to define the selection factor in (9). For interpretation, we define the export cost penalty as the negative log of the relative selection factor in category k over non-controlled category, $-\ln \hat{\Phi}_{d,k}$, and decompose it into its components:

$$\underbrace{-\ln \hat{\Phi}_{d,k}}_{k \text{ cost penalty}} \equiv \tfrac{\kappa}{\sigma-1} \underbrace{\ln \frac{\hat{f}_{d,k}}{\hat{\rho}_{d,k}}}_{k \text{ risk penalty}} + \tfrac{\kappa}{\sigma-1} \underbrace{\left(-\ln \hat{Q}_{d,k}\right)}_{k \text{ delay/quality penalty}} - \ln \hat{f}_{d,k}, \tag{16}$$

where we define a *risk penalty* and a *delay penalty*. Both operate through the productivity cutoff, so the sum of these two terms is the penalty on the entry margin, which we refer to as the entry penalty. The reduced form does not estimate the overall cost penalty directly, only the differentials across MECR status. But it does provide estimates of the risk penalty by MECR status and we can use these along with external data to bound the levels.

We start by decomposing the differential export cost penalty. Recall that $\Delta_A \ln \hat{\Phi}_{d,k} = \tilde{\delta}^{\text{Exports}}_{M,k}$ and that, from the average value margin, $\Delta_A \ln(\hat{f}_{d,k}/\hat{\rho}_{d,k}) = \tilde{\delta}^{v}_{M,k}$ is the risk penalty differential. Using (16) and taking the difference between MECR and other countries we obtain

$$-\tilde{\delta}^{\text{Exports}}_{M,k} = \frac{\kappa}{\sigma-1}\tilde{\delta}^{v}_{M,k} - \left(\tfrac{\kappa}{\sigma-1}\Delta_A \ln \hat{Q}_{d,k} + \Delta_A \ln \hat{f}_{d,k}\right).$$

We measure each term in turn. On the left, $\tilde{\delta}^{\text{Exports}}_{M,k}$ is 86 lp, from column 5 of Table 8. On the right, $\tilde{\delta}^{v}_{M,k}$ is 22.5 lp, from column 6, and enters scaled by $\kappa/(\sigma-1) = 1.2$, contributing 27 lp; the bracketed term is therefore the remainder, 59 lp. That bracket bundles the delay/quality and fixed cost differentials. We separate the two using the BIS approval rates from Section 2, which imply an 11 lp differential in the approval component $-\ln \hat{\rho}_{d,k}$; since the risk penalty is $\ln \hat{f}_{d,k} - \ln \hat{\rho}_{d,k}$, the differential in the fixed cost component $\ln \hat{f}_{d,k}$ is $22.5 - 11 = 11.5$ lp. The differential in the delay/quality component $-\ln \hat{Q}_{d,k}$ then follows from the bracket, $(59 + 11.5)/1.2 = 58.75$ lp. The last column of Panel A in Table 9 reports these differentials.

From differentials to levels. The GE counterfactuals below vary only these differentials. But it is also useful to provide a range for the penalties for each group of countries. The first two columns of Panel A report these levels: the penalties on controlled relative to non-controlled exports within each group. We use the average value margin to obtain the risk penalty for each group, 33 lp for non-MECR and 10.5 lp for MECR destinations.[26] We use the BIS approval rates to measure $-\ln \hat{\rho}_{d,k}$ and recover the fixed cost penalties $\ln \hat{f}_{d,k}$ as the remainders. Only the delay level requires new information. We calculate the cost arising from licensing delays for MECR countries

[26] From Table 8, column 6: the CCL classification effect for non-MECR destinations, and its sum with the MECR interaction.

Table 9: Structural Decomposition of Export and Entry Penalties (CCL)

	Parameter	Non-MECR ($\bar{A}$)	MECR (A)	$\bar{A} - A$
A. Friction Parameters				
Risk penalty	$\ln(\hat{f}_{d,k}/\hat{\rho}_{d,k})$	**33.00**	**10.50**	**22.50**
Approval contribution	$-\ln \hat{\rho}_{d,k}$	**18.00**	**7.00**	**11.00**
Fixed cost penalty	$+\ln \hat{f}_{d,k}$	**15.00**	**3.50**	**11.50**
Delay/quality penalty[a]	$-\ln \hat{Q}_{d,k}$	*81.75*	*23.00*	58.75
B. Export and Entry Penalties				
Export penalty[c]	$-\ln \hat{\Phi}_{d,k}$	*122.70*	*36.70*	**86.00**
Risk contribution	$\frac{\kappa}{\sigma-1}\ln(\hat{f}_{d,k}/\hat{\rho}_{d,k})$	39.60	12.60	27.00
Other (residual)	$-(\frac{\kappa}{\sigma-1}\ln \hat{Q}_{d,k} + \ln \hat{f}_{d,k})$	*83.10*	*24.10*	59.00
Entry penalty[b]	$\frac{\kappa}{\sigma-1}(\ln \frac{\hat{f}_{d,k}}{\hat{\rho}_{d,k}} - \ln \hat{Q}_{d,k})$	*137.70*	*40.20*	97.50

Notes: Values in log points (×100). **Bold**: identified directly (Table 8, rounded to nearest 0.5 lp) and BIS approval rates (second row); roman: computed from entries in bold and $\kappa = 3.0$, $\sigma = 3.5$; italics: country-group specific values that also rely on MECR penalty lower bound. [a] The MECR penalty is $-\ln \hat{Q}_{A,k} = \chi \bar{T}_{A,k}$, where $\bar{T}_{A,k} = 23.0$ days is the mean processing time for MECR (EAR-A) licenses (BIS, 2016–2022) and $\chi = 0.01$/day is the lower bound on time costs from Hummels and Schaur (2013). Non-MECR value adds the estimated differential. [b] Equivalently $\kappa \ln \hat{z}^*_{d,k}$: the reduction in firm entry relative to non-controlled goods, holding M fixed. [c] See equation (16) for the full decomposition.

as $\ln Q_{A,k} = -\chi \bar{T}_{A,k}$, with $\bar{T}_{A,k}$ the average licensing delay reported by BIS over this period, 23 days for MECR members, and χ the ad-valorem time cost of delay, for which we use the lower bound estimate of Hummels and Schaur (2013), 0.01 per day. The non-MECR delay level is then the sum of this MECR level and the differential already calculated (column 3).

Table 9 reports these results in log points. Entries in bold are estimated or measured directly, entries in roman are computed from them using κ and σ, and entries in italics are the levels that rely on the imputed delay cost. Appendix Table A8 reports the same decomposition for EAR99.

We begin by noting two broad points. First, all penalty measures in the first two columns of Table 9 are positive, implying higher costs relative to non-controlled exports. Second, the penalties are higher for non-MECR, as shown by the positive entries in the last column. Multiplying the risk penalty differential by $\kappa/(\sigma - 1)$ gives about 27 lp, over 30% of the export differential.

We next examine the three fundamental frictions one by one. Each is also more costly for non-MECR destinations:

- **Approval.** The approval penalty $-\ln \hat{\rho}_{d,k}$ is 18 lp for non-MECR versus 7 lp for MECR destinations.
- **Fixed costs.** The fixed cost penalty $\ln \hat{f}_{d,k}$ is 15 lp for non-MECR destinations but only a

Table 10: Differential Licensing Ad-Valorem Equivalents

	Export		Entry	
	CCL	EAR99	CCL	EAR99
LAVE (Non-MECR − MECR)	28.7	15.2	32.5	22.3

Notes: Respective penalty divided by $\kappa = 3$ from last column of Panel B in Tables 9 and A8.

modest 3.5 lp for MECR members.

- **Delay/quality.** The largest of the three, $-\ln \hat{Q}_{d,k}$, is 81.75 lp for non-MECR versus 23 lp for MECR. As a check against observed licensing outcomes, some of this 58 lp differential can be accounted for by time as a trade barrier. Using standard estimates (1% ad-valorem per day), the additional 20 days required to process licenses for adversary destinations relative to MECR members can explain about a third of the gap. The rest is interpreted as a quality friction.

In Panel B we also provide entry penalties. These capture reductions in firm export entry of controlled relative to non-controlled products, $\kappa \ln \hat{z}^*_{d,k}$. This is a hidden cost of the regulation: statistics on applications and approvals capture only firms that already invested in licensing. The entry penalty is almost 100 lp higher for non-MECR countries.

Licensing ad-valorem equivalents ($\ln \tau^y_{d,k}$). We summarize the export and entry penalties using the licensing ad-valorem equivalent (LAVE) costs of export controls. We define a LAVE $\ln \tau^y_{d,k}$ as the iceberg cost that generates the same effect as the penalty for outcome y (for a given set of existing firms M); in this setting this is simply the penalty scaled down by κ. In Table 10 we summarize these using the penalties in Table 9 for CCL and in Appendix Table A8 for EAR99. The export penalty for non-MECR is equivalent to facing an export iceberg cost about 29 lp higher than MECR countries for CCL and half that for EAR99. Using the decomposition we also obtain the corresponding values for entry: 33 and 22 lp for CCL and EAR99. So there is an important selection effect, which is larger for non-MECR destinations, particularly in the more stringent CCL category.

In sum, the decomposition clarifies the mechanisms underlying the partial equilibrium estimates. It allows us to provide economically interpretable frictions: approval risk, compliance fixed costs, and delay/quality costs. Each penalty is ordered as predicted by the model: systematically larger for non-members. Approval risk explains just under one third of the 86 log point export differential and the results are consistent with higher delay and quality costs for non-MECR countries. Importantly, we identify a nearly 100 log-point higher entry penalty for non-MECR than MECR destinations—a hidden cost borne by firms that never apply. The loss of MECR status corresponds to a 29 log-point iceberg cost on export value for CCL exporters and about 33 on the entry margin. These estimates

link export control costs to observable licensing outcomes and policy relevant frictions, which we vary in the general equilibrium counterfactuals in Section 7.

4.9 Alternative Identification: Control List Status Changes

The baseline estimates in Section 4.5 rely on cross-sectional variation in MECR membership to identify the differential effect of export controls. A potential concern is that MECR membership is correlated with persistent, *unobserved* country characteristics such as institutional quality, alliance depth, or the composition of import demand, which independently affect the level of controlled exports relative to uncontrolled.

We address this concern by exploiting discrete changes in countries' control list status between 2009 and 2024 as a different identification strategy. During this period, 30 countries experience an upgrade in their control list status, which we define as a country moving onto an EAR-A sublist (A:1 to A:4) or off an EAR-D sublist (including D:1 to D:5). Similarly, there are nine countries which are downgraded, i.e. moved onto EAR-D (sublists D:1 to D:5) or off an EAR-A sublist. Table A9 lists these reclassifications, their dates and motives. Importantly, we also document that these list changes are not driven by changes in U.S. export interests, but rather by events in the destination related to conflict, democratization or accession to a multilateral agreement. Thus the treatment timing and destinations are plausibly exogenous.

In Table 11 Panel A we estimate a simple difference-in-differences comparison of treated and never-treated countries separately for each control type. We find large effects on CCL exports in the expected directions—upgrades increase U.S. exports and downgrades decrease them. Exports without controls also decline following downgrades, but the point estimate is imprecise. This suggests that downgrades can coincide with armed conflict in the target country or other factors that depress their imports of all products. We can difference out those factors by extending the analysis to a triple-difference specification which uses non-controlled exports as a within country-time reference group:

$$\ln(Y_{dkt}) = \beta_k \, \mathbf{1}(\text{treated}_d) \times \mathbf{1}(\text{Post}_t) \times \mathbf{1}(\text{Ctrl}_k) + \alpha_{dt} + \alpha_{dkq} + \alpha_{kt} + \varepsilon_{dkt} \tag{17}$$

Here t denotes time (year-quarter) and q denotes quarter and the fixed effects absorb destination-time, destination-control-quarter, and control-time variation. Here β_k identifies how exports of controlled goods change relative to uncontrolled exports in treated countries versus never-treated countries, before versus after the reclassification. The estimation uses a stacked cohort design to address concerns about heterogeneous treatment timing in staggered difference-in-differences settings; details are provided in Appendix B.3.

Table 11 Panel B reports these triple difference results. Upgrades are associated with a statistically significant 33 log point increase in CCL exports relative to uncontrolled exports. Downgrades

Table 11: Export Effects of Control List Changes (Average Effects)

Dependent Variable:	exports (ln)			transactions (ln)		
	1	2	3	4	5	6
Panel A: Difference-in-Differences						
Sample:	No control	CCL	EAR99	No control	CCL	EAR99
Upgrade	0.05	0.373	0.091	0.003	0.171	0.088
	(0.082)	(0.124)	(0.109)	(0.066)	(0.085)	(0.062)
Downgrade	−0.573	−1.113	−0.565	−0.745	−0.708	−0.63
	(0.379)	(0.563)	(0.45)	(0.379)	(0.307)	(0.341)
Panel B: Triple Difference						
Sample:		CCL	EAR99		CCL	EAR99
Upgrade		0.329	0.035		0.171	0.08
		(0.059)	(0.047)		(0.032)	(0.023)
Downgrade		−0.67	0.007		−0.052	0.117
		(0.144)	(0.141)		(0.105)	(0.095)

Notes: Panel A estimates have country and time fixed effects with standard errors clustered by country. Panel B estimates have country-year-quarter, control-year-quarter and country-control-quarter fixed effects with standard errors clustered by country-control-quarter. Columns 1 and 4 display results for no control. Columns 2 and 5 display results for CCL, with Panel A showing within-CCL effects and Panel B showing effects relative to None. Columns 3 and 6 display results for EAR99, with Panel A showing within-EAR99 effects and Panel B showing effects relative to None. All regressions exclude the year-quarter prior to treatment, of treatment and after treatment. Treated cohorts are stacked so that never-treated countries are replicated across treatment waves, creating wave-specific datasets which are stacked to ensure identification comes from comparisons between treated cohorts and never-treated units.

are associated with a statistically significant 67 log point decrease. Reclassification has insignificant effects on EAR99 flows except for increased transactions after an upgrade.

These estimates reinforce the cross-sectional findings using a separate source of identifying variation. CCL exports are positively associated with MECR membership and the magnitudes exceed those for EAR99. Given the relatively small sample of switchers we focus on the cross-sectional estimates.

5 General Equilibrium with Dual-Use Inputs and Military Demand

Sections 3 and 4 characterize the effects of export controls on individual exporters. The relevant policy questions, however, are often comparisons across regimes, and the consequences that drive them are general equilibrium: controls reallocate trade across origins, propagate through input–output linkages, and shift firm entry and scale in the long run. We therefore develop a novel

quantitative framework to quantify the following:

- **Export Controls' GE Trade and Leakage Impacts.** How much of an origin's exports change in general equilibrium and what share is replaced by non-participating suppliers—i.e. what is the leakage rate and how much higher is it under unilateral vs. multilateral controls.
- **Export Controls' Income, Real Expenditure and Security Impacts.** The direction and magnitude of income and price effects that determine real civilian and military expenditure for both imposing and target countries and how to evaluate the security gain from reducing the adversaries' military purchasing power relative to one's own.
- **Regime design.** Multilateral versus unilateral control counterfactuals, the value of individual allies and marginal effects of controls across sectors.

In order to capture these outcomes, we embed the partial equilibrium mechanism of Section 3 into a multi-country, multi-sector general equilibrium model with firm entry and export selection, similarly to Melitz (2003), and roundabout input-output linkages as in Caliendo and Parro (2015). Three key extensions are: (i) within each sector, firms operate civilian or dual-use technology, each with its own input requirements, so that policy shocks propagate along both standard sectoral and technology-specific IO linkages; (ii) an export control policy block with the two components from Section 3—classification of products into regimes and regime-specific frictions; and (iii) endogenous exporting *and* entry, which generate external economies of scale. We describe the key elements next and summarize the notation and relation with Section 3 in Table A10.

5.1 Economic Environment

Countries, sectors, and product categories. Countries, indexed by o and d, are classified using the empirical groups defined earlier: allies, neutrals and adversaries, notated by A, N and V, respectively.

Within each sector $i, j \in \{1, \ldots, J\}$, firms produce differentiated intermediate goods and operate one of two technology types, $t \in \{C, D\}$: respectively civilian or dual-use. Civilian firms' output is disproportionately used by other civilian firms and civilian final consumers; dual-use firms' output is disproportionately used by other dual-use firms and the military. Both final users and intermediate buyers are indexed by $b \in \{C, D\}$; and when both subscripts are used, bt, this denotes a buyer with technology b and seller with technology t. Technology types are intrinsic features of the economy, shaping final demand composition and input sourcing.

Entry, classification, and control frictions. Potential entrants pay entry cost $f_e^{o,i,t}$ in labor units to enter in country o, sector i, technology t. Upon entry, they draw productivity $z \sim \text{Pareto}(\kappa^i)$ and are assigned export control classification $k \in \{\text{NC}, \text{EAR99}, \text{CCL}\}$ with probability $\Pr(k \mid t)^i$. This is the first component of export control policy: the *classification* of products into

control regimes. We model classification as probabilistic because, in the data, even within the same HS10 product exported to the same destination, individual shipments receive different export control classifications—some are classified as CCL, others as EAR99 or NC. Classification depends on the seller's technology type t, reflecting that dual-use producers face more stringent controls: $\Pr(\text{CCL} \mid D)^i > \Pr(\text{CCL} \mid C)^i$. We condition on seller type rather than buyer type, since regulators classify products based on technical characteristics at the point of production.[27]

The second component of the export control regime is the set of frictions introduced in Section 3, $\{\rho^i_{od,k},\ Q^i_{od,k},\ f^i_{od,k}\}$, now with sector superscripts. These do not vary by buyer or seller type directly; all type dependence enters through $\Pr(k \mid t)^i$.

Income and final demand of civilian and military users. Country d's income is $Y_d = w_d L_d$ and it is split between military and civilian final users so the income accounting identity and final user share definitions are respectively [28]

$$Y_d = Y_{d,C} + Y_{d,D} \quad ; \quad s_{d,b} \equiv Y_{d,b}/Y_d. \tag{18}$$

Preferences are Cobb-Douglas across sectors i with shares $\beta^i_{d,b}$, so type-b final demand is:

$$E^i_{d,b} = \beta^i_{d,b}\, Y_{d,b}. \tag{19}$$

Within each sector a final user b consumes a different non-traded composite of differentiated varieties, shown in Figure 4.

5.2 Production and Input-Output Linkages

Figure 4 illustrates the production and demand structure within a sector. Varieties are produced using civilian or dual-use technology, traded internationally subject to bilateral frictions (including export controls), and aggregated into non-tradable type-specific composite bundles. These bundles are combined via nested CES into a sectoral composite that serves both final consumption (civilian and military) and intermediate use in a roundabout input-output structure.

