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Derisking in the time of Decoupling: U.S. Critical Supply Chains and Reliance on China

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Abstract

Growing geopolitical tensions between the U.S. and China have compounded concerns about supply chain resiliency, emphasizing the importance of widening supply-chain relationships with other partner nations. Using firm-level import data from the U.S. Census, this study quantifies the sunk costs firms incur when de-risking critical supply chains by transitioning to an alternative supplier country and constructs two policy scenarios of supply chain disruptions. The results suggest that the sunk costs firm face in the first year of importing limit firms' ability to respond to trade shocks. Our scenario analysis suggests an unexpected decoupling from China could decrease U.S. firm's operating profits by 15%-50% across critical sectors, but preemptive changes in trade policy that decreases tariffs for non-Chinese nations could offset these losses in some sectors. These results highlight the importance of policies aimed at reducing reliance on China and diversifying supply chains, such as promoting domestic production of critical goods, incentivizing diversification of supply chains, and strengthening alliances and trade relationships with other countries.

JEL Codes: D24, F10, F14, F51, F52, L14
Keywords: Intermediate Goods, Imports, Sunk Costs, Geopolitics, Supply-chain risks, Economic Security, Critical Commodities

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1. Introduction

Shortages of high-tech goods, such as semiconductors, that arose during the COVID-19 pandemic left many U.S. consumers and firms facing higher prices. More recently, growing geopolitical tensions between the U.S. and China have compounded U.S. concerns about supply-chain resiliency and security, which have been pronounced in high-tech products required for transitioning to greener technologies, or to ensure public health. These concerns led to Executive Order (EO) 14017 which led to a 100-day review of the supply chains of four critical products: semiconductors and advanced packaging, critical minerals and materials, large-capacity batteries for vehicles and grid storage, and active pharmaceutical ingredients.

Increased collaboration with partner countries will be critical to ensuring a reduced reliance on China as a supplier. U.S. firms have spent decades building relationships, manufacturing, and shipping networks across China. These relationships represent costly investments developing customized manufacturing processes as well as developing knowledge of Chinese regulations and business conditions that may be sector specific. Reducing reliance on China will require U.S. importers to either import less, which will likely reduce U.S. productivity. Or it will require that U.S. importers pay these sunk costs all over again in a new country to establish new sourcing relationships.

This backdrop motivated a year's long research effort by MITRE's Center for Policy and Strategic Competition (CPSC) establish the status of the existing reliance on China in these critical sectors and to quantify the sunk costs U.S. firms pay when establishing new trading relationships in a new country across the products listed in in EO 14017. We then estimate a sourcing model of U.S. production where firms self-select into importing that incorporates these sunk costs. The model is used to simulate two counterfactual scenarios. The first scenario estimates the impact of an unexpected decoupling between the U.S. and China, both with and without an existing trade agreement centered around the Indo-Pacific Economic Framework (IPEF) in place prior to the decoupling. The second scenario simulates the impact of a disruption in shipping lanes in the South China Sea. In both scenarios we quantify the effects of the disruption on U.S. production, while considering the sunk costs that firms must pay to search for suppliers in a new source country.

This effort used confidential U.S. Census firm-level data. To fully quantify the effects of decoupling requires firm-level data. Publicly available data on import values alone lacks important information on how firms source products from different countries. To understand why information on a firm's sourcing activities is important consider an example where one firm sources a product from a single location, say China, and another firm sources the same product from five locations, say China and four other countries. As part of decoupling, if U.S. companies are limited in their ability to import products from China, the first firm will see its access to its one and only supplier fall. Its revenues and employment are likely to be more negatively impacted compared to the diversified firm. Without firm-level data on imports it is impossible for researchers to understand how U.S. firms have diversified their suppliers.

Using confidential census data we present three stylized facts regarding this status of U.S. reliance on the critical products outlined in EO 14017. Fact one, importers of critical commodities hold significant importance as they generate higher revenues and provide more employment to Americans compared to firms that import other types of commodities. Fact two, China plays a crucial role as a supplier across all critical subsectors, often ranking as the top supplier based on the count of firms sourcing from the country. Fact three, some countries who import to only a few firms still play a significant role in the imports for a specific critical sector meaning a small number of importing firms may have disproportionately large share of U.S. import values and may provide opportunities for other firms. These facts motivated the development of the model which incorporates the marginal costs, fixed costs, and sunk costs firms incur to better model how shocks to US suppliers and changes in policy may affect firms.

The sunk costs associated with importing from a new country determine the ability of importers to respond to shocks. For a product where the sunk cost of finding a new supplier is high, importers will be less likely to find alternative suppliers in response to a shock. These sunk costs limit the ability of firms to find new suppliers in response to foreign supply shocks. For example, a company that relies on a highly customized input that it has only ever sourced from China, will find it difficult to source from alternative suppliers in instances where there is a negative supply shock in China. The company would have to find a new supplier outside of China, transfer its blueprints to the new supplier, understand the regulations around importing from the new country, and establish a new logistics network. For many of the products in the EO 14017 list this report estimates that finding a new supplier could represent billions of dollars in up-front costs per U.S. importer. Therefore, the sunk costs associated with shifting suppliers can serve as a significant deterrent to firms considering such a move, even in the face of potential supply shocks.

International trade policy can facilitate increased supply chain resiliency and diversification by reducing firms' sunk costs on switching to a different foreign supplier through two channels. First by lowering the amount of the sunk costs themselves – this could come in the form of trade facilitation measures, product standardization, increased intellectual property rights, or other non-tariff measures. Alternatively, trade policy could instead focus on market access by lowering tariff rates which increases the value of supplier relationships making it easier to overcome sunk costs. Using the model in this paper we can develop scenarios for a variety of import disruptions and decoupling events as well as potential policy decisions to mitigate these events.

We extend the work of Antras, Fort, and Tintelnot (2017) and Hoang (2022) to consider multiple industries. Including multiple industries allows for a more complete picture of the effects of a potential supply chain issue as well as the effects of changes to trade policy. Using the approach in Hoang to estimate fixed and sunk costs bounds allows us to extend counterfactual scenarios to include both the fixed and sunk costs firms face when making a new import decision. Additionally, we present a discrete choice model of transportation mode types, based on the works of Allen and Arkolakis (2014) and Jaworkski, Kitchens and Nigai (2023), to estimate firm-specific shipping costs for each subsector. Unlike AFT and Hoang who use country-specific wage variations, our model uses transaction-specific shipping costs data, which vary by commodities, source country, and mode, to estimate import elasticities for each sector, providing a more detailed variation in cost shifters.

This remainder of the paper is organized as follows. In Section 2 we describe the data used in our analysis. In Sections 3 and 4 we discuss basic facts about critical supply chains and U.S. dependence on China. In Section 5 we describe the theoretical model and the estimation approach. Section 6 used the model estimate to perform 2 counterfactual scenarios, and Section 7 concludes.

1.1 Data Description

This analysis utilizes data from a variety of sources. Our primary data source comes from restricted-use Census data. This includes specifics on firms' domestic activities from the U.S. Census Longitudinal Business Database (LBD) and Economic Census (EC) and firms' import activities from the Longitudinal Foreign Trade Transactions Database (LFTTD). Additionally, we use publicly available data on critical supply chain subsectors defined from Executive Order number 14017 and other data sources on country characteristics, fuel prices, and shipping costs.

1.2 Restricted-Use Census Data

1.2.1 The Longitudinal Business Database and the Economic Censuses

The Longitudinal Business Database (LBD) is a restricted-use annual census of businesses. It covers information on a sample of establishments operating in the United States and provides information on the main industrial activity of the surveyed establishment at a NAICS 6-digit level. It also includes specific information about the establishment's employment, revenues, and a unique firm identifier.