Unit cost. A type-t firm in sector i at origin o has unit cost:

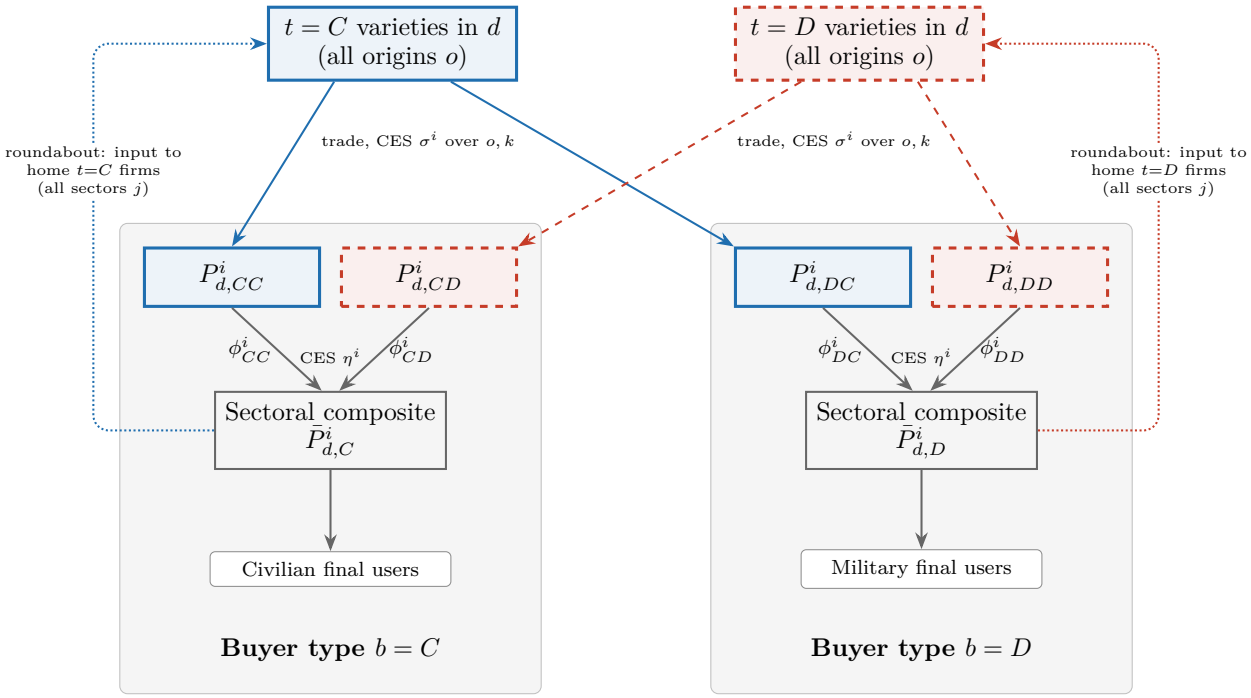
$$A^i_{o,t} = B^i_o\, w_o^{\gamma^{iL}_o} \prod_{j=1}^{J} (\bar{P}^j_{o,t})^{\gamma^{ij}_o}, \tag{20}$$

where B^i_o is a sector-origin cost shifter for country o, $\gamma^{iL}_o + \sum_j \gamma^{ij}_o = 1$, and $\bar{P}^j_{o,t}$ is the composite input price for type-t firms sourcing sector-j inputs. The partial equilibrium analog A_o is therefore

[27] For instance, NVIDIA's A100 and H100 chips were subject to export restrictions based on their technical specifications (compute performance thresholds), but different configurations of the same product line can receive different classifications.

[28] The calibration uses the observed military share, $s_{d,D}$, so we do not explicitly model this allocation; but it could be achieved via a non-distortionary tax by a government on its workers.

Figure 4: Production and Demand Structure within a Sector



Notes: The figure illustrates the production and demand structure of the model within a sector, as described in the text. Varieties are traded internationally subject to trade costs and export controls, and then aggregated for downstream intermediate and final users. Blue solid and red dashed elements denote seller technology $t = C$ and $t = D$; the shaded bands denote buyer type b. The dotted arrows show the roundabout use of the sectoral composite as intermediate inputs.

now a function of wages and intermediate input prices.

Composite input prices and shares. Input aggregation is nested CES, so that substitution across the two technology types can differ from substitution across varieties within a type. In the **lower nest** with elasticity σ^j, the individual type-t varieties in sector j are aggregated into a type-specific bundle with price index $P^j_{d,bt}$. This price index varies by the technology type of the downstream user b because in the presence of control frictions and technology heterogeneity, the mass of firms serving user b differs by firms' technology t. The **upper nest** has elasticity η^j and combines the C and D bundles into a composite with input price:

$$(\bar{P}^j_{d,b})^{1-\eta^j} = \sum_{t\in\{C,D\}} \phi^j_{bt} \left(P^j_{d,bt}\right)^{1-\eta^j}, \tag{21}$$

where ϕ^j_{bt} is the CES weight of a type-b firm on type-t inputs and $\sum_t \phi^j_{bt} = 1$. Dual-use firms are relatively intensive in dual-use inputs and civilian firms in civilian inputs ($\phi^j_{DD} > \phi^j_{CD}$ and $\phi^j_{CC} > \phi^j_{DC}$). The endogenous expenditure share of type-t inputs for a (d, b) user is:

$$s^j_{t|d,b} = \frac{\phi^j_{bt} \left(P^j_{d,bt}\right)^{1-\eta^j}}{(\bar{P}^j_{d,b})^{1-\eta^j}}. \tag{22}$$

5.3 Pricing, Demand, and Cutoffs

Pricing is identical to the partial equilibrium model, now with explicit type and sector indices. Revenue from type-b buyers under classification k:

$$r^i_{od,bt,k}(z) = Q^i_{od,k}\, p^i_{od}(z)^{1-\sigma^i}\, \frac{X^i_{d,bt}}{(P^i_{d,bt})^{1-\sigma^i}}, \tag{23}$$

where $X^i_{d,bt} = s^i_{t|d,b} X^i_{d,b}$ is the expenditure allocated by type-b buyers to type-t inputs.

The export cutoff generalizes (4):

$$(z^*_{od,bt,k})^{\sigma^i-1} = (\mu^i\, A^i_{o,t}\, \tau^i_{od})^{\sigma^i-1} \frac{\sigma^i\, w_o\, f^i_{od,k}}{\rho^i_{od,k} Q^i_{od,k} X^i_{d,bt} (P^i_{d,bt})^{\sigma^i-1}}. \tag{24}$$

Note that here the cutoff $z^*_{od,bt,k}$ varies with buyer type b (through demand $X^i_{d,bt}$ and price $P^i_{d,bt}$, since serving civilian versus military buyers involves separate entry decisions as explained below). The cutoff also varies with seller type t, both directly through unit cost $A^i_{o,t}$ and indirectly via $\Pr(k \mid t)^i$.

5.4 Price Indices and Trade Shares

Both the price index and the trade shares are built from the following bilateral competitiveness measure of origin (o,t) under classification k for (d,b) user:

$$\Lambda^i_{od,bt,k} = M^i_{o,t} \Pr(k \mid t)^i\, \rho^i_{od,k}\, Q^i_{od,k}\, (\mu^i A^i_{o,t} \tau^i_{od})^{1-\sigma^i}\, (z^*_{od,bt,k})^{-\theta^i}. \tag{25}$$

The terms in this expression reflect, respectively, the mass of potential exporters $M^i_{o,t}$ (determined by free entry below), the classification probability $\Pr(k \mid t)^i$, the fraction of approved and quality-adjusted shipments ($\rho^i_{od,k} Q^i_{od,k}$), cost competitiveness, and the selection cutoff term.

The sub price $P^i_{d,bt}$ aggregates this competitiveness over origins and classifications for seller type t; the second line below substitutes (24) and (25) to show the drivers of the price index: the mass of firms $M^i_{o,t}$, costs through wages and input prices, the control frictions $\Phi^i_{od,k}$ and $\Pr(k|t)^i$, and destination absorption $X^i_{d,bt}$ through selection.[29]

$$(P^i_{d,bt})^{1-\sigma^i} = \frac{\kappa^i}{\theta^i} \sum_{o,k} \Lambda^i_{od,bt,k} \tag{26}$$

$$(P^i_{d,bt})^{-\kappa^i} = \frac{\kappa^i}{\theta^i} (X^i_{d,bt})^{\theta^i/(\sigma^i-1)} \sum_{o,k} M^i_{o,t} \Pr(k \mid t)^i \Phi^i_{od,k} (\mu^i A^i_{o,t} \tau^i_{od})^{-\kappa^i} (w_o)^{-\theta^i/(\sigma^i-1)}. \tag{27}$$

The trade share, the fraction of type-b buyers' total expenditure in sector i sourced from origin o,

[29] We derive these price indices in Appendix C.2.

seller type t, classification k, is the normalized competitiveness:

$$\pi^i_{od,bt,k} = s^i_{t|d,b} \frac{\Lambda^i_{od,bt,k}}{\sum_{\tilde{o},\tilde{k}} \Lambda^i_{\tilde{o}d,bt,\tilde{k}}}. \tag{28}$$

Bilateral trade shares aggregate over classifications: $\pi^i_{od,bt} = \sum_k \pi^i_{od,bt,k}$.

5.5 Absorption, Entry, and Market Clearing

Total absorption by type-b buyers in sector i at d combines final and intermediate demand:

$$X^i_{d,b} = \beta^i_{d,b} Y_{d,b} + \sum_j \gamma^{ji}_d \frac{V^j_{d,b}}{\mu^j}, \tag{29}$$

where $V^j_{d,b}/\mu^j$ is the variable cost expenditure of type-b firms in sector j at d (i.e. its revenue adjusted by markup). The expression for total revenue is:

$$V^i_{o,t} = \sum_{d,b} \pi^i_{od,bt} X^i_{d,b}. \tag{30}$$

Potential entrants pay a sunk entry cost $f_e^{o,i,t}$ in labor units to draw productivity. Free entry requires that the expected profit per entrant equals the entry cost. We allow this cost to depend on the mass of entrants through a congestion parameter $\psi^i \geq 0$:

$$\frac{V^i_{o,t}}{M^i_{o,t}} \frac{1}{\kappa^i \mu^i} = w_o f_e^{o,i,t} (M^i_{o,t})^{\psi^i}, \tag{31}$$

where the left hand side is expected profit per entrant prior to drawing productivity.[30] The right hand side is the entry cost, rising in the mass of firms $M^i_{o,t}$ with an elasticity that captures congestion in entry. If $\psi^i = 0$, this is the standard Melitz model, but if $\psi^i > 0$ then the effective entry cost rises with the number of firms and this congestion dampens the variety response to changes in market conditions.[31] Total labor income is the sum across sectors of production labor and overhead labor. Production labor is labor's share γ^{iL}_o of variable cost $(\sigma^i - 1)/\sigma^i \; V^i_{o,t}$; overhead labor is used for the fixed export and entry activities, which under free entry is $1/\sigma^i \; V^i_{o,t}$:

$$w_o L_o = \sum_{i,t} \left(\gamma^{iL}_o + \frac{1 - \gamma^{iL}_o}{\sigma^i} \right) V^i_{o,t}. \tag{32}$$

[30] $V^i_{o,t}/M^i_{o,t}$ is expected revenue per firm, and $1/\kappa^i\mu^i$ is the share of sales that is profit net of production costs and fixed market-penetration costs across all markets.

[31] In the limit $\psi^i \to \infty$, the mass of varieties is effectively fixed. Monopolistically competitive models with endogenous entry feature strong external economies of scale. Estimates of their magnitude, however, vary across urban and trade settings. We allow for flexible scale effects through ψ and test robustness to it.

Real final civilian and military expenditures. We deflate the nominal expenditure for each final user b, $Y_{d,b}$, by the respective composite price index:

$$W_{d,b} = \frac{s_{d,b} Y_d}{\prod_i (\bar{P}^i_{d,b})^{\beta^i_{d,b}}}. \tag{33}$$

We refer to these as real expenditures of civilian, $b = C$, or military, $b = D$. The two differ via the nominal expenditure and price deflators, with the latter reflecting differential reliance on dual-use inputs. We will quantify changes in these real expenditures to evaluate the impact of export controls beyond the trade values. In Section 7.4 we show how governments that value civilian welfare and a security objective (increasing in relative real military expenditures) can evaluate trade-offs between these and across regimes.

General equilibrium. We define this as a collection $\{w_o, A^i_{o,t}, P^i_{d,bt}, \bar{P}^i_{d,b}, X^i_{d,bt}, X^i_{d,b}, V^i_{o,t}, M^i_{o,t}, Y_d, Y_{d,b}\}$ satisfying equations (18)–(32) together with the income identity $Y_d = w_d L_d$ and one wage normalization.

6 Calibration

We calibrate the model to match the global economy using the 2016 OECD ICIO tables with 21 sectors (Yamano et al. 2023). We assign each of the 77 countries and rest of the world to a group A, N, V using 2016 group status.[32] The **model primitives** are: elasticities $(\sigma^i, \kappa^i, \eta^i, \psi^i)$, IO coefficients $(\gamma^{ij}_d, \gamma^{iL}_d)$, demand shares $(\beta^i_{d,b})$, CES weights (ϕ^j_{bt}), labor endowments (L_o), military spending shares of income $(s_{d,D})$, trade costs (τ^i_{od}), classification probabilities $(\Pr(k \mid t))$, selection factors $(\Phi^i_{od,k})$, and entry costs $(f_e^{o,i,t})$. Table 12 summarizes the sources for these.

The calibration proceeds in two parts. First, we construct the two components of the control regime: the selection factor $\Phi^j_{od,k}$ under each control regime and the classification probabilities $\Pr(k \mid t)^j$ that map C and D goods into regimes. We build Φ, which governs firms' export response to control frictions, from the reduced-form estimates reported earlier and features of observed MECRs (Section 6.1), and we recover $\Pr(k \mid t)^j$ from the composition of exports (Section 6.2). Together, Φ and the classification probabilities are sufficient to calibrate the control regime and run counterfactuals.[33] Second, we calibrate the remaining model parameters jointly in equilibrium (Section 6.3).

[32] See Appendix B.1 for the list. Given its importance in U.S. trade, Canada is included in quantification as an A country.

[33] The frictions $\rho^i_{od,k}$, $Q^i_{od,k}$, and $f^i_{od,k}$ affect the aggregate equilibrium only through the selection factor $\Phi^i_{od,k}$ (equation (9)). They enter the bilateral competitiveness $\Lambda^i_{od,bt,k}$ (equation (25)), which in turn determines the trade shares $\pi^i_{od,bt,k}$, the price indices $P^i_{d,bt}$ and $\bar{P}^i_{d,b}$, wages w_o, and real expenditures $W_{d,b}$. Appendix C.3 shows this formally: substituting the cutoff (24) into Λ eliminates $z^*_{od,bt,k}$, and the three frictions then appear only in the combination $\Phi^i_{od,k}$.

Table 12: Calibration Parameters

Parameters	Description	Target/Source/Description
A. Externally Calibrated		
$\{\kappa^i\}$	Trade elasticity (Pareto shape)	Ossa (2015), median by ICIO sector
$\{\sigma^i\}$	CES demand elasticity	$\sigma^i = \kappa^i + 0.5$
η	Cross-technology CES	$\eta = 2$ (Section 6.3)
ψ	Entry congestion	$\psi = 5$ (Section 6.3)
$\{s_{d,D}\}$	Military spending share	World Development Indicators (World Bank 2025)
$\{L_d\}$	Labor endowment	PWT 9.0 (Feenstra, Inklaar, and Timmer 2016)
$\{\gamma_d^{ij}\}, \{\gamma_d^{iL}\}$	IO coefficients (country-specific)	OECD ICIO, 2016 reference year (Yamano et al. 2023)
$\{\beta_{d,D}^i\}$	Military final use shares	U.S. BEA 2012 benchmark make-use tables (BEA 2018); applied to all countries
$\{\beta_{d,C}^i\}$	Civilian final use shares	Residual: ICIO total − military (BEA 2018; Yamano et al. 2023)
$\{B_o^i\}$	Cost shifter	Normalized to 1 (absorbed by τ)
B. Jointly Calibrated		
$\{\tau_{od}^j\}$	Bilateral iceberg costs	ICIO bilateral trade shares
$\{\phi_{bt}^j\}$	Technology-specific input weights	Tech-specific IO shares (BEA)
$\bar{s}$	Dual-use classification threshold	CCL share of U.S. exports to MECR destinations
C. Pre-Determined		
$\{\delta_{M,k}^j\}$	DID export control penalties	Section 4
$\{\alpha_k^j, \delta_k\}$	Classification probabilities	Section 6.2
$\{\widehat{\Phi}_{A,k}\}$	Baseline compliance frictions (selection ratio)	Section 6.1

6.1 Constructing the Sufficient Statistic for Export Control Frictions

We first construct the selection factor $\Phi_{od,k}^j$, the sufficient statistic for control frictions, from our reduced-form estimates. We build from the simplest case outward. Non-controlled products ($k = \text{NC}$) do not require export licenses, face no regulatory processing delay, and have minimal compliance paperwork. We set $\rho_{od,\text{NC}}^j = 1$ (all shipments approved), $Q_{od,\text{NC}}^j = 1$ (no delay), and $f_{od,\text{NC}}^j = f_{oo}^j = 1$ (compliance cost normalized to the domestic fixed cost). This normalizes $\Phi_{od,\text{NC}}^j = \Phi_{\text{const}}^j \equiv (\sigma^j)^{-\theta^j/(\sigma^j-1)}$. In sum, NC products face no export control friction beyond

iceberg trade costs τ_{od}^{j}.[34] Countries outside MECRs do not impose export controls so we set $\Phi_{od,k}^{j} = \Phi_{\text{const}}^{j}$ for all k and any $o \notin A$.

Sales of controlled products face compliance costs even between MECR members. We capture this with a baseline friction that lowers the selection factor relative to non-controlled products: $\widehat{\Phi}_{A,k} < 1$ for $k \neq \text{NC}$, applied to all ally-origin trade regardless of destination. Because the reduced-form estimates difference out this ally baseline, we leverage the structural estimates in Section 4.8, which use MECR destination approval rates, processing delays, and compliance costs of controlled goods to compute the selection factor in levels (equation (9)). These give $\ln \widehat{\Phi}_{A,\text{EAR99}} = -0.051$ and $\ln \widehat{\Phi}_{A,\text{CCL}} = -0.367$, reflecting that even among allies, controlled products, especially CCL, face materially higher export control frictions than uncontrolled products.

Allies impose additional restrictions when exporting outside the MECR destinations. We recover these from the sector-specific DID estimates $\delta_{M,k}^{j}$ of Section 4.6 and Table A7, which directly identify the required log gap in selection factors in (13). Neutrals receive a fraction of this penalty, reflecting their intermediate regulatory status. Combining the components, the selection factor is:

$$\Phi_{od,k}^{j} = \underbrace{\exp\Big(-\delta_{M,k}^{j}\,\mathbf{1}_{\text{ally}_o}\,\mathbf{1}_{o\neq d}\,d_{od}\Big)}_{\text{DID penalty (estimated)}}\underbrace{(\sigma^{j})^{-\theta^{j}/(\sigma^{j}-1)}\widehat{\Phi}_{A,k}^{\mathbf{1}_{\text{ally}_o}\mathbf{1}_{o\neq d}}}_{\text{baseline (differences out)}}. \tag{34}$$

We set the d_{od} to 1 for ally-to-adversary trade, 1/3 for ally-to-neutral, and 0 between allies.[35] Thus, only ally-origin exports are subject to controls. We estimate $\delta_{M,k}^{j}$ separately by ICIO sector. Ten manufacturing sectors have positive and statistically significant estimates for both CCL and EAR99, which we refer to as the controlled sectors; Appendix Table A7 reports them. These sectors account for 99% of U.S. manufacturing CCL exports and 53% of manufacturing EAR99 exports. We set $\delta_{M,k}^{j} = 0$ for the remaining goods sectors so they bear no differential control across destinations; service sectors have no classified goods in our data and face no control frictions.

6.2 Parameterizing Classification Probabilities

We now estimate the classification probabilities $\Pr(k \mid t)^{j}$ over $k \in \{\text{NC}, \text{EAR99}, \text{CCL}\}$. Classification is probabilistic: the same type-t product can be assigned to a different control by BIS. We treat each NAICS 6-digit industry as a distinct product within its ICIO sector j; we assume each product is either civilian (C) or dual-use (D), and $\Pr(k \mid t)^{j}$ is the probability that a type-t product in sector j is classified as k. We first label each product C or D, then estimate $\Pr(k \mid t)^{j}$ from the export composition of these products across classifications. Absent selection, that composition would equal $\Pr(k \mid t)^{j}$; but since controlled products face higher export cutoffs, they are underrep-

[34] In principle, fixed export costs $f_{od,\text{NC}}^{j}$ could differ between domestic and international trade. We let τ_{od}^{j} absorb all non-control bilateral differences, so Φ isolates the regulatory component.

[35] This is consistent with the time series estimates in Panel A of Table 11. They imply that an upgrade increases CCL exports by 37 lp, whereas a downgrade reduces them by 111 lp. We therefore set the neutral-country penalty to approximately one third of the full ally-to-adversary penalty.

resented in the trade data. Using the structure of the model we correct for this selection, which could be quantitatively important.

Parameterization. We model the classification probabilities using a multinomial logit:

$$\Pr(k \mid t)^j = \frac{\exp(\alpha_k^j + \delta_k \mathbf{1}_{t=D})}{\sum_{k'} \exp(\alpha_{k'}^j + \delta_{k'} \mathbf{1}_{t=D})}, \qquad \alpha_{\text{NC}}^j = \delta_{\text{NC}} = 0 \text{ (normalization)}. \tag{35}$$

The sector fixed effects α_k^j capture the differences across ICIO sectors in their likelihood of including controlled goods. Other transport equipment manufacturing, a sector that includes aircraft and submarines, for example, has a far higher CCL share than textiles or food products, and these cross-sector differences are absorbed by α_k^j. Additionally, within any given industry the $t = D$ producers are more likely to face strict classification because their products are more likely to have dual-use applications. The parameter δ_k captures this within-industry dual-use premium in classification. We restrict δ_k to be common across industries because the CCL targets dual-use technology regardless of sector. Classification does not depend on destination d or buyer type b, since regulators classify products based on technical characteristics at the point of production.

Classifying products as civilian (C) or dual-use (D). We classify each 6-digit NAICS industry as C (civilian) or D (dual-use). For each NAICS 6d code, we compute the share of U.S. exports (by value to MECR destinations) that carry a CCL classification, averaging over 2016–2024 to obtain a long-run measure. We label an industry n as D if its CCL export share exceeds a threshold $\bar{s}$:

$$\text{dual-use}_n = \mathbf{1}\left[\frac{\text{CCL exports}_n}{\text{total exports}_n} > \bar{s}\right]. \tag{36}$$

We set $\bar{s} = 0.15$ so the model's aggregate share of CCL exports to MECR countries matches the observed share (Section 6.3). This binary classification affects two model objects: (i) the classification probabilities $\Pr(k \mid t)^j$ estimated below, and (ii) the technology-specific IO share targets $s_{t|b}^{j,\text{target}}$ used in the joint calibration. Of 366 NAICS 6-digit manufacturing codes with export data, 53 (14%) are classified as dual-use. These dual-use industries are concentrated in the high-control-intensity sectors documented in the stylized facts (Section 2, Table 3), notably aerospace and other transport equipment, and computers and electronics. Appendix C.4 lists example industries (Table C1).

An external benchmark corroborates this classification. Using the U.S. BEA input-output tables, we compute each NAICS-6 industry's share of sales to federal defense investment use; this defense-intensity share has a correlation of 0.49 with the CCL export share.[36]

We use the 2016 Census FTD special tabulations, which record U.S. exports by destination, product, and export control classification. We aggregate to the destination × NAICS-6d × classification level and restrict to MECR destinations; the unit of observation is a NAICS 6d (n) ×

[36] We also used a large language model to map CCL and NAICS-6 via their official detailed descriptions, which generates an independent dual-use indicator by NAICS-6; regressing this independent indicator on our CCL share measure yields a coefficient of 0.5.

destination (d) pair. For each observation, the log composition ratio satisfies

$$\ln \frac{s_{k,nd}}{s_{\mathrm{NC},nd}} = \delta_k \, \mathbf{1}_{t_n=D} + \underbrace{\alpha_k^{j(n)} + \ln \widehat{\Phi}_{A,k}}_{\text{sector baseline + selection ratio}} + \varepsilon_{nd}, \tag{37}$$

where $\frac{s_{k,nd}}{s_{\mathrm{NC},nd}}$ is product n's ratio of $k \in \{EAR99,\ CCL\}$ and NC exports to d. On the right hand side, the first term is the dual-use premium in the likelihood of being controlled. The bracketed term combines the sector-level classification baseline α_k^j with the ally selection ratio $\widehat{\Phi}_{A,k}$, the relative exporter selection induced by control-specific approval, delay, and compliance frictions.

We estimate (37) with sector × destination fixed effects, which absorb the bracketed baseline, so the coefficient on $\mathbf{1}_{t=D}$ identifies the dual-use premium δ_k from the within-cell D–C composition difference. We then back out the sector intercept α_k^j from the *level* of the log ratio by plugging the estimated $\tilde{\delta}_k$ and the selection ratio implied by the baseline compliance frictions of Section 6.1 into (37). Appendix C.4 presents the full two-step estimation and the resulting estimates (Table C2).

Classification probability. Given $(\tilde{\alpha}_k^j, \tilde{\delta}_k)$, the classification probabilities follow directly from (35). Table C3 reports the resulting probabilities by sector. The large dual-use premium $\tilde{\delta}_{\mathrm{CCL}}$ means a higher likelihood of being CCL for D-type producers: for example, in computers and electronics $\Pr(\mathrm{CCL}|D) = 44.4\%$ versus $\Pr(\mathrm{CCL}|C) = 8.6\%$; in electrical equipment, $\Pr(\mathrm{CCL}|D) = 27.2\%$ versus 4.2%. Without the selection correction (the $\widehat{\Phi}_{A,k}$ term in equation (37)), these probabilities would have been 36.0% and 6.2% in computers and electronics, and 20.9% and 3.0% in electrical equipment.

6.3 Calibration and Export Composition Fit

Given the estimated $\Phi_{od,k}^j$ just discussed, we set the remaining parameters either externally or through joint calibration to match observed data, as described below.

Trade elasticities. We pin down the Pareto shape κ^i based on the trade elasticity estimates of Ossa (2015), using the median of his HS-product-level estimates within each ICIO sector. The CES demand elasticity σ^i governs markups and the intensive margin of firm-level exports. The model requires that $\kappa^i - (\sigma^i - 1) > 0$; we set the difference to a common 0.5 across sectors, which pins down $\sigma^i = \kappa^i + 0.5$. The across-type elasticity η governs substitution between C- and D-technology composite inputs. Switching between civilian and dual-use input bundles requires retooling supply chains and is harder than substituting among varieties of the same type, so η lies below the within-type elasticity; we set $\eta = 2$, below the values we set for σ^i.

Scale parameter. With endogenous entry, the model features strong external economies of scale, which the congestion parameter ψ dampens; $\psi = 0$ corresponds to no congestion, as in the standard Melitz model. We set $\psi = 5$ in the baseline, which dampens external economies of scale to a level within the range of existing estimates. We discuss the implication of this choice and robustness to it in Appendix C.7.

Military expenditure shares. For each country d, we set the exogenous military spending share $s_{d,D}$ to match military expenditures as a fraction of GDP using the World Development Indicators series `MS.MIL.XPND.GD.ZS`, whose underlying source is SIPRI. This share is held fixed across counterfactuals, so military and civilian final demand respond proportionally to changes in nominal income.

Input–output coefficients. We take the IO coefficients γ_d^{ij} and labor shares γ_d^{iL} from the 2016 OECD ICIO tables: $\gamma_d^{iL} + \sum_j \gamma_d^{ij} = 1$ for all (d, i).

Military and civilian final demand shares. The OECD ICIO reports total final demand by sector for each country, but does not decompose it into military and civilian end users, and sector-level military demand is not reported for most countries. We therefore use the U.S. BEA make-use tables for federal defense consumption to construct military final use shares of sectors $\beta^i_{\text{US},D}$ (see Appendix C.5), and apply these shares to all countries: $\beta^i_{d,D} = \beta^i_{\text{US},D}$. We construct civilian shares $\beta^i_{d,C}$ by subtracting the military component from ICIO total final demand levels in each sector.

Bilateral iceberg costs τ^j_{od}. We calibrate the trade costs τ^j_{od} to match aggregate bilateral trade shares π^j_{od} from 2016 OECD ICIO tables. The ICIO data record total bilateral flows without distinguishing product classification or buyer and seller type. The model-implied aggregate shares sum over all three:

$$\pi^{j,\text{model}}_{od} = \sum_{b,t,k} \frac{X^j_{d,b}}{\sum_{b'} X^j_{d,b'}} \pi^j_{od,bt,k}, \tag{38}$$

where $\pi^j_{od,bt,k}$ is given by (28). We choose τ^j_{od} so that $\pi^{j,\text{model}}_{od} = \pi^{j,\text{data}}_{od}$ for all (d, o, j).[37]

Technology-specific input weights ϕ^j_{bt}. We calibrate the CES weight parameters ϕ^j_{bt}, which govern how intensively type-b firms use type-t inputs in sector j, to match input-use share targets $s^{j,\text{target}}_{t|b}$ constructed from U.S. BEA make-use tables (2012 benchmark) where each supplying and using NAICS-6 code is labeled C or D via the classification in (36). Appendix Table C4 summarizes these targets: dual-use buyers source 17% of their inputs from dual-use suppliers, civilian buyers 11%. The model-implied expenditure share of type-t inputs for type-b firms is:

$$s^{j,\text{model}}_{t|d,b} = \phi^j_{bt} \left(\frac{P^j_{d,bt}}{\bar{P}^j_{d,b}} \right)^{1-\eta^j}. \tag{39}$$

These shares vary by country due to variations in relative prices. We choose the invariant ϕ^j_{bt} so that $s^{j,\text{model}}_{t|\text{US},b} = s^{j,\text{US target}}_{t|b}$ for all (b, t, j).

Dual-use classification threshold $\bar{s}$. The threshold $\bar{s}$ in (36) governs the C/D split and thereby $\Pr(k \mid t)^j$ and $s^{j,\text{target}}_{t|b}$. We choose $\bar{s}$ to match the U.S. aggregate CCL export share to

[37] Since the cost-shifter parameters B^i_o are not separately identified from bilateral trade costs in trade share data, we normalize $B^i_o = 1$ for all (o, i) and let τ^j_{od} absorb all bilateral variation.

Table 13: U.S. Export Composition to Other Allies in Model vs. Data

Classification	Data (%)	Model (%)
All goods sectors		
NC	52.2	55.7
EAR99	32.3	29.2
CCL†	**15.6**	**15.1**
Sectors with significant estimated control effects		
NC	28.6	27.6
EAR99	17.3	16.0
CCL	15.3	14.9

Notes: All entries are percentages of total U.S. goods exports to other MECR countries (common denominator across both panels). Data: Census FTD special tabulations (2016). Model: calibrated equilibrium. The lower panel restricts the numerator to exports in the 10 (of 21) ICIO sectors with significant estimated control effects ($\delta^j_{M,k} \neq 0$). † The CCL row is the calibration target (via $\bar{s}$); all other rows are untargeted.

MECR destinations: 15.6% in the trade data for these countries, 15.1% in the model at $\bar{s} = 0.15$. Table 13 reports the full export composition fit. All shares are expressed as a percentage of total U.S. goods exports to allies. The lower panel restricts the numerator to the 10 ICIO sectors with nonzero estimated control effects $\delta^j_{M,k}$ (Section 4), keeping the same denominator; these sectors drive the counterfactual results. The NC and EAR99 shares are not targeted directly but the model matches them closely (e.g., NC in controlled sectors: 28.6% data vs. 27.6% model).

7 Export Control Regime Counterfactuals

We use the calibrated model to evaluate the impacts of export controls on trade, prices and real civilian and military expenditures. We compute three policy scenarios each relative to a common "no-controls" counterfactual in which all MECR members drop the estimated differential controls on non-members.[38]

We report results for the **baseline** calibration scenario, but focus the discussion on the **MECR24** scenario, which better captures the more recent regime. In both scenarios the MECR countries apply the same differential controls toward non-members. Controls have tightened sharply since the early 2010s, particularly for adversaries, as shown in stylized Fact 4. Approval rates fell about 15 percentage points on average for adversaries (Figure 2a). In the underlying data, approval rates fall from 82% to 70% for China and from 90% to 15% for Russia, and their processing delays have also increased. Thus we recompute the selection factor for CCL by increasing delays by 60 days and reducing approval rates by 12 pp and 75 pp for China and Russia, respectively. For the remaining

[38]Specifically, we set the DID penalty term in equation (34) to zero, so EAR99 and CCL exports to adversaries and neutrals no longer bear the estimated penalties $\delta^j_{M,k}$, which apply in the 10 sectors with significant control effects.

adversaries we reduce approval rates by 15 pp and add 35 additional days of delay.[39]

After assessing the impact of MECR24 on trade, prices and real expenditures we show its implications for changes in national security and its civilian cost. To quantify the value of MECR24 to the U.S. we compare it to the **U.S.-Unilateral** regime where other MECR countries remove their controls on non-members. Finally, we use the framework to quantify the economic and security contribution to the U.S. of including any one country in the MECR and of marginally tightening controls on each sector.

7.1 Global Trade Impacts of Export Controls

Table 14 reports the trade impacts of export controls. These reflect general equilibrium effects from linkages and entry, and quantify not only the direct effect of controls on exports to specific countries but also how much of it is replaced by non-controlled suppliers, i.e. the leakage rate. All results are relative to a counterfactual where differential controls on non-allies are removed.

Panel A shows that the MECR24 controls substantially reduce U.S. exports to adversaries: −162 lp for CCL and −34 lp for EAR99. Other allies also reduce their controlled exports to adversaries, at similar rates to the U.S., but their absolute value decline is substantially larger—$329 billion against $88 billion for the U.S.—which is the first sign of the allies' importance.

Panel B reports adversary imports from all origins, which fall by less than ally exports in any given controlled category. This occurs because of non-ally export substitution, i.e. control leakage. Specifically, adversary CCL imports fall by $211 billion, whereas total ally CCL exports to them fall by $227 billion. The $15 billion difference is the increase from non-controlling countries and dividing it by $227 billion we obtain a CCL leakage rate of 6.7%. Aggregating CCL and EAR99 values we obtain the 6.9% leakage figure reported in Panel D.

We can also define leakage for each country V targeted by a set of countries, $o \in \mathcal{A}_V$, as follows

$$Leakage_V \equiv \frac{\sum_{o \notin \mathcal{A}_V, o \neq V} \Delta X_{oV}}{-\sum_{o \in \mathcal{A}_V} \Delta X_{oV}} \in [0,1], \tag{40}$$

so the aggregate 6.9% rate is obtained by weighting these country rates by their share in the total reduction of ally controlled exports. Country leakage varies by an order of magnitude over countries, from 3.8% for China to 37% for Burma, with a mean substantially higher than 6.9%, indicating lower leakage for countries with higher weights.

Panel C reports exports across all products and destinations, which fall for allies. U.S. total exports are 5.7 lp lower than with no controls, an $85 billion reduction, equivalent to nearly three-

[39] The approval rate enters directly through equation (9) as does the added delay, which we value at $\chi = 0.01$/day based on the estimates in Hummels and Schaur (2013).

Table 14: Trade Impacts of Export Controls

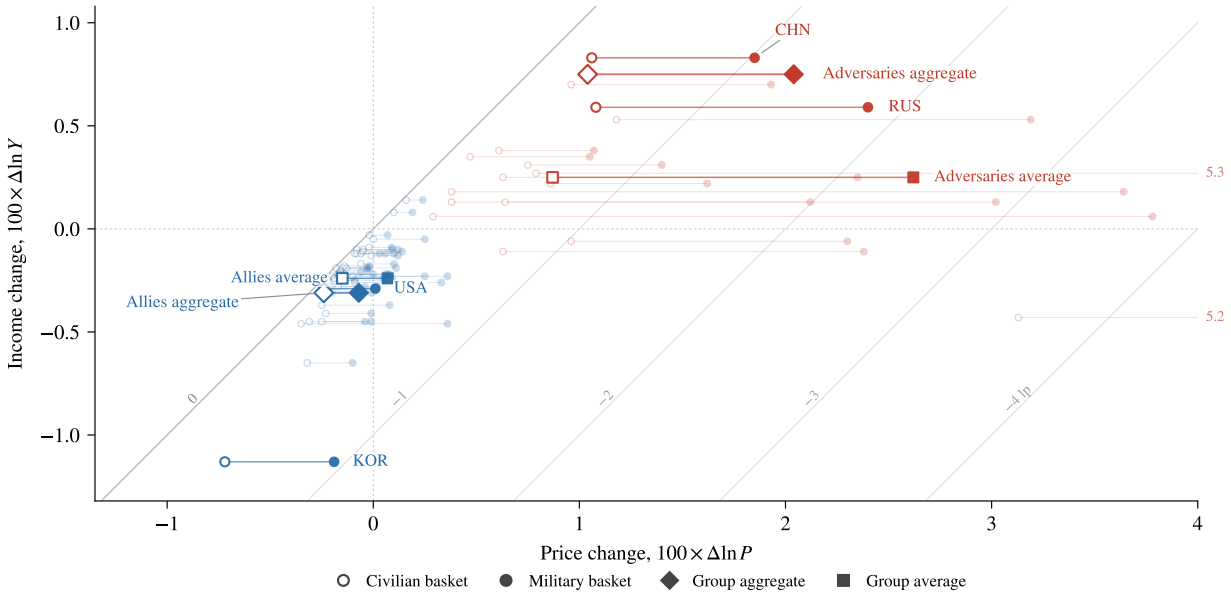
	(i) Baseline vs. none		(ii) MECR24 vs. none		(iii) U.S.-unilateral vs. none	
	$100 \times \Delta \ln$	Δ$B	$100 \times \Delta \ln$	Δ$B	$100 \times \Delta \ln$	Δ$B
Panel A: Exports of Allies to Adversaries						
U.S. origin						
CCL	−79.2	−45.9	−161.6	−67.3	−187.1	−71.1
EAR99	−35.0	−21.3	−33.5	−20.5	−39.3	−23.5
Total†	−17.7	−53.7	−24.0	−70.8	−31.5	−89.6
Other Allies						
CCL	−69.5	−100.7	−157.3	−159.2	7.8	16.4
EAR99	−37.8	−173.5	−36.7	−169.5	1.0	5.7
Total†	−11.3	−199.6	−13.8	−240.8	1.8	34.0
Panel B: Imports of Adversaries from all origins						
CCL	−38.0	−136.2	−67.5	−211.4	−12.9	−52.3
EAR99	−20.5	−183.6	−19.6	−176.3	−1.6	−16.0
Total†	−6.1	−211.1	−7.5	−256.8	−1.4	−47.7
Panel C: Total Exports of Allies to all destinations						
U.S.	−4.5	−67.4	−5.7	−84.6	−7.3	−106.7
Other Allies	−2.5	−256.2	−2.9	−300.3	0.4	40.1
Panel D: Leakage of Controlled Exports to Adversaries						
CCL + EAR99	6.3%		6.9%		27.8%	

Notes: $100 \times \Delta \ln$ denotes the change in log points. Δ$B is the change in the dollar level of the flow relative to the no-controls counterfactual, in billions. All three scenarios are reported relative to the no-controls counterfactual. Scenario definitions: (i) the calibrated baseline MECR; (ii) MECR24, which adds heightened CCL controls on China and Russia (CHN approval rates from 82% to 70%, RUS from 90% to 15%, plus a 60-day processing delay) together with a broad-based tightening on the other adversary destinations (−15 percentage points in CCL approval, +35-day delay), applied by all allied countries; (iii) U.S.-unilateral, in which the U.S. retains its tightened MECR24 CCL frictions on adversary destinations while non-U.S. allied countries drop their destination-specific penalties. † Sum of CCL, EAR99 and non-controlled. Leakage is the share of reduction in controlled export value to adversaries offset by countries not imposing controls in a given scenario and is defined in (40) for each adversary destination.

quarters of U.S. goods exports to China in 2016 ($116 billion). Other allies' exports are 2.9 lp lower. Thus any general equilibrium export shift to other products and destinations is insufficient to offset the export control reduction.