The Economic Censuses (EC) is a bi-decade census of industries which are broken out into broad economic sectors, such as Mining, Manufacturing, Construction, Finance etc. It is conducted at the establishment level and covers all establishments every 5 years (years that end in 7 and 2). The data collected by the economic censuses varies by sector, but all contain some information on firm industrial activity, employment, revenue, some measure of cost of inputs, and the establishment's firm identifier.

We construct a panel of firms using the LBD and the EC. Our sample covers 2007, 2012, and 2017 -the three most recent years where the EC is conducted and data is available. We select firms that are wholesalers or have at least one manufacturing establishment inside the United States in at least one of our sample years. We include wholesalers in our analysis as a growing literature, such as Ganapati (2024) [1] and Fort (2023) [2], has shown that the role of wholesale firms within the United States has grown in recent years due to the rise of superstar firms.[1] To ensure a consistent sample, we remove firms that enter or exit over this time. We restrict our sample to only include firms that directly import from outside the U.S.

The EC includes information on a firm's domestic expenditures which include worker's wages, cost of materials (including imports), total revenues, and employment. From this we estimate each firm's domestic expenditure as the cost of its materials minus its total imports. However, our measure of domestic expenditure cannot distinguish between types of domestic inputs purchases. In our theoretical model and estimation we attempt to correct for this by using a

[1] This literature shows that superstar firms tended to manufacture products in the United States during the 1980's and 1990's. However over time these firms shifted their manufacturing activities overseas while maintaining wholesale, headquarter and R&D operation within the United States. Because of the way NAICS industries are classified at an establishment level, these firms would be omitted from an analysis that considered firms with only manufacturing establishments despite the long historical ties between these firms and the United States.

nested production function which treats aggregate domestic inputs as substitutes for aggregate imported inputs.

1.2.2 The Longitudinal Foreign Trade Transactions Database

Longitudinal Foreign Trade Transactions Database (LFTTD) restricted use data records all U.S. import and export activities of firms and individuals in the United States. For each firm it includes import and export activities at the transaction unit of observation. This includes information on the total value of the good that the firm imported, date of importation, country of origin or destination, the HTS code of the products, the costs paid to ship goods and the shipping mode chosen (among other variables). We keep import transactions that occur in an EC year, a year prior to an EC year or a year following and EC year, which is 2006-08, 2011-13, and 2016-2018.

1.3 Critical Supply Chains

On February 24, 2021, President Joe Biden issued an "Executive Order on America's Critical Supply Chains." The Executive Order, numbered 14017, called out four supply chains: Public Health and Biological and Preparedness, Information and Communication Technology (ICT), Energy, and Critical Minerals. In response, the International Trade Administration in the Department of Commerce created a Draft List of Critical Supply Chains (henceforth DL). The DL is a classification system used to categorize these four supply chains. It is matched to a list of Harmonized Tariff Schedule (HTS) 8-and 10-digit codes.[2] The DL classification system includes information on the aggregate sector, a subsector, and stage of production which are listed in Table 1-1. We take the combination of an aggregate sector and subsector as our unit of analysis.[3] Using these sectors, we will assess the ability of U.S. manufacturing firms to source these DL products from abroad with the goal of quantifying how disruptions to the supply chains of these products impact U.S. production of goods.

[2] For a complete list and more information see: https://www.trade.gov/data-visualization/draft-list-critical-supply-chains. Some HTS products in the list are assigned to more than one industry. To deal with this we slightly alter the list using a procedure which is described in the appendix.

[3] The one exception to this is in the Critical Minerals and Materials aggregate sector, where there is only one subsector. For this aggregate sector we take the combination of the aggregate sector, subsector and stage of production as our unit of analysis. This provides us with two units of analysis for the Critical Minerals and Materials subsector: "Primary" and "Processed".

Table 1-1: Critical Supply Chain Subsectors

Aggregate Sector	Subsector	Aggregate Sector	Subsector
Critical Minerals and Materials	Critical Minerals	ICT	Audiovisual Equipment
Energy	Carbon Capture	ICT	Computer Equipment
Energy	Electric Grid	ICT	Other Electronic Components
Energy	Fuel Cells	ICT	Semiconductors
Energy	Hydropower	ICT	Semiconductors/Electronic components
Energy	Large Capacity Batteries	ICT	Telecom/Network Equipment
Energy	Neodymium Magnets	Public Health	PPE and Durable Medical Equipment
Energy	Nuclear Power	Public Health	Pharmaceuticals & API
Energy	Platinum Group Metals	Public Health	Pharmaceuticals & API; PPE and Durable Medical Equipment
Energy	Solar	Public Health	Pharmaceuticals & API; Testing and Diagnostics
Energy	Wind	Public Health	Testing and Diagnostics

Note: Classifications are taken from the Draft List of Critical Supply Chains defined by the U.S. ITA's Office of Industry and Analysis. Subsectors are broken down further into stages of production. For Critical Minerals and Materials these stages include "Primary" and "Processed." For the remaining Sectors, stages include "Input", "Capital Good", and "Final Good."

1.4 Other Data

In our analysis we will use data on transportation cost shifters to identify how U.S. importers change their sourcing behaviors. To construct our transportation cost shifters we also use data on energy and distances between ports. The great circle distance and shortest path distances are calculated using maritime shipping lanes between all U.S. ports and foreign ports. We also collect timeseries data on Jet Fuel and Diesel prices. Fuel price data comes from the Department of Energy's Energy Information Administration and includes a monthly price of both jet fuel and diesel. The EIA's jet fuel prices (dollars per gallon) come from the U.S. Gulf Coast kerosene-type jet fuel spot price fob. Monthly diesel price data is the average monthly price of all diesels across the United States. We merge jet fuel price data to U.S. imports that arrive via plane and diesel prices with all other shipment modes.

For data on the distances between U.S. and foreign ports, we take latitudes and longitudes from the United Nations Code for Trade and Transport Location list and the World Port Index. Using these, we calculate the great circle distance and the maritime route distance. Maritime route distances are calculated using Dijkstra's algorithm on a network of global maritime shipping lanes taken from Eurostat.

2. Stylized Facts on the DL Critical Supply Chains

In this section we present three stylized facts regarding U.S. imports of DL commodities. The stylized facts: 1) link the importance of these commodities to U.S. firms and workers, 2) emphasize China's importance as a supplier of these products to U.S. firms, and then 3) highlight groups of countries that are efficient at supplying critical products to U.S. firms but might be underutilized due to high barriers of entry.

2.1.1 Background on the Extensive Margin of Trade and the Importer Premium

Trade is conducted by firms; there are some government-to-government transactions that may occur, but most global trade is driven by firm-level decisions (see Redding, 2011 [3] and Bernard et al. 2012 [4]). To understand the risks to U.S. supply chains for DL commodities, requires analyzing firm-level import decisions. Furthermore, for U.S. policies to ensure easy access to DL commodities for U.S. firms, policymakers need to account for the firm-level incentives and barriers to importing these products.

Classical trade models have focused on what is known as the *intensive margin of trade*, which is the dollar value of trade, when analyzing the effectiveness of U.S. policies. This is largely for convenience, as data on trade values is readily available and in a consistent unit of measurement that makes it easy to work with. Since, at least, Melitz (2003) [5] trade economists have recognized the importance of firm-level export decisions in driving responses to trade policy changes.[4] The firm-level decision of whether or not to trade at all is known as the *extensive margin of trade*. Melitz (2003) [5] focused on extensive margin of exports, while Antràs et al. (2017) [6] build on Meltiz to model how extensive-margin importing decisions are made.