Comparing MECR24 to the baseline columns we learn the impact of tightening the CCL controls. The longer delays and lower approval rates under MECR24 reduce adversary CCL imports by an additional $75 billion. The EAR99 flows, which face similar controls across scenarios, barely change, and the overall leakage rate increases from 6.3% to 6.9%.

Figure 5: Income and Price Effects of MECR24 Controls: Civilian and Military



Notes: The vertical axis measures nominal income changes, $100\Delta \ln Y$, which are equal to nominal expenditure for both users. The diagonals are the real-expenditure contours, $100\Delta \ln \frac{Y}{P_b}$. We mark the value of military price index increases above 5 lp. Blue denotes Allies and red Adversary countries.

7.2 Nominal Income and Price Impacts of Export Controls

We examine how controls affect incomes and price indices, both their magnitudes and channels; in Section 7.3 we combine these into real expenditure effects.

Income and Expenditure. Nominal income effects reflect a country's wage change relative to the world. Controls lower the exports of the imposing countries, which reduces their labor demand and wages. In the target countries the reverse occurs: domestic production replaces controlled imports, which raises their wages and income. Thus we expect the income effects to go in opposite directions across these groups.

The income effects for MECR24 are plotted on the vertical axis of Figure 5 for all allies and adversaries. We label their respective aggregates and a few interesting countries, while the remaining observations show the cross-country dispersion. Income falls for all but two allies. The change is −0.29 lp for the U.S., which is similar to the overall allies' average. The average income change for adversaries is 0.25 lp, with the largest gain for China, 0.83 lp.

These income effects also measure the exact nominal expenditure growth of both civilian and military final users since their shares of income, $s_{d,b}$, are held fixed in the counterfactual. This channel operates in other quantitative trade models. What is specific to ours is that the trade shock has differential impacts on inputs and thus on final user prices.

Price Indices. The price index growth for each final user in a country is plotted on the horizontal axis of Figure 5. The MECR24 controls decrease the civilian price for Allies; the change is −0.15 lp

on average and −0.24 lp for the U.S. The civilian price increases for all adversaries—by 0.87 lp on average—because their nominal wage increases and their controlled inputs from allies are costlier. The adversary military price index rises by about 2.6 lp on average, which is considerably more than for civilians. Three features of the model produce this gap. First, military final demand is dominated by D goods and civilian demand by C goods. Second, D producers use other D goods as inputs more intensively than C producers do, which amplifies the effect of controls along the D supply chain. Third, D goods are more likely than C goods to face controls. The importance of these features in the data generates substantially larger price effects for the military final user.

The sectoral effects underlying the overall index are largest in the control-intensive sectors, as reported in Table C5. Controls raise the price of aerospace and other transport equipment by 18.7 lp on average for adversaries, which accounts for most of the 2.6 lp overall average, with other important contributions coming from price increases in motor vehicles (6.8 lp), and computers and electronics (2.8 lp). However, these three sectors account for only 20% of military expenditure, which limits the aggregate price impact of controls.[40]

For Allies, the military price index rises by 0.07 lp while the civilian index falls by 0.15 lp, a relative increase of 0.22 lp on average; for the U.S. the relative increase is 0.25 lp. The key mechanism explaining this relative increase is economies of scale.[41] Controls lower export revenue for the imposing countries and thus the entry and domestic variety of D producers, which raises D input prices (see (27)), both directly and via input-output linkages, and this raises the military price deflator relative to the civilian. In Appendix C.7 we quantify how sectoral scale economies magnify this price differential for Allies. This force shrinks the price differential for adversaries since, as they substitute towards domestic suppliers, their domestic D input variety expands, which partially offsets the effect of controls on imports. Thus economies of scale limit how much controls raise the military price index in the target relative to the control country and, in turn, the effect on relative real military expenditure, which we now examine.

7.3 Real Civilian and Military Expenditure Impacts of Export Controls

Real expenditures are defined in (33), so their growth is simply the difference of the income and price channels just discussed. Since these go in opposite directions for several countries, the impact of controls on real expenditures is a quantitative question.

Real civilian expenditure falls for all countries under MECR24. We can see this in Figure 5 since all points are below the zero real-expenditure contour, which marks no change. The reduction is 0.05 lp for the U.S. and 0.09 lp for allies on average (Table 15, Panel A, column 3). Adversaries'

[40] Table C5 also reports estimates by country and we see that Russia is typical in terms of the overall and sectoral effects. China is less affected than the average both overall, and specifically in the aerospace and motor vehicles sectors, which is consistent with a greater ability to substitute imported inputs with domestic ones.

[41] The military price index does not change much for most allies because of two offsetting forces. The lower wage reduces costs, but smaller scale increases them. The wage effect is similar for the civilian price and so the difference between the two reflects the scale economies.

Table 15: Real Expenditure Impacts of Export Controls (log points)

	(i) Baseline vs. none		(ii) MECR24 vs. none		(iii) U.S.-Unilateral vs. none	
	Civ.	Mil.	Civ.	Mil.	Civ.	Mil.
Panel A: Allies						
USA	−0.04	−0.23	−0.05	−0.30	−0.04	−0.28
DEU	−0.11	−0.36	−0.12	−0.45	0.01	0.06
JPN	−0.12	−0.33	−0.14	−0.41	0.01	0.03
KOR	−0.33	−0.71	−0.41	−0.94	0.04	0.10
Allies average	−0.07	−0.24	−0.09	−0.31	0.00	0.01
Allies aggregate	−0.07	−0.20	−0.07	−0.24	−0.01	−0.03
Panel B: Adversaries						
CHN	−0.19	−0.79	−0.23	−1.02	−0.05	−0.40
RUS	−0.41	−1.29	−0.49	−1.81	−0.07	−0.45
EGY	−0.19	−2.63	−0.20	−3.46	−0.01	−0.32
VNM	−0.91	−1.95	−1.02	−2.36	−0.13	−0.56
PAK	−0.11	−0.58	−0.12	−0.70	−0.02	−0.13
Adversaries average	−0.53	−1.85	−0.62	−2.37	−0.10	−0.56
Adversaries aggregate	−0.24	−0.99	−0.29	−1.29	−0.05	−0.42
Panel C: Neutrals						
SGP	−0.29	−0.79	−0.27	−0.76	−0.14	−0.38
THA	−0.16	−0.38	−0.15	−0.36	−0.02	−0.06
MYS	−0.11	−0.27	−0.10	−0.23	−0.01	−0.03
Neutrals average	−0.18	−0.76	−0.18	−0.77	−0.03	−0.15
Neutrals aggregate	−0.21	−0.76	−0.21	−0.78	−0.05	−0.25

Notes: All entries are $100 \times \Delta \ln x$, where x is real expenditure by Civilian or Military defined in (33). The counterfactual scenarios are defined in Table 14. The full list of Allies, Neutrals and Adversaries is in Appendix B.1 and, if in ICIO, used to calculate the aggregate and average rows.

losses are larger, 0.62 lp on average and 0.23 lp for China (Panel B). Since civilian expenditure accounts for about 96% of final consumption, these effects would be close to the welfare effects that a standard input-output model without the C vs. D distinction would report, and they are the relevant measure of the economic cost of controls. These costs are comparable to the real wage impacts of the 2018 trade war in a standard quantitative model.[42]

Real military expenditure also falls in all countries under MECR24, and by more than civilian expenditure, reflecting the relative military price increases described above. The price and income channels contribute very differently across groups. For adversaries, the price channel dominates and offsets their income gains, so their real military expenditure changes by −2.37 lp on average

[42]Those impacts are −0.13% for the U.S. and −0.11% for China, when we exclude tariff revenue, according to Caliendo and Parro (2022). Their quantification implies a U.S. export reduction of 7.8%, about 2 pp larger than under MECR24.

and −1.29 lp in the aggregate (Table 15, Panel B, column 4). For the U.S., the military price index is essentially unchanged, so the 0.30 lp decline in real military expenditure comes almost entirely through the income channel. Therefore controls also impose a military cost on the U.S.

A central purpose of export controls is to limit adversaries' capabilities relative to one's own. Controls may therefore be desirable even if they lower the U.S. real expenditure, so we also examine their effects relative to adversaries. Figure 5 shows that U.S. real expenditure rises relative to each adversary for both final users. The U.S. civilian point lies close to the zero expenditure contour whereas all adversary observations lie below it. Relative to the adversary aggregate, U.S. real civilian expenditure rises by 0.24 lp. The real increase is even larger for the military, which rises by 0.99 lp relative to the adversary aggregate. Offsetting income and price effects remain important in accounting for these relative magnitudes. The adversary aggregate military price index rises by 2.03 lp relative to the U.S., but about half of that is offset by their relative nominal income increase of 1.04 lp.

In sum, controls increase the real military expenditure of the U.S. relative to adversaries. If national security increases with this relative expenditure, then controls improve it. This raises two questions: what is the price of this security increase, and how efficiently does MECR24 deliver it compared with other regimes. Answering them requires a government objective, which we turn to next.

7.4 The Price of National Security

To evaluate the trade-offs associated with export controls we formalize a simple government objective and map it to the outcomes and counterfactuals we perform. In Appendix C.8 we provide a microfoundation based on a government that values an economic and security outcome, with a contest function mapping increases in relative real military expenditures into increases in security.

Our analysis adopts the perspective of the U.S., given its historically important role in MECRs and the data we use. Since we are comparing alternative regimes we focus directly on the change in the objective in a regime, e, versus a baseline (generally no controls). To a first order that change is captured by

$$\Delta_e G_{US} = \underbrace{\Delta_e \ln W_{US,C}}_{\text{Economic Impact}} + \alpha \underbrace{(\Delta_e \ln W_{US,D} - \Delta_e \ln W_{V,D})}_{\text{Security Impact}}. \tag{41}$$

The "Economic Impact" reflects the change in real civilian expenditure for the U.S., which we previously discussed. The "Security Impact" is defined as the change in the U.S. real military expenditure relative to a set of adversaries. Here we focus on the aggregate, $W_{V,D} \equiv \sum_{d \in V} W_{d,D}$, but we can also apply it to any given country or their average. The parameter $\alpha > 0$ reflects the relative value of these outcomes in the government objective.[43]

[43] In Appendix C.8 we discuss alternative aggregation approaches for alliances and adversaries in the literature, and provide a structural interpretation for α as the product of a security preference and contest parameters.

Applying the definitions in (41), the **security impact of MECR24 is** 0.99 **lp**, i.e. the change in U.S. real military expenditure vs. that of the adversary aggregate ($= -0.30 - (-1.29)$ in Table 15); it is 2.07 lp if we compare to the adversary average. The economic impact for the U.S. in this scenario is -0.05 lp.

The framework makes precise what each control regime buys and at what cost. We define the *price of security* implied by a particular regime e as,

$$\omega_e \equiv \frac{-\Delta_e \ln W_{\text{US},C}}{\Delta_e \ln W_{\text{US},D} - \Delta_e \ln W_{V,D}}, \tag{42}$$

which captures the civilian real expenditure forgone per unit of security impact.

A natural comparison for this price is the U.S. valuation of security, α in the government objective (41): a regime is worth adopting when the valuation exceeds the price. If the U.S. chooses a regime e over the no-controls baseline, then $\Delta_e G_{\text{US}} \geq 0$, which for a regime delivering a security gain is equivalent to $\alpha \geq \omega_e$. Applying this to the U.S. remaining in the MECR24 regime implies the following bound for that parameter

$$\alpha \geq \alpha^* \equiv \omega_{\text{MECR24}} = \frac{0.05}{0.99} \approx 0.05. \tag{43}$$

This suggests the U.S. was willing to accept at least 0.05 lp of civilian welfare loss per log point of security gain.[44] When a membership change, or a sector-specific tightening improves both the economic and security dimensions for the U.S. then the ranking is simple; otherwise we can use this bound as a benchmark to determine if a regime change benefits the U.S.

7.5 The Value of Multilateral Agreements

We assess the value of multilateral agreements for the U.S. by quantifying the changes in MECR24 outcomes relative to a counterfactual U.S.-unilateral scenario.

Exports and Leakage. Table 14 presents the export impacts. U.S. controlled exports to adversaries fall slightly more under unilateral controls, yet adversaries' *aggregate* controlled imports fall by much less. Two forces explain this difference. First, under MECR24, the other allies account for about four-fifths of the reduction in controlled exports ($329 billion of $417 billion), so unilateral controls forgo most of this effect. Second, those other allies substitute toward adversary markets when the U.S. acts alone: their controlled exports to adversaries increase by $22 billion, accounting for most of the leakage. The leakage rate is 28% under unilateral controls, compared with only 7% under MECR24.[45] Overall, MECR24 reduces adversaries' imports of controlled products by 5.7 times as much as unilateral U.S. controls, which drives its substantially greater security effect.

[44] We obtain a similar threshold if the alternative used the baseline controls.

[45] Under unilateral controls, leakage rates are higher across all adversary destinations, but less dispersed, e.g. 20% for China and 40% for Burma.

Economic and Security Trade-offs. Under the unilateral scenario the U.S. bears about the same civilian cost as under MECR24, but achieves only a third of the effect on aggregate adversary real military expenditure: 0.42 versus 1.29. From the U.S. perspective, the case for multilateral coordination is therefore clear: comparable economic cost but three times the effect on adversary real military expenditure.

Even if the U.S. were willing to tighten controls and absorb a larger economic cost to act alone, it could not reach the multilateral security level. Figure 6 traces the security–civilian welfare trade-off for the U.S. under both regimes. The baseline and MECR24 regimes raise U.S. relative real military expenditure by 0.76 and 0.99 lp, respectively, at a roughly similar civilian cost of about 0.05 lp. The *slope* of the line connecting each regime to the no-controls origin *is its price of security*, ω_e, the lp of real civilian expenditure forgone per lp of relative real military expenditure gain.

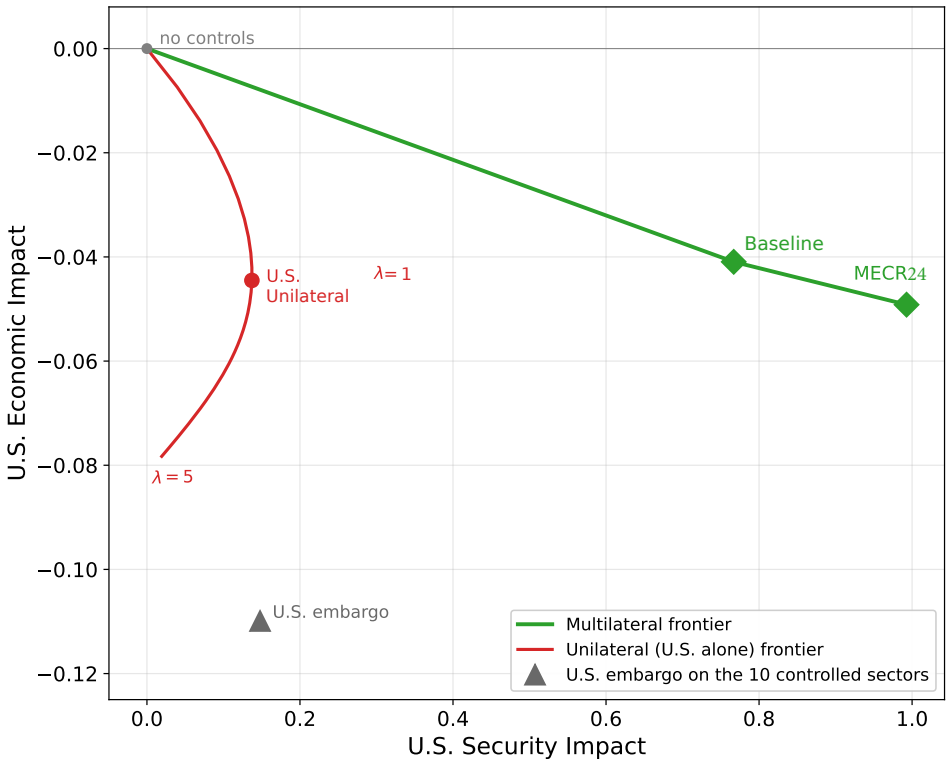
The red curve traces the trade-off when the U.S. acts alone, scaling the export controls it imposes on neutral and adversary destinations by a factor $\lambda \in [0.1, 5]$, with $\lambda = 5$ the most stringent and $\lambda = 1$ the calibrated U.S.-unilateral regime. Acting alone, the U.S. reaches a maximum security impact of only about 0.14 lp; tightening further reduces U.S. exports and erodes its scale economies, reducing U.S. real military expenditure by more than that of its adversaries, so the curve bends back and additional civilian losses buy *less* security. The triangle denotes a U.S. embargo on adversaries applied to the 10 controlled sectors. It shows the U.S. obtains far less security than under the multilateral regimes, at a greater civilian cost. Ally participation is therefore not just cheaper for the U.S. but the only way to reach the current multilateral security level.

7.6 The Value of Individual Partners and Sectors

Most-valued partners. We now ask which membership changes would improve the trade-off if the U.S. could admit countries into MECRs or expel them. We reclassify each country individually relative to MECR24 so the effect isolates that country's contribution. We do so by changing only the differential, destination-based controls, holding the baseline compliance friction $\widehat{\Phi}_{A,k}$ fixed as in our other counterfactuals. A reclassified country is affected both as an exporter and an importer. When a neutral joins, as an exporter it begins differentially restricting its CCL and EAR99 flows to non-members (full restriction on adversaries, one third on the remaining neutrals), and as an importer the existing members stop differentially restricting their exports to it; moving a member to neutral applies the reverse.

A switch can either help or hurt the U.S. trade-off, depending on the relative size of two channels. First, a country joining the agreement reduces its dual-use exports to adversaries and raises U.S. security. Because the new member is no longer differentially targeted, the U.S. exports more to it, raising U.S. income and competitiveness. Second, the joining country reduces its sales to non-members, and the resulting loss of scale raises its export prices to all buyers, including the U.S. and its suppliers. The two channels can move U.S. security and civilian outcomes either in the same or opposite directions and thus require quantification.

Figure 6: The Price of Security: Multilateral vs. Unilateral



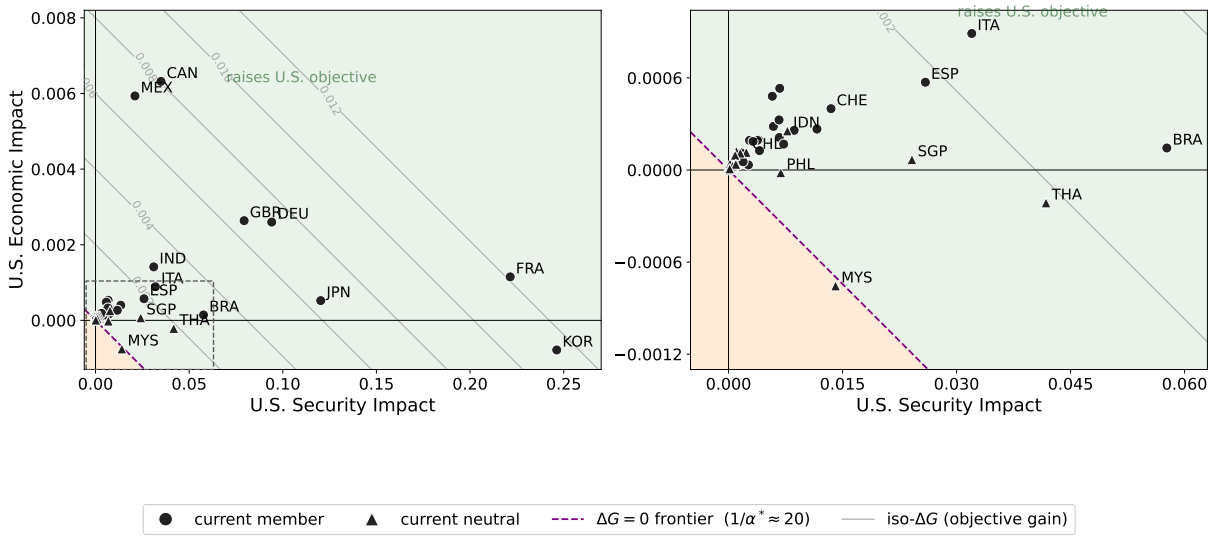
Notes: The security–civilian trade-off of equation (42); axes in log points relative to no controls (horizontal: U.S. security impact $100\Delta \ln(W_{\mathrm{US},D}/W_{V,D})$; vertical: U.S. civilian impact $100\Delta \ln W_{\mathrm{US},C}$). Green: the multilateral control effect (three points: no controls, Baseline, MECR24). Red: the U.S.-unilateral effect, scaling the intensity of U.S. controls over $\lambda \in [0.1, 5]$ ($\lambda = 1$ is the U.S.-unilateral regime). Gray triangle: a U.S. embargo on the 10 controlled sectors (all classifications, not only CCL).

Figure 7 plots the two effects for each country: the security effect on the horizontal axis ($100\Delta \ln(W_{\mathrm{US},D}/W_{V,D})$) against the civilian effect on the vertical ($100\Delta \ln W_{\mathrm{US},C}$). The dashed line through the origin is the break-even line at the lower-bound willingness to pay: a country above it raises the U.S. objective. Almost every country lies above the line, so keeping any current member or admitting most neutral countries to the agreement raises the U.S. objective. The thin lines parallel to the break-even line are iso-objective contours, and a country on a higher contour raises the objective by more. At α^*, France contributes the most to the U.S. objective, followed by Korea, then a comparable group of Canada, Germany, Mexico, Japan, and the United Kingdom. Because α^* is only a lower bound, the U.S.'s true valuation of security may be higher. We can recompute and plot Figure 7 with the steeper break-even and iso-contours reflecting other reasonable values of α^*. But the key insights are clear: an increased value of countries with relatively higher security contribution, and possibly a change in ranking of those with similar value at α^*, e.g. Japan overtaking Mexico.

The right panel enlarges the cluster around the origin in the left panel, where most current neutrals fall. Among them, Thailand and Singapore would contribute the most if admitted.

Most valuable sectors (to tighten). We next explore whether tightening individual sectors

Figure 7: Value of Individual MECR Members to the U.S.



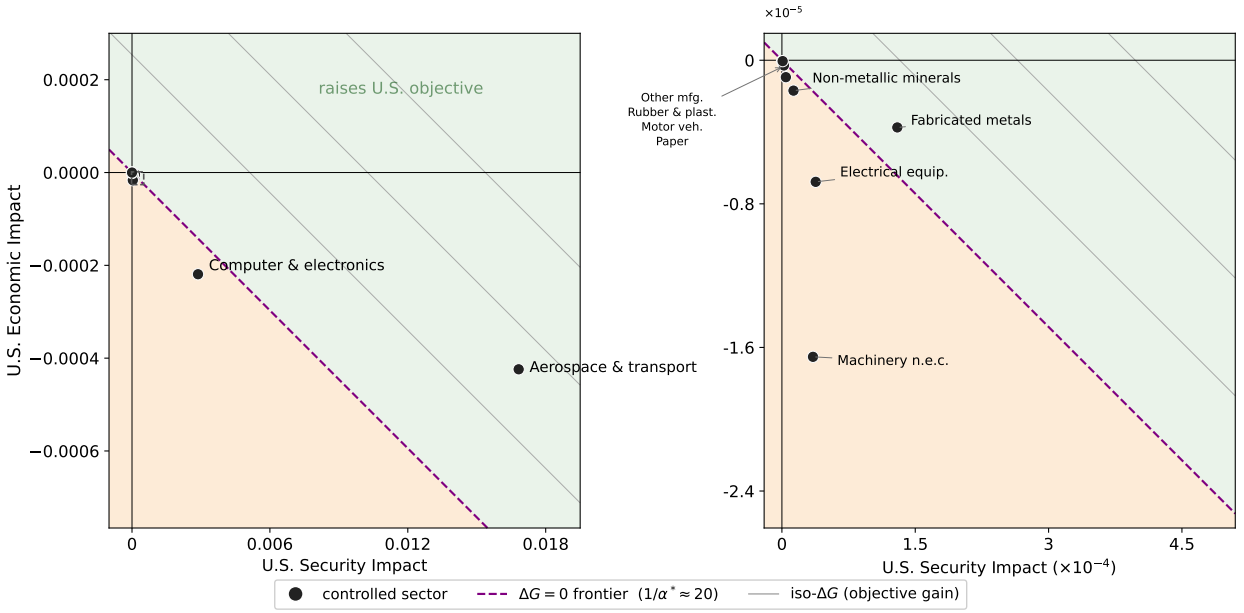
Notes: Each point is the effect on the U.S. of one country's agreement membership, reclassified alone from the MECR24 equilibrium. Horizontal: security effect $100\Delta \ln(W_{\mathrm{US},D}/W_{V,D})$; vertical: civilian effect $100\Delta \ln W_{\mathrm{US},C}$. Circles: current members; triangles: current neutrals. Dashed line: the break-even locus at $\alpha^* \approx 0.05$; light lines: iso-objective contours. The right panel enlarges the cluster around the origin in the left panel.

could improve the security trade-off. For each of the 10 controlled sectors, we apply a marginal shock to MECR24: a uniform 10% proportional cut in the CCL approval rate on ally exports to adversary destinations. Figure 8 plots the civilian vs. security gains of tightening each sector separately, using the iso-objective lines as in Figure 7. At α^*, aerospace and other transport equipment, the one we found has the largest price impacts on adversaries, contributes by far the most to the U.S. objective, and is well above the break-even line. Computers and electronics is slightly below the line. The right panel zooms in on the sectors in which further tightening produces small effects. Among these, only fabricated metal products are above the break-even line.

If the U.S.'s true valuation of security is higher than the lower bound α^*, then the parallel lines would be steeper, which means a heavier weight on the security margin. This would bring high-security-value sectors above the line, most notably computers and electronics.

Taking stock, the revealed preference approach shows that the U.S. accepts a civilian cost to raise its relative real military expenditure, and that the price of security is far lower under multilateral coordination than under unilateral action. Among current members, France and Korea contribute the most to the U.S. objective, and tightening sectors such as aerospace and other transport equipment would raise it most.

Figure 8: The Price of Security across Sectors



Notes: Each point is one controlled sector's effect of a marginal tightening: a uniform 10% proportional cut in the CCL approval rate on ally→adversary exports, on top of MECR24. Axes as in Figure 7. Dashed line: the break-even locus at $\alpha^* \approx 0.05$. Points are labeled by sector. The right panel enlarges the cluster around the origin in the left panel (security $\times 10^{-4}$, civilian cost $\times 10^{-5}$).

8 Conclusion

We develop a framework for measuring the economic and national security effects of export controls and the role of international coordination. Using new data on U.S. exports by control classification and licensing outcomes, we estimate substantial trade frictions associated with export controls that are systematically lower for MECR destinations. For the more stringently controlled CCL goods, the implied export cost equivalent is about 29 lp higher for non-MECR than MECR destinations. We use these estimates to discipline a quantitative general equilibrium model with dual-use production, input-output linkages, and endogenous entry.

Multilateral export controls reduce adversaries' imports of controlled products by 5.7 times as much as unilateral U.S. controls. When the U.S. acts alone, about 28% of its controlled exports reduction to adversaries is offset by other suppliers, compared to only 7% under multilateral controls. Under MECR24, U.S. real military expenditure relative to its adversaries increases by about 1 lp compared to only 0.14 under unilateral controls. Tightening unilateral controls, even a U.S. embargo, cannot eliminate this gap. International coordination therefore does more than lower costs of a given security outcome. It expands the set of security outcomes that export controls can attain.

Finally, we provide a framework for measuring the price of security to compare economic and security effects across control regimes that vary by country participation and differential sectoral

tightening of controls. Our framework can be applied to trade and foreign policies justified by expanding national security motives across major economies where international coordination, supply substitution, and domestic production jointly determine their effectiveness.

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A Appendix Tables

Table A1: U.S. Export Differential—Alternative Standard Errors

Sample:	No Controls vs EAR99 and CCL			
Dependent Variable:	exports (ln)			
	Cluster on country-year	Robust	Jackknife	Bootstrap
	1	2	3	4
MECR*CCL	1.075	1.075	1.075	1.075
	(0.067)	(0.063)	(0.169)	(0.069)
MECR*EAR99	0.521	0.521	0.521	0.521
	(0.042)	(0.051)	(0.101)	(0.040)
Observations	5,152	5,152	5,152	5,152
R-squared	0.934	0.934	0.934	0.934
adjusted R-squared	0.900	0.900	0.900	0.900

Notes: All specifications include country-year and control type-year fixed effects. Column 1 is the baseline cluster by country-year. Jackknife leaves one country cluster out for each replication. Bootstrap resamples 400 times over country-year clusters. A6 group interactions with CCL and EAR99 indicators included in regression but omitted from table.

Table A2: U.S. Export Differential—Sample Robustness

Sample:	No Controls vs EAR99 and CCL				
Dependent Variable:	exports (ln)				
	Full Sample	Drop Adversaries	Drop Neutrals	Drop Adversaries and Low Population	Drop Neutrals and Low Population
	1	2	3	4	5
MECR*CCL	1.075	1.246	0.664	0.971	0.650
	(0.067)	(0.073)	(0.100)	(0.075)	(0.099)
MECR*EAR99	0.521	0.540	0.474	0.446	0.454
	(0.042)	(0.047)	(0.057)	(0.049)	(0.057)
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Control Type by Year Effects	Yes	Yes	Yes	Yes	Yes
Observations	5,152	3,991	2,349	3,188	2,286
R-squared	0.934	0.941	0.941	0.946	0.941
adjusted R-squared	0.900	0.910	0.909	0.917	0.910

Notes: Standard errors clustered by country-year in parentheses. A6 group interactions with CCL and EAR99 indicators included in regression but omitted from table. Adversaries and Neutrals groups are defined in Section 2 and Appendix B.1.

Table A3: U.S. Average Shipment Differential—Sample Robustness

Sample:	No Controls vs EAR99 and CCL				
Dependent Variable:	Average Exports per Shipment (ln)				
	Full Sample	Drop Adversaries	Drop Neutrals	Drop Adversaries and Low Population	Drop Neutrals and Low Population
	1	2	3	4	5
MECR*CCL	-0.163	-0.070	-0.387	-0.118	-0.414
	(0.049)	(0.052)	(0.072)	(0.053)	(0.070)
MECR*EAR99	-0.379	-0.461	-0.181	-0.401	-0.208
	(0.036)	(0.042)	(0.047)	(0.043)	(0.046)
CCL FE Mean	0.296	0.203	0.519	0.222	0.519
	(0.031)	(0.036)	(0.061)	(0.04)	(0.061)
EAR99 FE Mean	0.305	0.387	0.107	0.299	0.107
	(0.028)	(0.035)	(0.041)	(0.038)	(0.041)
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Control Type by Year Effects	Yes	Yes	Yes	Yes	Yes
Observations	5,152	3,991	2,349	3,188	2,286
R-squared	0.480	0.495	0.517	0.478	0.525
adjusted R-squared	0.215	0.236	0.266	0.209	0.278

Notes: Standard errors clustered by country-year in parentheses. A6 group interactions with CCL and EAR99 indicators included in regression but omitted from table. Adversaries and Neutrals groups are defined in Section 2 and Appendix B.1.

Table A4: U.S. Export Differential—Heterogeneity by Country Size

Sample:	No Controls vs EAR99 and CCL			
Dependent Variable:	exports (ln)			
	Country Size by GDP		GDP Per Capita	
	Below Median	Above Median	Below Median	Above Median
	1	2	3	4
MECR*CCL	1.936	0.505	0.676	0.941
	(0.190)	(0.076)	(0.110)	(0.091)
MECR*EAR99	0.598	0.262	0.781	0.237
	(0.140)	(0.041)	(0.107)	(0.054)
Observations	2,614	2,538	2,587	2,565
R-squared	0.848	0.931	0.896	0.942
adjusted R-squared	0.769	0.895	0.842	0.911

Notes: Standard errors clustered by country-year in parentheses. All regressions include country-year and control type-year fixed effects. Median GDP and per capita GDP computed using each country's average annual value over 2016–2019 and are fixed over time. A6 group interactions with CCL and EAR99 indicators included in regression but omitted from table.

Table A5: U.S. Export Differential—Government and Military Controls

Sample:	Government Share of GDP			Military Expenditure Share of GDP		
Dependent Variable	Exports (ln)	Number of shipments (ln)	Exports per Shipment (ln)	Exports (ln)	Number of shipments (ln)	Exports per Shipment (ln)
	1	2	3	4	5	6
MECR*CCL	0.586	0.813	-0.227	0.796	1.039	-0.242
	(0.086)	(0.061)	(0.065)	(0.083)	(0.067)	(0.058)
MECR*EAR99	0.294	0.593	-0.299	0.379	0.722	-0.343
	(0.055)	(0.051)	(0.046)	(0.049)	(0.051)	(0.044)
Govt or Military Interaction Term						
CCL*Share	0.668	0.670	-0.002	0.515	0.426	0.089
	(0.124)	(0.112)	(0.085)	(0.074)	(0.072)	(0.053)
EAR99*Share	0.393	0.414	-0.02	0.286	0.376	-0.090
	(0.086)	(0.085)	(0.069)	(0.042)	(0.051)	(0.046)
Observations	2,745	2,745	2,745	2,724	2,724	2,724
R-squared	0.94	0.96	0.49	0.94	0.96	0.49
adjusted R-squared	0.91	0.93	0.22	0.91	0.93	0.23

Notes: Standard errors clustered by country-year in parentheses. All regressions include country-year and control type-year fixed effects. A6 group interactions with CCL and EAR99 indicators included in regression but omitted from table. Sample is for 2016–2022 when government and military share of GDP measures are observed. Government and military share measures are demeaned within sample so the main effect coefficients are marginal effects at the mean.

Table A6: U.S. Export Differential by Level of Industry Aggregation

Sample:	CCL trade by country-industry aggregation			
Dependent Variable:	Exports(ln)			
	HS Sections	NAICS 3 digit	ISIC	CCL Categories
	1	2	3	4
MECR*CCL	0.479	0.425	0.480	1.064
	(0.050)	(0.052)	(0.049)	(0.052)
MECR*EAR99	0.535	0.436	0.414	0.521
	(0.033)	(0.032)	(0.030)	(0.042)
Observations	72,828	90,946	55,425	17,732
R-squared	0.911	0.906	0.909	0.873
adjusted R-squared	0.852	0.843	0.862	0.859

Notes: Standard errors clustered by country-year in parentheses. All regressions include control type by year fixed effects; columns 1, 2, 3 also include country-industry-year whereas column 4 includes country-year. A6 group interactions with CCL and EAR99 indicators included in regression but omitted from table. CCL categories refer to the 10 groups defined by the leading digit of the ECCN.

Table A7: Sector-Specific MECR Export Differentials $\tilde{\delta}^j_{M,k}$ Used in the Quantification

		CCL		EAR99	
Sector (j)	ISIC Rev. 4	$\tilde{\delta}^j_{M,\text{CCL}}$	(s.e.)	$\tilde{\delta}^j_{M,\text{EAR99}}$	(s.e.)
Paper & printing	17–18	0.742	(0.239)	0.523	(0.139)
Rubber & plastics	22	0.770	(0.261)	0.743	(0.140)
Non-metallic minerals	23	0.807	(0.286)	1.020	(0.168)
Fabricated metals	25	1.042	(0.189)	0.444	(0.131)
Computers, electronics	26	0.586	(0.118)	0.512	(0.105)
Electrical equip.	27	1.293	(0.181)	0.463	(0.111)
Machinery n.e.c.	28	1.258	(0.196)	0.480	(0.105)
Motor vehicles	29	1.076	(0.284)	1.194	(0.188)
(Aerospace and) Other transport equip.	30	1.158	(0.190)	0.447	(0.132)
Other mfg.; repair	31–33	0.527	(0.244)	0.592	(0.131)

Notes: MECR × classification coefficients from equation (15) estimated separately by sector; log aggregate U.S. export value by destination and classification, 2016–2024. Standard errors in parentheses. The table lists the sectors where estimates are statistically significant; these enter $\Phi^j_{od,k}$ in equation (34). We deviate from the official ISIC descriptions by noting "Aerospace" is included in Other transport equipment.

Table A8: Structural Decomposition of Export and Entry Penalties (EAR99)

	Parameter	Non-MECR ($\bar{A}$)	MECR (A)	$\bar{A} - A$
A. Friction Parameters				
Risk penalty	$\ln(\hat{f}_{d,k}/\hat{\rho}_{d,k})$	**23.00**	**-9.50**	**32.50**
Approval contribution	$-\ln \hat{\rho}_{d,k}$	**18.00**	**7.00**	**11.00**
Fixed cost penalty	$\ln \hat{f}_{d,k}$	**5.00**	**-16.50**	**21.50**
Delay/quality penalty[a]	$-\ln \hat{Q}_{d,k}$	*23.33*	*0.00*	23.33
B. Export and Entry Penalties				
Export penalty[c]	$-\ln \hat{\Phi}_{d,k}$	*50.60*	*5.10*	**45.50**
Risk contribution	$\frac{\kappa}{\sigma-1}\ln(\hat{f}_{d,k}/\hat{\rho}_{d,k})$	27.60	-11.40	39.00
Other (residual)	$-\left(\frac{\kappa}{\sigma-1}\ln \hat{Q}_{d,k} + \ln \hat{f}_{d,k}\right)$	*23.00*	*16.50*	6.50
Entry penalty[b]	$\frac{\kappa}{\sigma-1}\left(\ln \frac{\hat{f}_{d,k}}{\hat{\rho}_{d,k}} - \ln \hat{Q}_{d,k}\right)$	*55.60*	*-11.40*	67.00

Notes: Values in log points (×100). **Bold**: identified directly (Table 8, rounded to nearest 0.5 lp) and BIS approval rates (second row); roman: computed from entries in bold and $\kappa = 3.0$, $\sigma = 3.5$; italics: country specific values that also rely on MECR penalty lower bound. [a] We assume MECR destinations don't face delays for EAR99 exports and normalize the delay penalty to zero $-\ln \hat{Q}_{A,k} = 0$. Non-MECR value adds the estimated differential. [b] Equivalently $\kappa \ln \hat{z}^*_{d,k}$: the reduction in firm entry relative to non-controlled goods, holding M fixed. [c] See equation (16) for the full decomposition.