To demonstrate the importance of the extensive margin of imports for DL products, we estimate an importer premium for firms that actively source DL products, and compare that to the importer premium seen from sourcing other products. The importer premium is measured by estimating a non-parametric relationship between the number of countries that a firm sources DL products from and the log of its revenues.[5] Figure 2-1 plots the estimated coefficients from this regression where the horizontal axis is the number of sources where a firm sources inputs from. For a firm that only sources domestically we normalize the importer premium to be 0.

Figure 2-1 shows that importing DL products carries a larger importer premium than the importer premium for other products. For, example firms that import any product from at least one foreign country earn approximately \$2,000[6] more in revenue compared to a firm that does not import from anywhere. However, a firm that imports at least one ICT product from anywhere earns an importer premium of approximately \$4,500[7]. This implies that the importer premium for a firm that imports an ICT product from a single location earns a premium that is twice as large

[4] We forgo listing papers that have built of Melitz as they are too many to conveniently enumerate.

[5] In this estimation we also control for the industrial composition of the firm's establishments.

[6] $\$3,100 \approx (\exp(1.149) - 1) \times \$1,000$

[7] $\$5,500 \approx (\exp(1.701) - 1) \times \$1,000$

than if it had imported a non-DL product from a single country. We will refer to the difference in the importer premia as the DL premia gap.

The DL importer premia gap is not just larger for firms that import DL commodities from a few firms. The importer premia gap widens in dollar value as firms source imports from more than one location. If a firm imports ICT products from more than 10 countries it earns an importer premium of approximately $176,000,[8] while a comparable importer of non-DL products earns an importer premium of approximately $103,000.[9]

Importing DL products carry a larger importer premium across all of the DL aggregate sectors, and the DL premia gap is increasing across all aggregate sectors as well. In addition to the effects presented in Figure 2-1 we also show in Appendix Figure E-1 these patterns hold when measuring a firm-level employment premium rather than sales premium. The patterns suggest that DL products are important to both U.S. production and employment. Policies meant to encourage the sourcing of these products can boost U.S. production and employment if effectively implemented. If a policy encourages a firm to increase the number of countries it sources a DL product from, this can be an effective way to increase U.S. employment as the employment premium is positively correlated with the number of countries that a U.S. firm sources from. Furthermore, this employment premium is increasing at a faster rate for DL commodities, in response to increasing the number of countries that a firm sources from, implying that policies that encourage firms to expand the scope of their sourcing decisions to additional countries can have positive net effects for employees. This brings us to our first stylized fact:

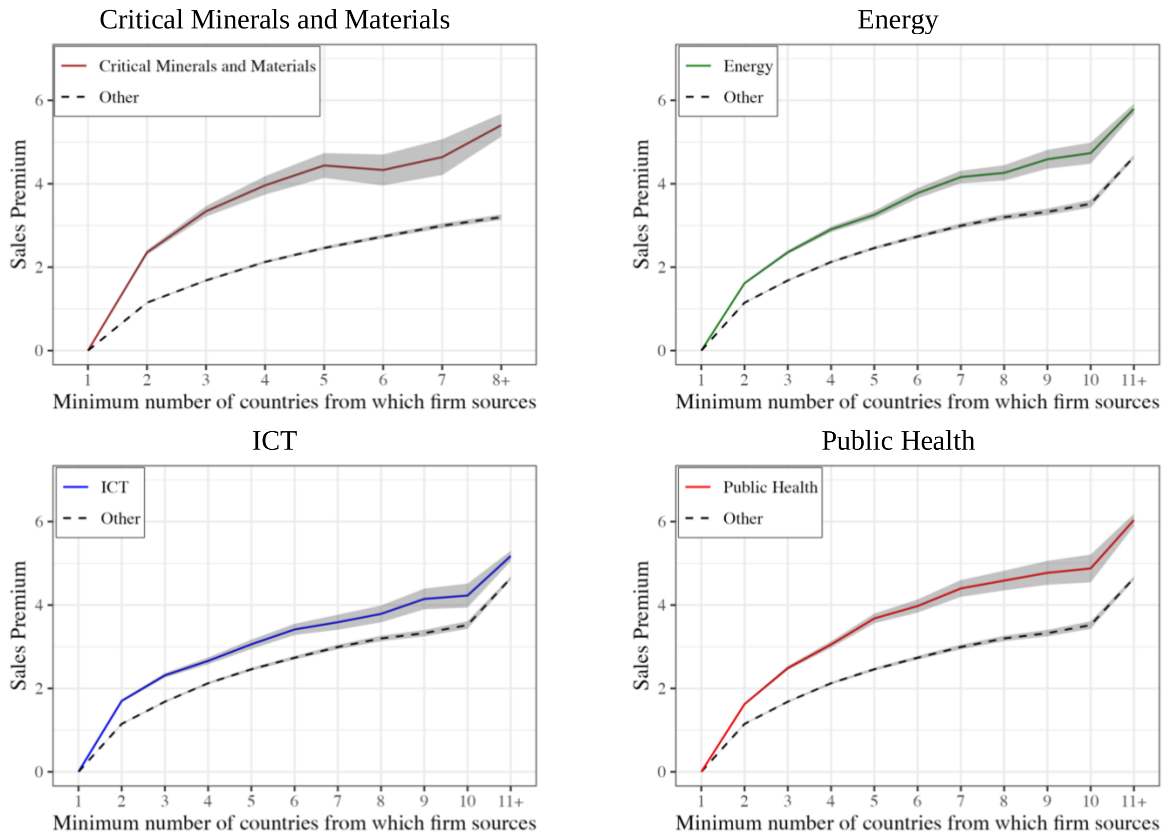
Stylized Fact 1: *Importers of critical commodities tend to earn higher revenues and employ more Americans compared to firms that only import other types of commodities. Furthermore, firms that import these critical products from more countries are associated with even greater revenue and employment.*

The findings in Figure 2-1 and Stylized Fact 1 beg the question “how do policies encourage firms to begin sourcing from a new country?” In general, this report will consider trade policy and risks to sourcing occurring across two dimensions at the firm-level: these are the intensive and extensive margins of trade. Policy can reduce the variable costs of importing by reducing the per-unit cost of sourcing inputs from abroad. The most salient example of this would be a tariff reduction that is negotiated as part of a free trade agreement, however other policy decisions such as infrastructure improvements or reductions in uncertainty could also reduce variable import costs. Policies can also reduce fixed costs of importing. These costs represent the time and effort firms must spend understanding foreign business environments, engaging in product customization, searching for suppliers, and understanding logistic and shipping networks. Policies that aid in trade facilitation or reduce transaction costs can reduce fixed costs of sourcing.

[8] $\$176{,}000 \approx (\exp(5.175) - 1) \times \$1{,}000$

[9] $\$103{,}000 \approx (\exp(4.645) - 1) \times \$1{,}000$

Figure 2-1: The Extensive Margin of Trade and the Importer Premium



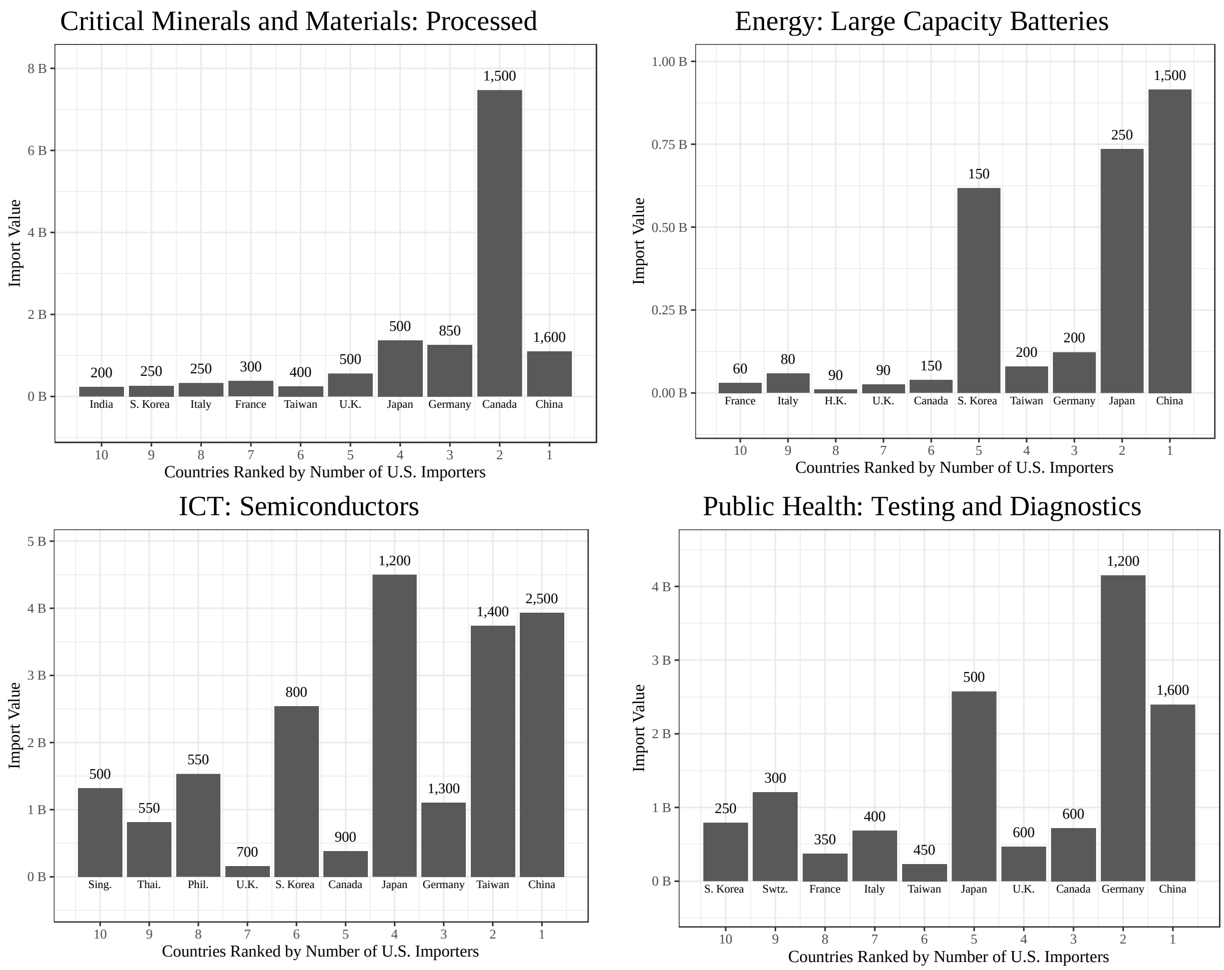
Notes: To construct the figure, we partition firms into groups based of their import activity across the DL sectors, with the "Other" Category reflecting importers of non-DL products. For each group we regress the log of firm sales on cumulative dummies for the number of countries from which a firm sources its DL products from, along with industry controls for the firm. The omitted category is non-importers, so the premia are interpreted as the difference in size between non-importers and firms that import from at least one country, at least two countries, etc. The horizontal axis denotes the number of countries from which a firm sources, with 1 corresponding to firms that use only domestic inputs. The grey shaded areas represent a 95% confidence interval.

2.1.2 Top Suppliers in Each DL Sector and China's Role

The fixed and variable costs of sourcing a particular product from a given country are not necessarily aligned. For example, a country may be a low variable-cost supplier to the United States due to laxed environmental regulations, for example, but U.S. firms might also face a high fixed cost of importing from the country if corruption is high or business norms differ substantially from the United States. Likewise, the divergence between fixed and variable costs of sourcing from a particular country likely vary by the commodity that is being sourced. For example, differences in environmental regulations likely have a greater impact on the variable cost of sourcing inputs related to mining than they do for the manufacturing of semiconductors. If corruption, business norms or distribution networks, vary by subnational regions, for example, it would imply differing fixed costs of sourcing inputs across commodities within a country.

Figure 2-2 and Appendix Table C-1 provide evidence for our stylized facts 2 and 3. It plots the relationship between the intensive and extensive margin of trade by source country in 2017 for four subsectors of the DL: processed critical minerals and materials, large capacity batteries, semiconductors, and public health testing and diagnostic equipment.[10] The figure shows variation exists in the relationship between the intensive and extensive margins across countries and DL commodities. The horizontal axis ranks countries by the number of firms that source products from those countries. The vertical axis is the dollar value of U.S. imports belonging to the subsector that arrive from each country. The number of firms that import from each country is printed at the top of each bar, and the country's name is printed at the bottom of the bar for convenience. The relationship between the extensive-margin rank and imports is non-monotonic; the bars are not smoothly increasing moving from right to left.

Figure 2-2: The Relationship Between the Intensive and Extensive Margin of Trade



Notes: Figures are calculated using import data for firms with at least one manufacturing establishment or are wholesale firms which import from given DL subsector. The numbers at the top of each bar reflect the number of U.S. firms that import subsector products from a given country and have been rounded according to Census disclosure rules. Likewise the import values on the vertical axis have also been rounded. The horizontal axis ranks the top 10 countries by the the number of U.S. firms that imoprt from the country, with 1 being the country where the most U.S. firms import from.

[10] We will follow these four subsectors across the remainder of the paper. We present the results for each subsector in Appendix Table C-1.

The patterns presented in Figure 2-2 are not unique to the four subsectors presented here. In Appendix Table C-1 we list the top three supplying countries as measured by the number of U.S. firms and show that the patterns presented in Figure 2-2 are consistent across each DL subsector.

Based on the extensive margin of trade, China is the top supplying country for the majority of the critical subsectors. China is also an important supplier with respect to the intensive margin of trade. For the majority of the DL subsectors more U.S. firms source from China than from any other country.[11] This suggests that U.S. importers face low variable and or fixed cost when importing DL commodities from China.

<u>Stylized Fact 2:</u> *Across each critical subsectors, China is an important supplier. Based on the number of firms that source from each country, China is the top supplier for most of the subsectors. When China is not the top supplier, it is never ranked lower than third.*

Stylized fact two demonstrates China's significant role as a supplier of critical commodities to the United States. This poses risks to U.S. firms; if supply chains were to be disrupted due to decoupling, or other shocks to the Chinese economy, many U.S. firms would be impacted in a way that might limit their ability to source critical commodities at all. Policymakers should consider strategies to encourage U.S. importers to diversify their sources of critical imports to reduce dependencies on China.

This implies that a forced decoupling between the U.S. and China would be costly for many U.S. firms. Policies undertaken today, prior to any forced decoupling, can minimize this hypothetical pain, if they encourage U.S. importers to diversify their suppliers. If U.S. policies encourage firms to search for new supplier countries across these DL sectors prior to any forced decoupling scenario, then the policy can reduce the future impacts of any surprise decoupling.