Table A9: Changes in Control List Status by Country

Country	Treatment Time	Cohort	Effective Date	Motive Type
Upgrades				
Malta	2014Q4	1	Aug 7 2014	Inclusion in NSG list[a]
Serbia	2014Q4	1	Aug 7 2014	Accession to NSG[a]
Argentina	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Austria	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Bulgaria	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Croatia	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Czech Republic	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Estonia	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Finland	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Hungary	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Iceland	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Ireland	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Latvia	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Lithuania	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
New Zealand	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Poland	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Romania	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Slovakia	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Slovenia	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
South Africa	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
South Korea	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Sweden	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Switzerland	2015Q3	2	May 21 2015	WA 2014 Plenary Agreement
Fiji	2016Q1	3	Dec 3 2015	Democratization
Cote d'Ivoire	2017Q1	4	Nov 4 2016	Democratization
Liberia	2017Q1	4	Nov 4 2016	Democratization
Sri Lanka	2017Q1	4	Nov 4 2016	Democratization
Vietnam	2017Q1	4	Nov 4 2016	Diplomatic Relations
Cyprus	2021Q1	5	Dec 28 2020	Security
Ukraine	2021Q1	5	Dec 28 2020	Administrative
Downgrades				
Central African Republic	2014Q3	1	Jun 5 2014	Civil War
South Sudan	2018Q4	2	Aug 3 2018	Civil War
Venezuela	2019Q3	3	May 24 2019	Political Crisis
Russia	2020Q2	4	Feb 24 2020	Security
Yemen	2020Q2	4	Feb 24 2020	Regional War
Hong Kong	2021Q1	5	Dec 23 2020	Security
Burma (Myanmar)	2021Q2	6	Mar 8 2021	Political Crisis
Cambodia	2022Q1	7	Dec 9 2021	Security
Belarus	2022Q3	8	Apr 8 2022	Regional War

Country names embed links to Federal Register notices. Treatment time is one quarter after effective date.

[a] This rule (79 FR 46316) also added Croatia, Estonia, Iceland, Lithuania, Mexico, and Serbia to the NSG group. Serbia is not a Wassenaar Arrangement member, so this is its only upgrade. Malta is a Wassenaar member but the U.S. excludes it from its Group, A:1, so this is its only upgrade too.

Table A10: Notation and Mapping between Partial and General Equilibrium

Symbol	Meaning	Origin
Panel A. Indices, Controls, Aggregate Prices and Demand		
Indices and sets		
o, d	origin, destination; {A,N,V} = {allies (A), neutrals (N), adversaries (V)}	§3
$i, j \in \{1, \ldots, J\}$	sectors (producing / supplying)	new
$t \in \{C, D\}$	**seller** type: civilian or dual-use	new
$b \in \{C, D\}$	**buyer / final-user** type: civilian or military	§3
$k \in \{\text{NC}, \text{EAR99}, \text{CCL}\}$	export-control regime, least to most stringent	§3
Export-control policy block		
$\rho_{od,k} \in [0, 1]$	shipment approval probability	§3
$Q_{od,k} = e^{-\chi T_{od,k}}$	quality shifter from delay (χ = depreciation)	§3
$T_{od,k} \geq 0$	observed processing delay (days); enters only through Q	§3
$f_{od,k}$	compliance fixed cost (labor units)	§3
τ_{od}	iceberg trade cost	§3
$\Phi^i_{od,k}$	**selection factor**: sufficient statistic for control frictions; falls as controls tighten	§3, eq. (9)
$\Pr(k \mid t)^j$	**probabilistic classification** of type-t into regime k	new (cf. § 3, fn. 21, 22)
Prices and demand		
$P^i_{d,bt}$	lower-nest price of type-t bundle for type-b user	§3 ($P_{d,b}$), nested §5
$\bar{P}^i_{d,b}$	sectoral composite price for type-b user (upper nest)	new
$X^i_{d,b}$, $X^i_{d,bt}$	absorption by type-b users; portion on type-t inputs	§3 ($X_{d,b}$), split §5
σ^i	CES elasticity across varieties (lower nest)	§3
η^i	CES elasticity across C/D composites (upper nest)	new
ϕ^j_{bt}	type-b firm's CES weight on type-t inputs	new
$\beta^i_{d,b}$	Cobb–Douglas final-demand share	new
$s_{d,D}$	military spending share of GDP; splits $Y_{d,C}$, $Y_{d,D}$	new
Panel B. Firms and Entry		
Firm-level objects		
$z \sim \text{Pareto}(\kappa^i)$	productivity draw; κ = shape	§3
$\theta^i \equiv \kappa^i - (\sigma^i - 1)$	selection parameter (entry responsiveness)	§3
$\mu^i = \sigma^i/(\sigma^i - 1)$	markup	§3
$A^i_{o,t}$	unit input-bundle cost; **endogenous**	§3 (A_o), eq. (20)
B^i_o, γ^{iL}_o, γ^{ij}_o	cost shifter (inverse productivity); labor & intermediate shares	new
$z^{*i}_{od,bt,k}$	export productivity cutoff	§3 (eq. 4), eq. (24)
$M^i_{o,t}$	mass of type-t firms; **endogenous** (free entry)	§3 ($M_{o,k}$), §5
w_o	wage; **endogenous**	§3 (given), §5
Entry and equilibrium aggregates		
$f_e^{o,i,t}$	sunk entry cost (labor units)	new
$\psi^i \geq 0$	entry-congestion parameter; $\psi = 0$ is standard Melitz	new, eq. (31)
$V^i_{o,t}$	total revenue of type-t firms	new
$W_{d,b}$	real final expenditures: civilian, $b = C$, military, $b = D$	new, eq. (33)

B Empirical Appendix

B.1 EAR Country Lists

The Export Administration Regulations assign countries to several country groups that determine licensing requirements and the availability of license exceptions. Countries may appear on multiple lists simultaneously. The lists used in the paper correspond to the BIS country groups EAR-A, EAR-B, and EAR-D. There is also an EAR-E list covering countries that are embargoed or designated as state sponsors of terrorism, Iran and North Korea in our data, which we drop from the analysis sample.

EAR-A is subdivided into A1–A6. Groups A1–A4 correspond to the multilateral export control regimes (MECRs): Wassenaar Arrangement, MTCR, Australia Group, and Nuclear Suppliers Group. Group A5 includes countries that receive favorable Strategic Trade Authorization (STA) license exceptions. In our data, all A5 countries also appear on at least one of A1–A4, so A5 does not create a distinct country group for our analysis. Group A6 identifies destinations eligible for STA license exceptions, but countries on A6 need not be a member of an MECR. In our analysis group A6 is the set of countries that are not members of a MECR (A1–A4) and also not on any of the EAR-D lists.

The EAR-D lists (D1–D5) identify destinations associated with specific security concerns such as national security, missile technology proliferation, and arms embargoes. Exports to these destinations are significantly more likely to require licenses and to face denial.

The EAR-B group is not subdivided in the regulations. Licensing for these destinations is generally determined on a case-by-case basis and is commonly described in BIS and export compliance training materials as more restrictive than exports to regime partners in EAR-A but less restrictive than exports to EAR-D destinations.[46]

Because countries may appear on multiple EAR lists simultaneously, we construct mutually exclusive groups for the empirical analysis. Countries in Group A are those participating in at least one MECR that do not appear on any EAR-D list. Group B consists of countries appearing on EAR-B that do not also appear on EAR-A or EAR-D. Group D includes all countries appearing on any EAR-D list. We additionally define an A6 group consisting of STA-eligible countries that are not members of an MECR and are not on EAR-D. Table B1 summarizes this mapping.

[46] See BIS, "License Exceptions Webinar," November 2011, https://www.bis.doc.gov/index.php/documents/compliance-training/export-administration-regulations-training/248-licenseexceptions-pdf/file (accessed April 11, 2025), and Export Compliance Training Institute, "Understanding the Difference Between the Various Country Lists in the EAR," https://www.learnexportcompliance.com/understanding-the-difference-between-the-various-country-lists-in-the-ear/ (accessed March 20, 2025).

Table B1: Mapping Statutory EAR Country Lists into Mutually Exclusive Empirical Groups

Empirical group	**Statutory EAR lists**	**Rule used in this paper**
MECR	A1–A4	Country appears on one or more EAR-A lists A1-A4 and does *not* appear on any EAR-D list.
A6 (STA)	A6	Country appears on A6 list for Strategic Trade Authorization (STA), but is *not* on any EAR-A lists A1–A4 and does *not* appear on any EAR-D list.
Neutrals	B	Country appears on the EAR-B list, but does *not* appear on any EAR-A list, is *not* in A6, and does *not* appear on any EAR-D list.
Adversaries	D1–D5	Country appears on an EAR-D list, regardless of whether it also appears on A1–A6 or B.
Excluded	E1–E2	Country appears on an EAR-E list for terrorist-supporting country or embargo.

We provide a list of the countries that fall into these groups in the period 2016–2024 below, sorted alphabetically. Countries in bold are included individually in the quantitative model as we have OECD ICIO data for them. Years in parentheses indicate periods in which a country belongs to the indicated group only if its classification changes during 2016–2024. The regression sample includes the 191 countries in bold or regular typeface. Canada, Ukraine, and Hong Kong appear in bold italics because they are excluded from the baseline regression sample, but included in the quantitative model. Controlled export values to Canada are not available, as described in the main text. Ukraine and Hong Kong are excluded from the baseline regression sample because they switch into or out of MECR/A6 status between 2016–2024, but they are used in the upgrade and downgrade estimates (see Table A9).

MECR group (labeled "Allies" in the quantitative model)

Argentina, **Australia**, **Austria**, **Belgium**, **Brazil**, **Bulgaria**, ***Canada***, **Croatia**, **Czech Republic**, **Denmark**, **Estonia**, **Finland**, **France**, **Germany**, **Greece**, **Hungary**, **Iceland**, **India**, **Ireland**, **Italy**, **Japan**, **Latvia**, Liechtenstein, **Lithuania**, **Luxembourg**, **Malta**, **Mexico**, **Netherlands**, **New Zealand**, **Norway**, **Poland**, **Portugal**, **Romania**, Serbia, **Slovakia**, **Slovenia**, **South Africa**, **South Korea**, **Spain**, **Sweden**, **Switzerland**, **Turkey**, ***Ukraine*** (2021–2024), **United Kingdom**.

A6 group

Albania, ***Hong Kong*** (2016–2019), **Singapore**. Our quantification uses 2016 group assignment, treating A6 countries as neutrals. As a result, Hong Kong falls under the neutral group.

Neutrals group

Algeria, Andorra, Angola, Antigua and Barbuda, Aruba, Bahamas, **Bangladesh**, Barbados, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, **Brunei**, Burkina Faso, Burundi,

Cabo Verde, **Cameroon**, Chad, **Chile**, **Colombia**, Comoros, Congo, **Costa Rica**, **Cote d'Ivoire** (2017–2024), Curacao, Djibouti, Dominica, Dominican Republic, Ecuador, El Salvador, Equatorial Guinea, Eswatini, Ethiopia, Fiji, Gabon, Gambia, Ghana, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Honduras, **Indonesia**, Jamaica, Kenya, Kiribati, Kosovo, Lesotho, Liberia (2017–2024), Madagascar, Malawi, **Malaysia**, Maldives, Mali, Marshall Islands, Mauritania, Mauritius, Micronesia, Monaco, Montenegro, **Morocco**, Mozambique, Namibia, Nauru, Nepal, Nicaragua, Niger, **Nigeria**, North Macedonia, Palau, Panama, Papua New Guinea, Paraguay, **Peru**, **Philippines**, Rwanda, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Samoa, San Marino, Sao Tome and Principe, **Senegal**, Seychelles, Sierra Leone, Sint Maarten, Solomon Islands, South Sudan (2016–2018), Sri Lanka (2017–2024), Suriname, Tanzania, **Thailand**, Timor-Leste, Togo, Tonga, Trinidad and Tobago, **Tunisia**, Tuvalu, Uganda, Uruguay, Vanuatu, Zambia.

Adversaries group

Afghanistan, Armenia, Azerbaijan, Bahrain, **Belarus**, **Burma**, **Cambodia**, Central African Republic, **China**, **Cote d'Ivoire** (2016), **Cyprus**, Democratic Republic of the Congo, **Egypt**, Eritrea, Georgia, Haiti, ***Hong Kong*** (2020–2024), Iraq, **Israel**, **Jordan**, **Kazakhstan**, Kuwait, Kyrgyzstan, **Laos**, Lebanon, Liberia (2016), Libya, Macao, Moldova, Mongolia, Oman, **Pakistan**, Qatar, **Russia**, **Saudi Arabia**, Somalia, South Sudan (2019–2024), Sri Lanka (2016), **Taiwan**, Tajikistan, Turkmenistan, UAE, ***Ukraine*** (2016–2020), Uzbekistan, Venezuela, **Vietnam**, Yemen, Zimbabwe.

B.2 Control List Reclassification: Data Construction and Events

Data construction. We identify changes in control list status from changes to the EAR published in the Federal Register. We exclude cases where changes resulted from BIS code revisions rather than actual policy changes toward specific countries, as indicated by reading the corresponding Code of Federal Regulations entries. These countries remain in the sample but are reclassified as untreated. If a country experiences both an upgrade and a downgrade more than one year apart, we drop it from the re-classification sample to avoid confounding from mixed treatment status; this results in Mexico, India, and Liechtenstein being dropped. If the two changes occur within one year, we retain only the later treatment. Burma is the only country that experiences both an upgrade and a downgrade in the same year; for this case we retain only the downgrade, as it occurs after the upgrade and is less likely to be confounded by mixed treatment status.

Reclassification motives. A large subset of the upgrades reflects scheduled implementation of pre-existing multilateral regime commitments applied simultaneously to many countries (the Nuclear Suppliers Group and Wassenaar Arrangement plenary rules), or administrative reclassifications. The largest cohort is a wave of upgrades occurring during 2015 that reflect countries being added to the A:1 Wassenaar Arrangement BIS list. These countries were Wassenaar members prior to the 2015 change, but the Code of Federal Regulations entry implementing the reclassification indicates it had regulatory consequences. For example, the rule implementing the 2014 Wassenaar Arrangement Plenary agreements states: "Country Group A column 1, the Coordinating Committee (CoCom) member countries, is replaced with the successor national security export regime the Wassenaar Arrangement Participating States. In addition, the second national security column and the second regional stability column of the Commerce Country Chart are amended to harmonize with each other, as well as make changes based on the risk of diversion to unauthorized end user, end uses or destinations." The main results include this cohort, but the upgrade results are robust to its omission.

The remaining reclassifications are primarily related to destination-specific political and security developments rather than industry demands for licensing relief, as listed in Table A9 and documented here.

- **Democratization (upgrades):** Fiji (return to democratic elections after 2006 coup), Liberia (UN Security Council lifts embargo citing post-conflict progress and disarmament), Sri Lanka (Congress does not renew appropriations act rider, following Sirisena's 2015 election), Cote d'Ivoire (UN Security Council lifts embargo citing security and democratic improvements).
- **Diplomatic relations (upgrade):** Vietnam (arms embargo lifted during President Obama's 2016 visit, alongside normalization of diplomatic ties).
- **Administrative (upgrade):** Ukraine (BIS reclassification citing sustained cooperation in control issues, with no distinct triggering event).
- **Security:** Cyprus (upgrade; arms sale waiver conditioned on annual State Department certification of anti-money-laundering cooperation and denial of port access to Russian military vessels), Russia (downgrade; national security and foreign policy concerns, including proliferation), Hong Kong (downgrade; China's imposition of the 2020 National Security Law), Cambodia (downgrade; Chinese military buildup at Ream Naval Base, plus corruption and human rights concerns).
- **Conflict (downgrades):** Central African Republic (civil war and sectarian violence), South Sudan (civil war and humanitarian crisis), Venezuela (political crisis amid Russian military deployment), Yemen (ongoing civil war and Houthi conflict), Burma (Feb. 2021 military coup), Belarus (enabling Russia's Feb. 2022 invasion of Ukraine).

B.3 Stacked Difference-in-Differences Design

We first estimate the effect of reclassifications within each control type separately starting with a DID framework:

$$\ln(Y_{dt}) = \gamma_k \, \mathbf{1}(\text{treated}_d) \times \mathbf{1}(\text{Post}_t) + \alpha_d + \alpha_t + \varepsilon_{dt} \tag{B1}$$

We exclude the year-quarter immediately prior to treatment, the treatment quarter itself, and the quarter after treatment when estimating γ_k. We exclude these quarters to avoid capturing anticipation effects or partial treatment exposure in the quarters where the reclassification takes effect partway through the period.

The estimation uses a stacked cohort design to address bias that arises in staggered settings when already-treated units serve as controls and treatment effects are heterogeneous (Goodman-Bacon 2021). Heterogeneity-robust estimators such as Callaway and Sant'Anna (2021) are designed for two-way designs and do not directly deliver our estimand, which is a triple difference against uncontrolled trade within the same destination-quarter and requires the fixed effects structure in (B1).

Stacking instead removes the source of that bias by construction. We define a treatment cohort as a group of countries which undergo a BIS upgrade or downgrade in the same year-quarter. For each treatment cohort we create a separate dataset which includes the treated countries in that cohort and all never-treated countries. Here we define never-treated countries as countries which never undergo a BIS change during our window of observation, 2009–2024. These cohort-specific

datasets are then stacked so that never-treated countries are duplicated for each cohort. This ensures all comparisons are between treated countries and never-treated countries within the same cohort-specific dataset, avoiding comparisons between early and late treated units. Within each cohort-specific dataset, identification comes only from comparisons between treated destinations and destinations never reclassified during 2009–2024.[47]

B.4 Stacked Difference-in-Differences Results

We now discuss the results of each specification. Panel A of Table 11 reports the DID results. Column 2 of this panel indicates that CCL exports significantly increase by 37.3 lp after a BIS upgrade but decrease by 111.3 lp after a downgrade. Column 5 shows the corresponding effects for the number of transactions. Here upgrades are associated with a 17.1 log point increase in CCL export transactions and downgrades are associated with a 70.8 log point decrease.

Non-controlled exports in columns 1 and 4 do not respond significantly to upgrades and point estimates are close to zero. However, downgrades are associated with a significant decline in non-controlled export transactions. While export values are not associated with a statistically significant decline, the point estimate suggests a 57.3 log point decline. This pattern is consistent with downgrades potentially coinciding with adverse events such as armed or political conflict which reduce exports broadly. This motivates the triple difference specification which looks at export effects relative to non-controlled exports.

The triple difference results are reported in Panel B of the same table. The upgrades are associated with a 33 log point increase in CCL exports and a 17.1 log point increase in CCL transactions both relative to non-controlled exports. These effects are similar to the DID results and in line with the previous observation that non-controlled exports did not appear to respond to BIS upgrades. By contrast, the effect of downgrades is attenuated by this comparison to non-controlled exports. CCL exports still decline but now by only 67 lp rather than 111.3 lp. However, CCL export transactions are now no longer significantly impacted by BIS downgrades.

B.5 Data Sources and Variable Construction

Table B2: Data Sources, Variable Construction, and Use

Variable or object	Definition and construction	Source and coverage	Main use
Panel A. U.S. Export Transactions			
Export value by control classification	Nominal U.S. goods export value, in dollars, classified as CCL, EAR99, or no reported control classification (NC). Any controlled export value is the sum of CCL and EAR99.	Authors' calculations using the quarterly U.S. Census Bureau Foreign Trade Division (FTD) *Data by Export Control Classification Number* downloads, 2009–2024. These special tabulations report Schedule B 10-digit product, destination, control classification, and license authorization.[a–d]	Figure 1; Tables 1, 3–5, 7–8, 11, and 13; Tables A1–A7 and C1–C3; Sections 2.2, 4, and 6.2–6.3.

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[47] These variance-weighted estimates are robust to a weighted regression following Wing, Freedman, and Hollingsworth (2024), which recovers an average of cohort-level effects by correcting for variation in the treated-to-control ratio across sub-experiments.

Table B2 (continued)

Variable or object	Definition and construction	Source and coverage	Main use
Number of transactions	Number of recorded export shipments in a cell, referred to by Census as the "card count."	Authors' calculations using the Census ECCN downloads, 2009–2024.[a–d]	Table 4; Table 8, column 3; Table 11, columns 4–6; Table A5.
Exports per shipment	Export value divided by the number of recorded shipments in the same destination × year × classification cell.	Authors' calculations from export value and transaction counts in the Census ECCN downloads.[a–d]	Table 4; Table 8, columns 2 and 6; Tables 9–10, A3, A5, and A8; Sections 4.7–4.8.
Traded products	Number of distinct Schedule B 10-digit products with positive exports in a destination × year × classification cell.	Authors' calculations using the Census ECCN downloads.[a–d]	Table 8, column 4; Section 4.7.
Control intensity	Share of export value in cell c reported under classification k, $s_c^k = \frac{\text{Exports}_c^k}{\sum_{k' \in \{\text{CCL,EAR99,NC}\}} \text{Exports}_c^{k'}}$. Any-control intensity is $s_c^{\text{CCL}} + s_c^{\text{EAR99}}$.	Authors' calculations using the Census ECCN downloads. Cells are sectors, industries, destinations, or sector–destination pairs.[a–d]	Figure 1; Tables 1, 3, 5, and 13; Section 2.2; dual-use classification in Section 6.2 and Table C1.
CCL value by license authorization	CCL export value reported as no license required (NLR), under a license exception, or exported under a BIS license. The tabulation also separately identifies the small amount authorized by other agencies.	Authors' calculations using the Census ECCN downloads.[a–d]	Tables 1–2; Section 2.2.
CCL technology category	One of the ten BIS technology categories, determined by the leading digit of the reported Export Control Classification Number (ECCN).	Authors' calculations using the ECCN field in the Census ECCN downloads and the Commerce Control List.[a–d]	Table 2; Figure 3; Table A6, column 4.
Industry and model-sector aggregates	Schedule B products are mapped to NAICS industries for the sector and industry analysis and then aggregated to ISIC Rev. 4 sectors for the quantitative model.	Authors' calculations using product and industry mappings applied to the Census ECCN downloads; 2016 for Tables 3 and 13, and 2016–2024 pooled where noted.[a–d]	Tables 3, 13, A6–A7, and C1–C3; Sections 4.6 and 6.1–6.2.
Dual-use industry indicator	A NAICS 6-digit manufacturing industry is classified as dual-use when its CCL share of U.S. exports to MECR destinations, pooled over 2016–2024, exceeds $\bar{s} = 0.15$; otherwise it is civilian.	Authors' construction using the Census ECCN downloads. The sample contains 366 manufacturing industries, of which 53 are classified as dual-use.[a,c,d]	Equation (36); Tables C1–C4; Sections 6.2–6.3.
Panel B. Export Control Status and Licensing Outcomes			
EAR country-list status	Annual placement on EAR Country Groups A1–A6, B, D1–D5, and E1–E2. Overlapping statutory lists are converted into the mutually exclusive MECR, A6, neutral, adversary, and excluded groups defined in Table B1.	Authors' digitization of the Export Administration Regulations, 2009–2024.	Figure 2; Table 5; Sections 2.2 and 4; Appendix B.1; country groups in Sections 6–7.
Control-list reclassification	Effective quarter of a destination's move onto or off an EAR-A or EAR-D list. Upgrades and downgrades, effective dates, and stated motives are coded from amendments to the EAR.	Federal Register notices and associated BIS rules, 2009–2024.	Table 11; Table A9; Section 4.9; Appendices B.2–B.4.
Approval rate by multilateral regime	Approved license applications divided by total applications for the AG, NSG, WA, and MTCR. The MECR series is the annual mean of the four regime approval shares. Missing application and approval totals within a regime series are linearly interpolated before shares are calculated.	BIS annual reports, digitized, 2010–2022; available for most regime-years.[e]	Figure 2a; Sections 2.2 and 4.8; Tables 9 and A8.

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Table B2 (continued)

Variable or object	Definition and construction	Source and coverage	Main use
Approval rate by destination	Approved license applications divided by total applications for each destination and year reported by BIS. Group series are simple means across the available country reports.	BIS annual country licensing and trade reports, digitized, 2012–2022; unbalanced across countries and years.[e]	Figure 2a; Sections 2.2, 4.8; tightened-control assumptions in Table 14.
World approval rate	BIS aggregate approvals divided by aggregate applications for all destinations.	BIS annual world licensing and trade reports, digitized, 2010–2022.[e]	Figure 2a.
License processing time	Mean calendar days to resolve reported license applications. MECR and adversary series are simple means across available country reports; the world series is the BIS aggregate.	BIS annual country reports, 2012–2022, and world reports, 2010–2022; unbalanced country coverage.[e]	Figure 2b; Table 9; Sections 2.2 and 4.8; tightened-control assumptions in Table 14.
Applications and approvals	Counts underlying the approval-rate series above.	BIS annual regime, country, and world reports, digitized.[e]	Figure 2a and the approval component of Tables 9 and A8.
Panel C. Country Characteristics			
GDP and GDP per capita	Country GDP and GDP per capita used to split destinations at the sample median. Each measure is averaged over 2016–2019 and held fixed over the regression period.	USITC Dynamic Gravity Dataset, version 2.1, supplemented where missing with World Development Indicators[g] and then the IMF World Economic Outlook Database (NGDPD).[h]	Table A4; Section 4.6.
Population	Country population used to exclude destinations with fewer than 500,000 people in robustness specifications and the structural decomposition sample. The screen is based on mean total population over 2016–2024.	USITC Dynamic Gravity Dataset, version 2.1, supplemented where missing with World Development Indicators (SP.POP.TOTL)[g] and then the IMF World Economic Outlook Database (LP).[h]	Table 8, columns 5–6; Tables A2–A3; Sections 4.6–4.8.
Government consumption share	General government final consumption expenditure as a share of GDP, interacted with control classification after demeaning within the estimation sample. The WDI series is NE.CON.GOVT.ZS.	World Development Indicators, annual observations for the available countries in 2016–2022.[g]	Table A5, columns 1–3; Section 4.6.
Military expenditure share	Military expenditure as a percentage of GDP. The WDI series is MS.MIL.XPND.GD.ZS and its underlying source is SIPRI. In the empirical specification, the annual share is demeaned within the sample before it is interacted with control classification.	World Development Indicators, annual observations for the available countries in 2016–2022.[g]	Table A5, columns 4–6; Section 4.6. The country share also determines $s_{d,D}$ in the model.
Panel D. Quantitative Model Inputs			
Input–output coefficients and trade shares	Country-sector intermediate input coefficients, labor shares, total final demand, and bilateral trade shares. The source industries are aggregated to the paper's 21 sectors.	OECD Inter-Country Input-Output (ICIO) tables, 2016 reference year (Yamano et al. 2023): 76 countries plus the rest of the world.[f]	Table 12; Sections 6–7; Tables 13–15 and C3–C7.
Military and civilian final-use shares	U.S. federal defense final use by sector determines military final-demand shares, which are applied to all model countries. Civilian shares are the residual of ICIO total final demand after military final demand is removed.	U.S. BEA 2012 Benchmark Input-Output Accounts, detailed supply and use tables; OECD ICIO total final demand.	Figure 4; Table 12; Sections 5 and 6.3.
Technology-specific input-use targets	Each supplying and using NAICS 6-digit industry in the U.S. make-use table is labeled civilian or dual-use using equation (36). Expenditure shares across the four buyer-supplier technology pairs are targets for φ^{J}_{bt} .	U.S. BEA 2012 Benchmark Input-Output Accounts, detailed make-use data, combined with the Census-based dual-use classification.[a,c,d]	Equation (39); Tables 12 and C4; Section 6.3.

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Table B2 (continued)

Variable or object	Definition and construction	Source and coverage	Main use
Defense-intensity benchmark	Share of each NAICS 6-digit industry's sales going to federal defense investment use, used as an external validation of the Census-based dual-use classification.	U.S. BEA 2012 Benchmark Input-Output Accounts.	Section 6.2.
Labor endowment	Country labor endowment L_d.	Penn World Table 9.0 (Feenstra, Inklaar, and Timmer, 2016).	Table 12; calibration in Section 6.
Trade elasticity	Pareto shape parameter κ^i, set to the median of Ossa's HS-product estimates within each ICIO sector. The model sets $\sigma^i = \kappa^i + 0.5$.	Ossa (2015), mapped to the paper's 21 ICIO sectors.	Table 12; Section 6.3.
Control-regime sufficient statistics	Sector-specific MECR export differentials $\widetilde{\delta}^j_{M,k}$, baseline selection ratios $\widehat{\Phi}_{A,k}$, and classification probabilities $\Pr(k \mid t)^j$.	Authors' calculations using the Census regressions, BIS licensing outcomes, and the dual-use classification described above.[a–f]	Equations (34)–(37); Tables 12, A7–A8, and C2–C3; Sections 6.1–6.2.

[a] We download the Census Bureau's quarterly Data by Export Control Classification Number files. These are Census special tabulations, distinct from the standard export series available through the Census data API. The record layout documents the Schedule B, ECCN, destination, license type, frequency, and value fields. For the baseline aggregate regressions, we collapse the 2009–2024 quarterly files to annual destination × classification cells for 2016–2024. The alternative identification design uses the quarterly data for the full 2009–2024 period.

[b] The transaction data contain 193 destinations after territories, Canada, Iran, and North Korea are removed. The baseline regressions contain 191 destinations after Hong Kong and Ukraine are additionally removed because their MECR/A6 status changes during 2016–2024. Those status changes are used in the alternative identification design.

[c] Canada is omitted from the Census-based empirical analysis because U.S. exports to Canada are compiled from Canadian import records, which do not report U.S. export control classifications. Canada is included as an MECR country in the OECD ICIO quantitative model.

[d] CCL denotes transactions reporting an ECCN on the Commerce Control List; EAR99 denotes items subject to the EAR but not listed under an ECCN; NC denotes transactions with no reported control classification. Classification is observed for an exported transaction and is not a time-invariant product characteristic.

[e] BIS does not report every licensing outcome for every country and year. The licensing panels therefore use all available reports and are unbalanced. Figure 2 contains country detail for 18 MECR or A6 destinations and 12 adversary destinations. The averages used in the structural decomposition cover 2016–2022.

[f] The OECD country set is assigned to the MECR, neutral, and adversary groups using the EAR classification. Service sectors have no classified goods in the Census data and are assigned no export-control friction.

[g] All World Development Indicators series were downloaded on June 18, 2025.

[h] The WEO supplement is the April 2025 *World Economic Outlook Database*, downloaded from IMF Data on June 18, 2025 (dataset IMF.RES:WEO(6.0.0)). We use NGDPD, nominal GDP at current prices in billions of U.S. dollars, and LP, population in millions. GDP per capita is calculated from these two series.

C Theory and Quantification

C.1 Average Shipment Value

Derivation of (10). Revenue scales with productivity: $r(z) = r(z^*)(z/z^*)^{\sigma-1}$. At the cutoff, $\rho r(z^*)/\sigma = w_o f$, so $r(z^*) = \sigma\, w_o\, f/\rho$. For Pareto-distributed z truncated at z^*:

$$\mathbb{E}\left[\left(\frac{z}{z^*}\right)^{\sigma-1} \;\middle|\; z \geq z^*\right] = \frac{\kappa}{\kappa-(\sigma-1)} = \frac{\kappa}{\theta}.$$

Therefore $\bar{v} = (\kappa/\theta)\sigma\, w_o\, f/\rho$. Since the Pareto moment is independent of z^*, and z^* is the only channel through which b, t, T, and demand conditions enter, the average value is invariant to all of these.

C.2 GE Price Index Derivation

With $z \sim \text{Pareto}(\kappa^i)$ and $p^i_{od}(z) = \mu^i A^i_{o,t}\tau^i_{od}/z$, the integral in the type-specific sub-index evaluates to:

$$\int_{z^*_{od,bt,k}}^{\infty} p^i_{od}(z)^{1-\sigma^i}\, dG^i(z) = (\mu^i A^i_{o,t}\tau^i_{od})^{1-\sigma^i}\, \frac{\kappa^i}{\theta^i}(z^*_{od,bt,k})^{-\theta^i}.$$

Multiplying by $\Pr(k \mid t)\rho^i_{od,k}Q^i_{od,k}M^i_{o,t}$ (the approval-weighted mass of entrants) gives $(\kappa^i/\theta^i)\,\Lambda^i_{od,bt,k}$ (equation (25)); summing over origins o and classifications k then yields the price index (26).

C.3 Sufficiency of Φ in Aggregate Equations

We show that the bilateral competitiveness $\Lambda^i_{od,bt,k}$ (equation (25))—and hence all aggregate equilibrium objects built from it (trade shares, price indices, wages, welfare)—depend on the regulatory frictions (ρ, Q, f) only through the selection factor $\Phi^i_{od,k}$.

Substitute the cutoff (24) into $\Lambda^i_{od,bt,k}$ (equation (25)) to eliminate $z^*_{od,bt,k}$:

$$\begin{aligned}
\Lambda^i_{od,bt,k} &= \Pr(k \mid t)\, \rho^i_{od,k}\, M^i_{o,t}\, Q^i_{od,k}\, (\mu^i A^i_{o,t}\tau^i_{od})^{1-\sigma^i}\, (z^*_{od,bt,k})^{-\theta^i} \\
&= \Pr(k \mid t)\, M^i_{o,t}\, (\mu^i A^i_{o,t}\tau^i_{od})^{-\kappa^i}\, w_o^{-\theta^i/(\sigma^i-1)} \\
&\quad \times \underbrace{(\rho^i_{od,k})^{\kappa^i/(\sigma^i-1)}\, (Q^i_{od,k})^{\kappa^i/(\sigma^i-1)}\, (\sigma^i f^i_{od,k})^{-\theta^i/(\sigma^i-1)}}_{\Phi^i_{od,k}} \\
&\quad \times (P^i_{d,bt})^{\theta^i}\, (X^i_{d,bt})^{\theta^i/(\sigma^i-1)},
\end{aligned} \tag{C1}$$

where we used $(1-\sigma^i)+(-\theta^i) = -\kappa^i$ to collect the exponents of cost terms, and $1+\theta^i/(\sigma^i-1) = \kappa^i/(\sigma^i-1)$ to collect the ρ and Q exponents.

Conditional on $P^i_{d,bt}$ and $X^i_{d,bt}$ the regulatory frictions appear in (C1) *only* through $\Phi^i_{od,k}$—defined in (9), now with sector superscripts. Since trade shares (28) are ratios of Λ terms, price indices (26) are sums of Λ terms, and all remaining equilibrium conditions (absorption, total sales, free entry, labor clearing, welfare) are functions of trade shares and price indices, the entire equilibrium system depends on (ρ, Q, f) only through $\Phi^i_{od,k}$.

Table C1: CCL Export Shares and Dual-Use Classification

NAICS	Industry	CCL share	Class.
336414	Guided Missile and Space Vehicle Mfg	0.978	D
332992	Small Arms Ammunition Mfg	0.924	D
336415	Guided Missile Propulsion Unit and Parts Mfg	0.860	D
33641X	Aerospace Product and Parts Mfg, n.e.c.	0.828	D
336411	Aircraft Mfg	0.789	D
		$\sim$	
335313	Switchgear and Switchboard Apparatus Mfg	0.154	D
325992	Photographic Film, Paper, and Chemical Mfg	0.153	D
339991	Gasket, Packing, and Sealing Device Mfg	0.148	C
314999	Misc. Textile Product Mills	0.144	C
327999	Misc. Nonmetallic Mineral Product Mfg	0.143	C

Notes: CCL share is the fraction of U.S. exports (by value, to MECR destinations, pooled over 2016–2024) classified under a Commerce Control List ECCN. Classification: D = dual-use (share $> \bar{s}$), C = civilian (share $\leq \bar{s}$). Industries sorted by CCL share (descending) to show the very top shares and those near the cutoff. The list is not exhaustive, indicated by $\sim$. The heavy rule marks the classification threshold $\bar{s} = 0.15$. These shares are slightly different from the 2016 data in Table 3 because we pool across all years.

C.4 Dual-Use Classification and Classification Probabilities

Table C1 illustrates the civilian/dual-use classification used in Section 6.2. It lists NAICS 6-digit industries sorted by their CCL export share, from aerospace and defense manufacturing at the top to industries just below the $\bar{s} = 0.15$ threshold.

Addressing selection in classification. CCL-classified goods face higher compliance costs, lower approval rates, and longer processing delays than NC goods, all of which raise the productivity cutoff for export (equation (24)) and depress the observed CCL share relative to the true classification share. Recovering the true classification probabilities therefore requires correcting for selection.

Two properties of the model let us back out $\Pr(k \mid t)^j$ from observed exports. First, the selection factor $\Phi_{od,k}$ is type-free: it depends only on classification-specific frictions and elasticities (equation (9)). Second, the buyer demand aggregate B_d carries no classification index k: buyers care about a good's type t, not the control regime it faces. So for a given product and destination, the ratio of classified to NC exports cancels both the seller supply conditions ($M_{o,t}, A_{o,t}$) and buyer demand (B_d), leaving only the classification ratio $\Pr(k \mid t)/\Pr(\text{NC} \mid t)$ and the selection ratio $\Phi_{od,k}/\Phi_{od,\text{NC}}$. Because the selection ratio is type-free, differencing across C and D products within the same sector and destination removes it and identifies the dual-use premium δ_k; the sector intercepts α_k^j are then recovered by applying the baseline selection correction of Section 6.1. We estimate the two components of the composition equation (37) in turn.