Also evident from Figure 2-2 is the fact that the number of U.S. firms importing critical goods and the total import value imports sourced from that country often rise concurrently. However, in some sectors, a few countries account for a significant amount of total U.S. imports, despite relatively few firms importing products from there. The extent to which countries follow a one-to-one ranked hierarchy between the number of firms that import and total import values, varies across subsectors. This implies that fixed costs of importing from a market likely varies by sector. This leads to our final stylized fact:

<u>Stylized Fact 3:</u> *The number of U.S. firms importing critical products from a country and the total value of those imports generally increase together. However, across sectors there are outlier countries, which may provide a significant amount of import value to relatively few U.S. firms.*

[11] Canada, Germany, Japan and Taiwan are also consistently among most important suppliers to U.S. manufacturers and wholesalers across the subsectors.

Consider the case of Japan and China as suppliers of testing and diagnostic equipment for public health purposes. Japan accounted for a similar value of imports of these products as China in 2017. However, more than three times the number of firms source these good from China than Japan.[12] This divergence suggests that the barriers facing U.S. firms when sourcing from Japan may be greater than those they face when sourcing from China. The Philippines, Singapore and Thailand, account for disproportionately large suppliers of semiconductors, given the number of U.S. firms that import from there. South Korea and Japan also supply a disproportionately large value of large capacity batteries to the United States, given the number of firms that import from there.

When taken together, these stylized facts construct a narrative around the sourcing of DL products by U.S. firms that serves as an alarm and offers a potential solution for U.S. policy makers. Stylized fact number one suggests that encouraging the importation of critical commodities benefit U.S. firms and workers. Firms that import these goods tend to generate more revenue and employee more workers, and these gains are increasing in the number of countries that a firm can source from. Policies that encourage firms to diversify their suppliers of critical products, could potentially stimulate economic growth and job creation within the United States. Stylized fact two, however, demonstrates China's significant role as a supplier of critical commodities to the United States. This degree of exposure poses a risk to U.S. firms. Policymakers should consider strategies to encourage U.S. importers to diversify their import sources of critical imports to reduce dependencies on China. Fact number three suggests there are country and sector specific barriers facing U.S. firms when they source these critical products. The presence of outlier countries (where relatively few U.S. firms import a disproportionately high value of critical products) suggests that policies that can reduce the barriers to importing from these places could serve to encourage U.S. importers to diversify away from China.

In what follows we develop an economic model of sourcing that will allow us to estimate subsector-specific costs of importing, for the commodities contained in the DL. The model allows us to estimate a country-specific variable cost of importing, and a fixed cost of importing. The country-specific variable costs consider manufacturing costs in the foreign country as well as the costs of transporting the good and tariffs. The fixed costs assume that the importer must pay an annual fixed cost to source the products each year, in addition to a sunk cost that the importer must pay in the first year that it sources the product from a particular country. In what follows we first present the model and then describe our strategy for estimation. We then apply the model to three counterfactual scenarios: A scenario of forced decoupling between the U.S. and China. A scenario of forced decoupling which assumes that prior to the decoupling, a trade agreement involving the Indo-Pacific Economic Framework (IPEF) countries has been put in place that reduces import tariffs across the DL products. Finally, we simulate the impact of a disruption in transporting goods through the South China Sea and analyze its effects on U.S. sourcing of DL products.

[12] There are a number of explanations for these divergences across sectors, such as differences in pricing, product quality or even multinational activity. However, for now we choose to focus on barriers to entry as an explanation. Later in the paper, we will separately estimate a country specific import price and formally control for as many of these potentially confounding factors as possible. As a slight preview of those results, the non-monotonic relationship between import prices and the extensive margin of trade persists suggesting barriers to entry do explain some of the variation between the intensive and extensive margins of trade here.

3. Structural Model

3.1 Theoretical Framework

We model individual firm production, costs, and profits for firms that import critical DL inputs (as defined by the Executive order 14017). Firms may import inputs from many countries but must pay an annual fixed cost (FC) for every country where they source inputs. An example of fixed costs associated with sourcing from an additional country could include the costs of maintaining an operations office to support import activities in each country. The first time a firm sources inputs from a country it must pay a sunk cost (SC) to establish import operations in addition to annual fixed costs. Sunk costs may include the time required for employees to learn local business customs or initial construction costs for production facilities. Ultimately, we model firms such that they source inputs from the lowest unit-cost supplier of the countries accounting for trade costs, FC, and SC to maximize firm profits[13].

We rely on the work Antras, Fort, and Tintelnot (2017) [6], henceforth (AFT) and Hoang (2022) [8] and extend their approaches to include multiple sectors. We also add a model of endogenous shipping mode choice as in done in Allen and Arkolakis (2014) [9] or Jaworski, Kitchens and Nigai (2023) [10]. The integration of the mode choice model makes it possible to identify sector-specific import elasticities using variation in observed import decisions and shipping costs that vary across countries sectors, rather than relying on wage data which is only available by country.

Our extension of the model allows firms to source goods from multiple DL sectors and subsectors. We nest firm production into three groups. The first allows the firm to substitute between domestic and imported inputs. The second allows the firm to substitute across the four aggregate sectors described in Table 1-1 which are indexed by S. The firm elasticity of substitution across the four aggregate sectors is denote as $\xi_{\mathcal{I}}$, where $\mathcal{I}$ denotes that the goods are imported. Within a given sector, the final nest allows firms to substitute across DL subsectors, which are indexed by $\mathcal{S}$, such that $\mathcal{S} \in S$. Similarly, firms substitute inputs within each subsector with the elasticity of substitution denoted by $\xi_{\mathcal{S}}$.

For example, a firm producing a heart monitor as a final product may import inputs from two aggregate DL sectors: Public Health (tubes, patches, etc.) and ICT (wires, circuit boards, etc.). Firms substitute across these aggregate sectors with an elasticity of $\xi_{\mathcal{I}}$. Within each aggregate sector, imports may include multiple subsectors, such as semiconductors and other medical equipment. Firms will substitute across these inputs with a different elasticity of $\xi_{\mathcal{S}}$. Firm input elasticity will affect production, costs, and profits for each firm, and these factors will inform the set of countries where firms choose to source inputs.

We present the model in three stages. We first derive the firm's optimal demand for DL inputs conditional on the set of countries that each firm has chosen to source from. We then derive firm profits conditional on the firm's optimal demand for DL inputs and its decision of where to source inputs from. Finally we derive firm's optimal decisions on where to source from.

[13] In a manner similar to Eaton and Kortum (2002) [7]

3.1.1 Firm Production Conditional on Firm Sourcing Decisions

3.1.1.1 Firm Sourcing

In this model we assume a Constant Elasticity of Substitution (CES) production function for U.S. firms. Firm production is made from a combination of domestically-sourced and foreign-sourced inputs. Given the example above, if a firm is producing a heart monitor, the components such as the tubes, electronics, and semiconductors may be imported from around the world or sourced domestically from other U.S. firms. We assume the production process is governed by the following functional form

$$q(\varphi) = \left([q^{\mathcal{I}}(\varphi)]^{\frac{\eta-1}{\eta}} + [q^{\mathcal{D}}(\varphi)]^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}} \qquad 3\text{-}1$$

Firms are indexed by φ which is also the U.S. firm's productivity. An individual's firm's productivity is assumed to be drawn from a distribution randomly. As a result, some firms are more productive than others and can operate a lower per-unit costs of production than others. The parameter η denotes the Armington elasticity, which governs the substitutability of between imported and domestic inputs. The firm's total output of its final product is denoted by $q(\varphi)$ and is a function of its imported inputs, $q^{\mathcal{I}}(\varphi)$, and its domestically purchased inputs, $q^{\mathcal{D}}(\varphi)$.

We represent the firm's per-unit production costs as a function of its per-unit imported input price, $c^{\mathcal{I}}(\varphi)$, and its domestically sourced input price, $c^{\mathcal{D}}(\varphi)$. Given these parameter's the firm's optimal unit cost of production, $c(\varphi)$, is given by:

$$c(\varphi) = \frac{1}{\varphi}\left([c^{\mathcal{I}}(\varphi)]^{1-\eta} + [c^{\mathcal{D}}(\varphi)]^{1-\eta}\right)^{\frac{1}{1-\eta}} \qquad 3\text{-}2$$

Continuing the example from above, if heart monitor tubes and semiconductors are imported and the remaining electronics are produced domestically, each component would enter the cost per unit of production in a different way. The costs of tubes and semiconductors would be captured in the imported input costs $c^{\mathcal{I}}(\varphi)$ and the cost of other electronics would be captured in the domestic input costs $c^{\mathcal{D}}(\varphi)$. Total per-unit cost of production is also governed by the Armington elasticity η and the firms productivity φ.

In our data we do not observe the quantity of domestic purchases, only the value. Likewise, we do not observe domestic purchases of inputs. Modeling production in this manner allows us to separate domestic purchases from imported purchases in a way that allows us to separately identify their impact on firm revenues. Given that we will have more detailed data for international firm purchases, we will largely focus on U.S. imports of DL commodities. We will include total domestic expenditures on inputs in our estimation of the model, which can be represented in the model as $E^{\mathcal{D}}(\varphi) = q^{\mathcal{D}}(\varphi)c^{\mathcal{D}}(\varphi)$. This will serve as a control for the importance of domestic sourcing in our model, but given the nature of our research question surrounds international trade policy, we will focus our attention on firm decisions to import.

Firms purchase intermediates abroad from the lowest cost options in the set of countries that it has searched. That is, conditional on a set of countries where a firm has paid a cost to search for a supplier, we assume that the firm will source from the lowest cost option. This setup follows

AFT, but follows a more broad class of models originally derived by Eaton and Kortum (2002)[7]. The distribution of country-specific production technologies governs the state of comparative advantage across the world and is assumed to follow the Fréchet distribution.

Under this setup and after some derivations, it can be shown that the value of a firm's subsector-s intermediate inputs sourced from country j can be given by:

$$x_j^s(\varphi) = \frac{T_j^s\left(w_j^s \tau_{j\varphi}^s\right)^{-\theta_s}}{\Phi^s(\varphi)} E(\varphi)^s \qquad 3\text{-}3$$

Here, w_j^s is the marginal cost of producing sector-s goods in country *j* and $\tau_{j\varphi}^s$ is a firm specific transportation cost. A technology shifter, T_j^s governs the state of absolute advantage across countries and sector-s. The import elasticity, θ_s determines the state of comparative advantage. $E(\varphi)^s$ is the firm's total expenditure on subsector-s imports.[14] $\Theta_j^s(\varphi)$ represents the country firm-specific **sourcing potential** as: $\Theta_j^s(\varphi) \equiv T_j^s\left(w_j^s \tau_{j\varphi}^s\right)^{-\theta_s}$. Sourcing potential is made up of factors such as country specific trade costs, wages, and technology that affect the how appealing a country is for importing firms. Note that the sourcing potential is (on average) increasing in the absolute advantage (T_j^s), and decreasing in production and transportation costs ($w_j^s \tau_{j\varphi}^s$). $\Phi^s(\varphi)$ represents the firm's **sourcing capacity** and it is given by $\Phi^s(\varphi) = \sum_{j \in \mathcal{J}_\mathcal{J}(\varphi)} \Theta_j^s(\varphi)$ and is the sum of the sourcing potential of a firm is importing inputs in sector s. If a firm imports from three countries the firm's sourcing capacity for semiconductors is the sum of the sourcing potential of the three countries. Put simply, a country's sourcing potential divided by the importer's sourcing capacity is the share of the firm's subsector-s imports that come from country j.

Both sourcing potential and sourcing capacity are determined at the subsector level. In our example of the heart monitor tubes and semiconductors, a single country will have two sourcing potentials, one for each subsector. Additionally, firm sourcing capacities would differ across firms and sectors. Firms are likely to source tubes from a different set of countries than semiconductors.

Similar to AFT, we can observe a U.S. manufacturing firm's unit cost of production for a single subsector s. A firm's unit cost of increasing its aggregate imports from subsector-s can be expressed as

$$c^s(\varphi) = [\gamma_s \Phi^s(\varphi)]^{-1/\theta_s} \qquad 3\text{-}4$$

where γ_s is a scalar[15]. Put in words this equation says that a firm's unit cost of increasing its imports from subsector-s is an inverse of its sourcing capacity in that subsector multiplied by a scalar. This indicates that the greater the subsector's sourcing capacity for a firm the smaller the unit cost of producing output that requires inputs from that subsector.

[14] A more technical of this derivation can be found in Appendix A.

[15] $\gamma_s \equiv \left[\Gamma\left(\frac{\theta_s+1-\eta}{\theta_s}\right)\right]^{\theta_s/(1-\eta)}$ and Γ is the gamma function.

Unit costs of importing for each sector and subsector are then aggregated to get the firm per unit production costs using a nested CES production function. Incorporating the nested structure of our CES production function, the firm's unit cost of producing one more unit of output can be expressed as:

$$c(\varphi)\frac{1}{\varphi} = \left(\sum_{\mathcal{S} \in \mathcal{S}} \left[\left(\sum_{s \in \mathcal{S}} [\gamma_s \Phi^s(\varphi)]^{(\xi_{\mathcal{S}}-1)/\theta_s} \right)^{\frac{1-\xi_{\mathcal{J}}}{1-\xi_{\mathcal{S}}}} \right]^{\frac{1-\eta}{1-\xi_{\mathcal{J}}}} + [c^{\mathcal{D}}]^{1-\eta} \right)^{\frac{1}{1-\eta}} \quad \text{3-5}$$

The per unit cost equation here is akin to the one presented in equation 2, but allows for differences in costs between sectors (eg. tubes and semiconductors, for imported inputs). This unit cost depends on the set of countries and subsectors that a firm chooses to search for suppliers in via the firm's sourcing capacity, $\Phi^s(\varphi)$. A firm's decision to source from a country will depend on the fixed cost of importing from each country and the increase in profit that the firm will accrue from adding the country to its set of suppliers.

3.1.1.2 Firm Profit Conditional on Sourcing Strategy

Next, we model individual firm profits. Like costs, profits are conditional on a firm's sourcing strategy. We follow AFT and assume that households do not import and must purchase goods from a U.S. manufacturer. We also assume that firms produce a unique variety and households have preferences with an elasticity of substitution of σ across goods. Note that we do not allow a firm's imports of DL commodities to affect the elasticity of demand it faces in the final goods market. Put differently we do not allow σ to vary be the types of DL commodities that the firm sources. Many firms may import products from more than one subsector in the DL and as such we do not differentiate the final goods that are manufactured using inputs from different subsectors. We assume the U.S. market for final goods is monopolistically competitive. The demand for a specific firm's final product is given by:

$$q_{US,t}(\omega) = E_{US,t} P_{US,t}^{\sigma-1} p_{US,t}(\omega)^{-\sigma} \quad \text{3-6}$$

Where $q_{US,t}(\omega)$ and $p_{US,t}(\omega)$ are the quantity demanded by and the price facing (respectively) U.S. households for a firm's final product in year *t*.[16] The total expenditure of U.S. households on manufactured products is denoted as $E_{US,t}$. The aggregate price index facing households is denoted as $P_{US,t}$.