Step 1: estimating δ_k. We estimate (37) with sector $\times$ destination fixed effects, which absorb the bracketed term. The coefficient on $\mathbf{1}_{t=D}$ therefore identifies δ_k from the composition difference between D- and C-type products in the same cell, purged of selection bias. We estimate separately for k = CCL and k = EAR99. Table C2 reports $\hat{\delta}_{\text{CCL}} = 2.16$ (dual-use products' CCL-to-NC

export ratios are approximately $e^{2.16} \approx 8.7$ times those of civilian products) and an insignificant $\hat{\delta}_{\text{EAR99}} = 0.056$, so EAR99 shares are largely independent of dual-use status given the sector.

Table C2: Estimation of δ_k: Composition Single Difference

	(1) ln(CCL/NC)	(2) ln(EAR99/NC)
$\mathbf{1}_{t=D}$	2.158	0.056
	(0.077)	(0.047)
Observations	5,438	10,672
Fixed effects	sector × dest.	sector × dest.
FE groups	529	737
Within R^2	0.154	0.000
R^2	0.482	0.212

Notes: Dependent variable is the log ratio of classified to uncontrolled (NC) U.S. export values by NAICS 6d × destination, for ally destinations. $\mathbf{1}_{t=D}$ is the dual-use indicator from (36). Fixed effects are ICIO sector × destination. Heteroskedasticity-robust standard errors in parentheses.

Step 2: estimating α_k^j. The sector baseline α_k^j enters the C- and D-type composition shares equally, so, unlike δ_k (which we identified from the within-cell D–C difference), it cancels in that difference and must be recovered from the level of the log ratio. We instead fix the selection ratio at the value implied by the baseline compliance frictions of Section 6.1, taken common across sectors ($\ln \widehat{\Phi}_{A,\text{CCL}} = -0.367$ and $\ln \widehat{\Phi}_{A,\text{EAR99}} = -0.051$), subtract this and the dual-use composition term $\tilde{\delta}_k D^j_{\text{share}}$ from the observed log ratios, and take the trade-weighted average within each ICIO sector:

$$\alpha_k^j = \overline{\ln(s_k/s_{\text{NC}}) - \ln \widehat{\Phi}_{A,k}}^{\,j,w} - \tilde{\delta}_k D^j_{\text{share}}. \tag{C2}$$

where D^j_{share} is the fraction of distinct NAICS 6d codes in sector j classified as dual-use.

Table C3 reports the resulting classification probabilities $\Pr(k \mid t)^j$ by ICIO sector.

Table C3: Classification Probabilities $\Pr(k \mid t)^j$ by ICIO Sector

		$\Pr(\text{CCL} \mid t)$		$\Pr(\text{EAR99} \mid t)$	
Sector (j)	ISIC Rev. 4	D	C	D	C
Agriculture	01–03	0.2	0.0	0.9	0.9
Mining	05–09	27.3	4.2	18.0	22.8
Food, beverages, tobacco	10–12	0.0	0.0	5.4	5.1
Textiles, apparel	13–15	1.5	0.2	19.1	18.5
Wood products	16	0.1	0.0	2.4	2.2
Paper & printing	17–18	0.9	0.1	26.7	25.8
Coke, ref. petroleum	19	0.0	0.0	75.7	74.7
Chemicals	20	2.2	0.3	44.1	43.6
Pharmaceuticals	21	0.4	0.0	51.0	49.8
Rubber & plastics	22	5.2	0.6	28.2	28.4
Non-metallic minerals	23	19.0	2.7	33.0	38.3
Basic metals	24	0.9	0.1	24.1	23.3
Fabricated metals	25	23.6	3.5	26.2	31.9
Computers, electronics	26	44.4	8.6	21.3	33.9
Electrical equip.	27	27.2	4.2	30.3	38.7
Machinery n.e.c.	28	20.6	3.0	32.8	38.8
Motor vehicles	29	2.3	0.3	45.7	45.3
(Aerospace and) Other transport equip.	30	91.3	54.9	1.7	8.6
Other mfg.; repair	31–33	0.8	0.1	34.0	33.0
Services I	35–56	0.0	0.0	0.0	0.0
Services II	58–99	0.0	0.0	0.0	0.0

Notes: Entries are percentages. $\Pr(\text{NC} \mid t)^j = 1 - \Pr(\text{CCL} \mid t)^j - \Pr(\text{EAR99} \mid t)^j$. Probabilities computed from (35) using $(\tilde{\alpha}_k^j, \tilde{\delta}_k)$. Services I and II are uncontrolled by assumption. We deviate from the official ISIC descriptions by noting "Aerospace" is included in Other transport equipment.

Input-use share targets. Table C4 reports the targets $s_{t|b}^{j,\text{target}}$ of Section 6.3, averaged across the 21 ICIO sectors. Dual-use buyers spend 17.2% of their input purchases on dual-use suppliers, civilian buyers 11.0%.

Table C4: Input Purchases by Buyer and Supplier Technology Type

	Supplier type	
Buyer type	C (civilian)	D (dual-use)
C (civilian)	89.0	11.0
D (dual-use)	82.8	17.2

Notes: Percentages; rows sum to 100. Unweighted average across the 21 ICIO sectors of $s_{t|b}^{j,\text{target}}$ (Section 6.3).

C.5 Military Final Use Shares

We construct $\beta^i_{\text{US},D}$ as U.S. federal defense final consumption expenditure on sector i over total federal defense final consumption expenditure across all goods and services sectors, from the BEA benchmark input-output table.

The major sectors for federal defense consumption and their shares are: Services I (38.4%), Services II (20.6%), coke and refined petroleum (11.6%), other transport equipment (10.6%), computers and electronics (7.3%), fabricated metals (2.6%), motor vehicles (2.1%), other manufacturing and repair (1.7%), food, beverages and tobacco (1.5%), rubber and plastics (0.9%), textiles and apparel (0.7%), chemicals (0.5%), electrical equipment (0.5%), paper and printing (0.5%), machinery n.e.c. (0.4%) and pharmaceuticals (0.2%). The remaining sectors, agriculture, mining, wood, non-metallic minerals, and basic metals, are below 0.1% each.[48]

Some goods sectors are overrepresented in military consumption relative to the rest of the economy. For example, other transport equipment, which includes aircraft and shipbuilding, represents 10.6% of military consumption; its shares in U.S. GDP and civilian final use are 0.7% and 0.6%, respectively. Computers and electronics is 7.3% of U.S. defense consumption, 2.9% of civilian final use, and 1.2% of U.S. GDP. These compositional differences partially explain why the effects of controls are concentrated in dual-use industries.[49]

[48] Services I includes industries like computer systems design, data processing, air transportation, non-residential maintenance and repair, and telecommunications. Services II includes industries such as architectural and engineering services and management consulting.

[49] In constructing the shares, we use federal defense consumption only. A separate category is federal defense investment, which captures capitalized physical or intellectual property. If we impose steady-state and common-depreciation-rate assumptions on these investments, then we can aggregate consumption and investment to construct shares. In that case, some of the weaponry goods industries' shares are even higher. For example, other transport's share would increase from 10.6% to 16%. Therefore, if anything, our current calibration is conservative on the distinction between military and civilian final use.

C.6 Military Price Index Effects of Controls on Adversaries for Main Sectors

Table C5: Sectoral Decomposition of the Adversary Military Price Index under MECR24

	Price change by adversary ($100 \times \Delta \ln P_k^D$)						
	Aero & other transp. eq.	Motor vehicles	Computer & electronics	Other goods	Coke & ref. petrol.	Services	Total
SAU	41.89	10.38	5.45	1.29	0.30	0.25	5.34
CYP	42.61	12.20	3.86	1.02	0.26	0.05	5.19
CIV	32.00	10.75	2.51	0.23	-0.12	-0.01	3.79
EGY	28.68	6.77	4.35	0.65	0.15	0.12	3.64
TWN	23.09	5.34	3.05	1.20	0.37	0.45	3.19
JOR	23.37	8.40	2.84	0.59	0.19	0.15	3.02
RUS	15.09	6.85	2.71	0.43	0.75	0.58	2.41
KHM	16.38	9.20	2.11	0.61	0.63	0.28	2.37
KAZ	15.64	5.02	3.72	0.97	0.47	0.31	2.36
VNM	15.43	4.93	3.89	1.17	0.17	0.26	2.30
ISR	13.23	11.41	2.40	1.22	0.24	0.28	2.12
BLR	12.45	2.59	1.90	0.78	0.74	0.45	1.93
CHN	9.26	1.93	2.35	0.68	0.83	0.85	1.85
UKR	7.81	9.42	3.14	1.21	0.57	0.33	1.63
MMR	8.63	4.12	1.23	0.60	0.35	0.37	1.40
LAO	6.44	4.40	0.77	0.25	0.12	0.35	1.07
PAK	6.02	2.24	1.20	0.43	0.32	0.35	1.05
Adversary Average	18.71	6.82	2.79	0.78	0.37	0.32	2.63
	Sector contribution to overall average $\beta_{D,k} \times 100 \Delta \ln P_k^D$						
Adversary Average.	1.98	0.14	0.20	0.07	0.04	0.19	2.63
	Military expenditure share $\beta_{D,k}$						
	0.106	0.021	0.073	0.094	0.116	0.590	1

Notes: All entries, except the last row, are 100× the log change in the military price index for sector group k under scenario (ii) in Table 15. Adversary average is unweighted. Total is the expenditure-share-weighted sum of the sector changes, $\sum_k \beta_{D,k} \Delta \ln P_{d,k}^D$, and the "Total" for the average row equals the change in nominal income minus the change in real military expenditure in Table 15. $\beta_{D,k}$ are the military final-use shares in this Appendix. Sorting is from highest to lowest change for countries (by Total) and sector (columns by average). We aggregate the estimates of Services I and II into the Services column. Other goods aggregates Agriculture; Mining; Food, beverages and tobacco; Textiles; Wood; Paper and printing; Chemicals; Pharmaceuticals; Rubber and plastics; Non-metallic minerals; Basic metals; Fabricated metals; Electrical equipment; Machinery n.e.c.; Other manufacturing. Each of these is available on request.

C.7 Scale Economy and Congestion Parameter ψ

The model of endogenous entry features economies of scale: larger sectors attract more entrants, which lowers price indices and raises measured productivity. We derive the mapping from model parameters to scale elasticity in a simplified closed-economy version.

Expenditure on sector i is $E^i = \beta^i wL$, and free entry ensures sectoral employment $L^i = \beta^i L$. Define measured real productivity as real output per worker: $A^i \equiv Y^i/L^i = w/P^i$. From the Pareto–CES price index and free entry with congestion:

$$(w/P^i)^{\kappa^i} \;\propto\; M^i (L^i)^{\theta^i/(\sigma^i-1)}, \qquad M^i \propto (L^i)^{1/(1+\psi)}. \tag{C3}$$

Taking logs:

$$\ln A^i = \text{const}_i + \varepsilon^i \ln L^i, \qquad \varepsilon^i = \underbrace{\frac{1}{\kappa^i(1+\psi)}}_{\text{variety}} + \underbrace{\frac{\theta^i}{\kappa^i(\sigma^i-1)}}_{\text{selection}}. \tag{C4}$$

The first term captures the variety channel (more entrants lower the price index) and the second captures selection (larger markets raise the productivity cutoff). Under $\kappa = 3$, $\sigma = 3.5$, $\theta = 0.5$, the baseline $\psi = 5$ implies a scale elasticity $\varepsilon = 0.122$, so doubling sector size raises measured productivity by about 8.5 lp.

Given the substantial cross-sectional and time variation in industry scale, even a moderate elasticity implies large differences in efficiency. For example, China's new-energy vehicle production grew from roughly 380,000 units in 2015 to over 16.6 million in 2025, a roughly 44-fold increase.[50] At $\varepsilon = 0.122$, this translates into about 46 lp of higher measured productivity from scale alone. Cross-sectionally, the ratio of sector size between the largest and smallest countries easily exceeds 300-fold, implying about 70 lp of productivity difference.

For comparison, the urban agglomeration literature finds elasticities of 3–5% (Rosenthal and Strange 2004; Combes and Gobillon 2015), while Bartelme et al. (2025), using sectoral demand shocks as instruments, estimate an average of 20% across manufacturing. Our baseline falls in the middle of this range. Table C6 reports the implied scale elasticity for the range of ψ values we consider in the counterfactual analysis.

Table C6: Sectoral Scale Economy Elasticity by Congestion Parameter

	ε
$\psi = 0.6$	0.275
$\psi = 1.5$	0.200
$\psi = 3$	0.150
$\psi = 5$ *(baseline)*	0.122
$\psi = 20$	0.083

Notes: Computed from (C4) with $\kappa = 3$, $\sigma = 3.5$, and $\theta = 0.5$. ε is the elasticity of sectoral real output per worker with respect to sector employment.

We assess the sensitivity of the counterfactual results to the strength of scale economies by re-running the baseline vs. no-controls comparison for $\psi \in \{0.6, 1.5, 3, 5, 20\}$. Table C7 reports the resulting log changes in real expenditures, exports, and D-production for each country group.

[50] China Association of Automobile Manufacturers (CAAM). The 2015 figure (379,000 units) is from http://gxt.hunan.gov.cn/sjfb_80675/201602/t20160203_2919580.html; the 2025 figure (16.626 million units) is from https://www.steelorbis.com/steel-news/latest-news/caam-new-energy-vehicle-sales-in-china-up-282-percent-in-2025-1429628.htm.

Table C7: Sensitivity of the Baseline MECR Effects to Scale Economy

	$\psi = 0.6$	$\psi = 1.5$	$\psi = 3$	$\psi = 5$*	$\psi = 20$
Scale elasticity ε	0.275	0.200	0.150	0.122	0.083
Real expenditure					
U.S. civilian	−0.04	−0.04	−0.04	−0.04	−0.04
U.S. military	−0.60	−0.38	−0.27	−0.23	−0.17
Ally civilian average	−0.12	−0.09	−0.08	−0.07	−0.07
Ally military average	−0.57	−0.35	−0.27	−0.24	−0.20
Adversaries civilian average	−0.47	−0.51	−0.52	−0.53	−0.53
Adversaries military average	−1.44	−1.70	−1.80	−1.85	−1.90
Exports					
U.S.	−5.90	−5.16	−4.73	−4.53	−4.30
Ally (excl. U.S.) aggregate	−3.92	−2.89	−2.59	−2.47	−2.33
D-production					
U.S.	−5.76	−4.96	−4.37	−4.09	−3.76
Ally average	−4.46	−2.92	−2.49	−2.32	−2.12

*Main calibration for Baseline scenario.

Notes: All entries are 100× log changes of the Baseline equilibrium relative to the no-controls counterfactual. Real expenditures and D-production are unweighted averages across countries in each group; exports are aggregate log changes. D-production in o is defined as $\sum_j V^j_{o,D}$ over the 19 goods sectors. The $\psi = 5$ column can be compared to scenario (i) of Tables 14 and 15.

Stronger scale economies amplify the cost of controls for allies while moderating the military harm to adversaries. Moving from $\psi = 20$ ($\varepsilon = 0.083$) to $\psi = 0.6$ ($\varepsilon = 0.275$), the adversary military average goes from −1.90 to −1.44 lp, while U.S. losses go from −0.17 to −0.60 lp. The difference between civilian and military impacts increases for allies and decreases for adversaries. The mechanism operates through the endogenous reallocation of dual-use production. Allies lose export market access, so controls shift production from dual-use goods toward civilian output. With stronger scale economies, this shift reduces efficiency in dual-use production relative to civilian production, so the relative decline in military real expenditure is larger. Adversaries, on the other hand, substitute toward domestic sources of dual-use goods. With stronger scale economies, this leads to a smaller relative decline in military real expenditure.

C.8 Government's Economic and Security Objective

We derive equation (41), interpret the relative value parameter and provide a microfoundation for the security index. The government objective values both an economic and security outcome,

respectively $\mathcal{W}_o$ and $\mathcal{S}_o$, both of which depend on the export regime denoted by a vector $\boldsymbol{\rho}$:

$$G_o(\boldsymbol{\rho}) = G(\mathcal{W}_o(\boldsymbol{\rho}), \mathcal{S}_o(\boldsymbol{\rho})) \ ; G_{\mathcal{W}} > 0, G_{\mathcal{S}} > 0. \tag{C5}$$

We denote a change to a counterfactual regime e relative to a baseline by $\Delta_e G_o^{exact} \equiv G(\boldsymbol{\rho}^e) - G(\boldsymbol{\rho})$, and the first-order approximation term in $\Delta_e G_o^{exact} = \Delta_e G_o + \mathcal{O}(2)$ is

$$\Delta_e G_o = \Delta_e \ln \mathcal{W}_o + a \Delta_e \ln \mathcal{S}_o, \tag{C6}$$

where $a \equiv \left(\frac{\partial G}{\partial \ln \mathcal{S}_o} / \frac{\partial G}{\partial \ln \mathcal{W}_o} \right) |_\rho$ is the marginal benefit of security relative to the economic outcome. We use the relative change in real military expenditure for the U.S. vs. some adversary to capture the change in security

$$\Delta_e \ln \mathcal{S}_o = \eta_{\mathcal{V}} (\Delta_e \ln W_{o,D} - \Delta_e \ln W_{\mathcal{V},D}), \tag{C7}$$

where $W_{o,D}$ is the origin's real military expenditure and $W_{\mathcal{V},D}$ is the analogous aggregate for a set of adversaries $\mathcal{V}$, so $\eta_{\mathcal{V}} > 0$ captures the impact of relative real military expenditure increases on the security index. We can derive this from an underlying Tullock (1980) contest function where $\mathcal{S}_o(\mathcal{V}) = \frac{(W_{o,D})^r}{(W_{o,D})^r + (W_{\mathcal{V},D})^r}$ and $r > 0$ is the contest decisiveness, e.g. if it is unity then victory is proportional to relative capability; if it is infinite then the winner takes it all. Under this interpretation we have $\eta_{\mathcal{V}} = r(1 - \mathcal{S}_o(\mathcal{V})|_\rho)$. Substituting (C7) into (C6), and using real civilian expenditures as the economic outcome we obtain

$$\Delta_e G_o = \underbrace{\Delta_e \ln W_{o,C}}_{\text{Economic Impact}} + a\eta_{\mathcal{V}} \underbrace{(\Delta_e \ln W_{o,D} - \Delta_e \ln W_{\mathcal{V},D})}_{\text{Security Impact}}. \tag{C8}$$

This is equation (41) after defining $\alpha \equiv a\eta_{\mathcal{V}}$, $\mathcal{V} = V$ and $o =$U.S.

The adversary real expenditure aggregation we use is standard in the defense economics literature. It is a special case of a joint production function that also nests others. Specifically, $W_{\mathcal{V},D} = \left[\sum_{d \in \mathcal{V}} W_{d,D}^{\mu}\right]^{1/\mu}$ with $\mu = 1$. The $\mu \to 0$ with equal share parameters gives the equal-weighted geometric mean, and $\mu \to \infty$ gives a best-shot index in which only the largest adversary matters as in Hirshleifer (1983). Conybeare, Murdoch, and Sandler (1994) apply this CES aggregation to military real expenditures to test which case applies to alliances such as NATO. Table 15 reports values for these three cases. The aggregate row ($\mu = 1$), which we use, lies between the adversary average (the $\mu \to 0$ case at equal weights) and China (the largest and thus best-shot case). MECR24 has a larger security impact at a similar civilian cost than the unilateral approach under any of the alternative aggregations. We could also aggregate the U.S. and its allies' real expenditures in a similar way in scenarios (i) and (ii).