Firm marginal costs of production $c_t(\varphi)$, expenditures on domestic inputs ($E_{US,t}$), market prices ($P_{US,t}^{\sigma-1}$) and the elasticity of substitution (σ) can be used to formulate firm variable profit as:

$$\pi(\varphi) = B_{US,t}[c_t(\varphi)]^{1-\sigma} \quad \text{3-7}$$

[16] We return to the use of time subscripts here to emphasize the specific role of dynamics in determining a firm's profits. Until this point, a firm's actions were conditional on its set of suppliers in a specific time period.

Where $B_{US,t} \equiv (1/\sigma)\mu^{1-\sigma}E_{US,t}P_{US,t}^{\sigma-1}$. Variable profit only includes the revenue and per unit cost of production. However, in addition to variable costs, firms must also pay country-specific fixed cost (f_{ij}^{s}) and sunk costs $\left(\psi_{ij}^{s}\right)$. Fixed costs of importing are costs incurred by the firm to import from any country j. These include the costs include costs not associated with production such as operating a local office to handle sourcing operations. These costs exist as long as the firm sources from country j regardless of the quantity of inputs sourced. However, in addition to fixed costs, there are additional costs incurred for each firm that chooses to begin importing from a new country. These costs could include the costs of training employees in local customs and initial investment in production facilities and are incurred the first year a firm source from a new country j. With FC and SC the specification of the firm's total operating profits as:

$$\Pi_t(\varphi) = B_{US,t}[c_t(\varphi)]^{1-\sigma} - w_{US,t}\sum_{s}\sum_{j\in\mathcal{J}_t^s(\varphi)} f_j^s + \psi_j^s \cdot \mathbb{I}\left(j \in \mathcal{J}_t^s(\varphi)\backslash\mathcal{J}_{t-1}^s(\varphi)\right) \qquad \text{3-8}$$

That is, the firm's operating profit is its variable profit net the sunk costs firms must pay to search for suppliers across countries and sectors and additional fixed costs of importing. The term $\mathbb{I}\left(j \in \mathcal{J}_t^s(\varphi)\backslash\mathcal{J}_{t-1}^s(\varphi)\right)$ is an indicator function equals one when sunk costs are incurred for country j.

3.1.2 Optimal Firm Sourcing Decisions

Absent fixed and sunk costs, firms would simply import from the set of countries with the lowest per unit cost of production in each subsector-s. The existence of FC and SC requires firms to be forward looking in their sourcing decisions. Firms make sourcing decisions that maximize their discounted profit over a fixed number of years, L. This is in contrast to a firm that does not have to pay SC when sourcing, in that instance the firm would simply source from the location that provides it with the greatest operating period today. But because SC must only be paid one time, and as such weighed against future profit streams, it provides firms with an incentive to be forward looking in their sourcing decisions. Incurring the fixed and sunk costs of sourcing from a new country may not increase firm profits in year 1 but may maximize profits over 30 years. A firm's profit discounted over time is defined as:

$$\mathrm{E}[\sum_{\tau=t}^{t+L} \delta^{\tau-t}\pi_{\varphi\tau}\left(\mathcal{J}_{\varphi\tau}^s, \mathcal{J}_{\varphi s\tau-1}^s\right)\middle|\mathcal{J}_{\varphi\tau}^s, \Omega_{\varphi t}] \qquad \text{3-9}$$

Where $\mathcal{J}_{\varphi\tau}^s$ is a subset of countries a firm may choose to import sector s inputs from in the set of all possible countries J. $\Omega_{\varphi t}$, is the firm's information set about each country, which is based on its previous import experience $\mathcal{J}_{\varphi\tau-1}^s$. δ is the discount factor. A firm who has imported from a set of countries in previous year will use its knowledge about practices, wages, and laws as its information set $\Omega_{\varphi t}$ when making sourcing decisions in year t. Firms will choose the optimal countries sources to maximize profit. This is modeled such that the maximum firm profit given the firm's country set in the previous year and Ω will satisfy the Bellman optimality principle:

$$V_{\varphi t}(\Omega_{\varphi t}) = \max_{\mathcal{J}^s} \overline{\pi_{\varphi t}}\left(\mathcal{J}^s, \mathcal{J}_{\varphi t-1}^s\right) + \delta\, \mathrm{E}\left[V_{\varphi t+1}(\Omega_{\varphi t+1})\middle|\mathcal{J}^s, \Omega_{\varphi t}\right] \qquad \text{3-10}$$

$\overline{\pi_{\varphi t}}$ is the expected value of firm profits and $V_{\varphi t}$ is the value to the firm of sourcing from countries $\mathcal{J}^s$ given the firm's information set Ω. A firm will choose an import from country set $\mathcal{J}^s$provided it satisfies the condition $V_{\varphi t}(\mathcal{J}^s, \Omega_{\varphi t}) > V_{\varphi t}(\mathcal{J}^{s'}, \Omega_{\varphi t})$ where the value of the country set $\mathcal{J}^s$ at least as great as any other country set $\mathcal{J}^{s'}$. Solving for the optimal country is not trivial due to the trivial due to large number of possible country choice sets.

3.2 Estimation Approach

In this section we describe our approach to estimating all stages of the model. We describe this in two stages. First, we describe the approach to estimate sourcing potential for DL subsectors. This happens in two steps: we first estimate a model of transportation mode choice that allows us to estimate transportation cost by country and subsector, we then use these trade costs to predict country-specific sourcing potential in the second step. After we discuss how we estimate sourcing potential, we then discuss how we identify the upper bounds for sunk and fixed cost across the DL subsectors.

3.2.1 Firm Specific Trade Costs

Temporarily departing from the firm's production problem, we lay out a discrete choice model of transportation mode types. The model follows Allen and Arkolakis (2014) and Jaworski, Kitchens and Nigai (2023) [3] and [4], respectively. This framework is used exclusively to estimate firm specific shipping costs $\tau^s_{j\varphi}$ for each subsector. We choose to estimate a firm-country-specific trade cost for each DL subsector because we will use variation in these trade costs to estimate import elasticities for each DL sector. This is a departure from AFT and Hoang who use country-specific variation in wages. However, wages may vary across industries within a source country depending on the DL sector the country specializes in. Our approach uses observed data on transaction-specific shipping costs which likely vary by commodities, source country and mode, which provides richer variation in cost shifters across DL commodities.

We assume that each firm chooses a transportation mode to minimize its shipping costs. Shipments are subject to random shocks that vary across mode type. We assume that these shocks are distributed i.i.d. across firms and modes via an extreme value distribution. Under this assumption the average trade costs for a firm that ships products from country j can be expressed as:

$$\tau^s_{j\varphi} = B^s_{\varphi}\tau^s_j \qquad \text{where } \tau^s_j \equiv \left[\sum_{m\in\mathcal{M}^s_j}\left(\tau^s_{mj}\right)^{-\rho_s}\right]^{-1/\rho_s} \tag{3-11}$$

B^s_{φ} is a firm specific trade cost shifter, and τ^s_j is an aggregate subsector-s shipping cost τ^s_{mj} calculated by averaging the cost of shipping a DL product-s via mode m from country j. This aggregation is taken across the set of all mode choices that are available as viable modes of transportation from country-j and subsector-s products ($\mathcal{M}^S_j$).

Under this model we can give a firm's share of subsector-s imports that arrive via mode m as:

$$\varsigma_{mj\varphi}^{s} = \frac{\left(\tau_{mj}^{s}\right)^{-\rho_s}}{\left(\tau_{j\varphi}^{s}\right)^{-\rho_s}} \qquad \text{3-12}$$

This expression will be leveraged below as our key estimating equation that will allow us to predict values of $\tau_{j\varphi}^{s}$ and estimate ρ_s.

3.2.1.1.1 Estimating Trade Cost

We use data from LFTTD to estimate trade costs. LFTTD has information on each firms' mode choice allowing us to calculate the share of the firm's subsector-s imports that arrive from each country via transportation mode-m. For example, we calculate each firm's share of imports of Critical Minerals that arrive from Canada via maritime shipment. This allows us to capture for each firm a measure of $\widehat{\varsigma_{mj\varphi}^{s}}$, where the $\widehat{\cdot}$ notation denotes a variable identified in the data.

We also use information on shipping costs recorded in LFTTD to estimate the cost of importing an additional unit of DL commodities from country-j via a specific mode (τ_{mj}^{s}). We calculate this as a year-country-sector-mode average cost of shipping by taking the total cost of shipments and dividing by the total value of imports.

$$\widehat{\tau_{mjt}^{s}} = \text{Total Shipping cost}_{mjst} / \left(\text{Import Value}_{mjst}\right)$$

To estimate trade costs, we take our measure of a firm's share of imports that arrive via a specific mode and regress those on the sector-country-mode specific average trade costs plus two sets of fixed effects. That is to say we take the log of equation 3-12, and substitute in 3-11 and use fixed effects to proxy for B_{φ}^{s} and τ_{j}^{s}. Put more concisely we regress:

$$\log\left(\widehat{\varsigma_{mj\varphi t}^{s}}\right) = \beta^{s}\log\left(\widehat{\tau_{mjt}^{s}}\right) + \mu_{\varphi s\, t} + \delta_{jst} + \epsilon_{mj\varphi t}^{s}$$

Where t has been added to indicate the year of the observation. We instrument our measure of per-unit costs of shipping with distance interacted with a mode specific fuel price variable that varies over time.[17] This reduces concerns around measurement error by allowing fuel price changes to shift the estimated mode specific cost of transportation.[18]

We can recover the components of the firm's specific trade cost from the estimated fixed effects and the regression coefficient β^{s}. Note that the fixed effect $\mu_{\varphi st}$ varies by firm, sector and year, which is the same as the variation in $B_{\varphi t}^{s}$ and the fixed effect δ_{jst} varies by the same as τ_{jt}^{s}. We can recover ρ_s from the negative of $\widehat{\beta^{s}}$ (where the hat denotes it is the estimated value). We

[17] We also control for economies of scale in shipping by including shipment weight in the regression.

[18] The inclusion of trade value in the denominator could introduce measurement error because it contains information on demand, which vary with unobserved factors such as exchange rate fluctuations or price inflation. We also estimate our equation using a two-stage Poisson Pseudo Maximum Likelihood (PPML) estimator. The use of PPML allows us to include zero mode shares in our regression. These zero flows are meaningful for our regression as they reflect important differences across countries and subsectors that restrict the set of available mode choices. For example, shipments may not travel by rail into the U.S. from any country other than Canada or Mexico. Likewise hazardous or heavy materials may not be able to be shipped via air.

recover $B_{\varphi t}^{s}$ from the expression $\exp(\hat{\mu}_{\varphi st})^{1/\widehat{\beta^s}}$ and τ_{jt}^{s} from the expression $\exp(\hat{\delta}_{jst})^{1/\widehat{\beta^s}}$. After recovering these structural parameters, we can estimate firm specific shipping costs as:

$$\log(\widehat{\tau_{j\varphi}^{s}}) = \frac{1}{\widehat{\beta^s}}(\hat{\mu}_{\varphi st} + \hat{\delta}_{jst}) \quad \text{3-13}$$

Note that this measure will vary by sector. Intuitively this arises because different commodities have different weights, shipping requirements that govern their shipping costs and the set of transportation modes available to ship products in a particular sector.

Table 3-1 presents our estimates of the mode choice elasticity of substitution, $\widehat{\beta^s}$. Critical Minerals and Materials has the most inelastic elasticity estimate. This is likely due to the sector's reliance on maritime shipments due to the heavy weight associated with shipping natural materials. On the other end of the spectrum, ICT products have the largest estimated mode choice elasticity. This likely reflects a higher number of shipping modes available to importers of these products as they are lighter in nature.

Table 3-1: Mode Choice Elasticity Estimates

	Mode Choice Elasticity
Critical Minerals and Materials	-0.7914**
	(0.3447)
Energy	-2.618***
	(0.8547)
ICT	-3.077**
	(1.251)
Public Health	-2.841*
	(1.502)
Fixed Effects:	Firm-sector-year
	Country-sector-year
Bootstrap S.E. Clustered	Sector

Notes: Estimates reflect a two-stage Poisson Pseudo Maximum Likelihood estimator. Standard errors are clustered by sector and calculated using a bootstrapped estimator. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

3.2.2 Estimating the Elasticity of Demand

In the outline of our model, the elasticity of demand for U.S. manufacturers' products, σ, is required to estimate the additional profits a firm from adding an additional supplier. To estimate this parameter we apply the methodology used in AFT to the Census of Manufacturers and the Census of Wholesalers in 2017. In a monopolistically competitive market, the optimal markup of a manufacturer is given by $\sigma/(\sigma - 1)$. We assume that the U.S. final goods market is monopolistically competitive to estimate σ from observed markups in the Economic Censuses. The Census of Manufacturers and Census of Wholesalers have data on total revenues and total variable costs by establishment. To estimate our elasticity of demand we take data on the establishment's total sales and divide by its total variable input expenditure to calculate observed markups. We then use back out an estimate for σ under the condition that the markup equals $\sigma/(\sigma - 1)$ in a monopolistically competitive market. For our estimate we find that the median firm's markup is 28.5% with a bootstrapped standard error of 0.0015. This implies that σ = 4.5. This estimate is in line with previous estimates of demand elasticities in the economics literature, see Ahmad et al. 2020 [12] for a summary of estimates.

3.2.3 Sourcing Potential and Import Elasticities

Our next task is to compute country-sector-firm specific sourcing potential, a parameter that reflects a country's ability to supply a certain product to a DL sector to U.S. firms at a competitive price. By considering disparities in technology, production costs, transportation costs, and economic policies among source countries and DL sectors, this measure provides valuable insights into the relative efficiencies of different countries in meeting the demand for a particular product.

Prior work, such as AFT, has relied on variation cross-country variation in wages to identify import elasticities and estimate an aggregate sourcing potential for each country. However our analysis is concerned with specific countries' ability to supply U.S. firms with products from many different sectors. Countries may have different sets of sector-specific technologies or production costs that influence their efficiency at supplying a product that makes the effect of wages differ across countries. Furthermore, wages might vary within a country in a meaningful way across sectors. Therefore, we depart from using variation in wages across countries as a key source of variation and instead use our estimated measures of shipping costs from equation 3-13.

We also must consider a potential domestic supply of inputs across the DL despite not being able to directly observe a firm's purchases of inputs of commodities from these sectors. To do this we make two assumptions. The first is that the domestic sourcing potential in a particular sector is the same for all U.S. firms within a given year. The second is that production takes place via the nested CES structure in section 3.1 . We then proceed in two steps. In the first step we isolate our domestic sourcing potential away from international sourcing potential. We then identify the country-sector-firm-year specific sourcing potential estimates.

3.2.3.1 Isolating Domestic Sourcing Potential

Firms can source critical inputs from abroad, or domestically. We observe firm purchases of imported critical sector inputs from LFTTD. However, we only have limited information on the nature of domestically purchased inputs that is available in the Economic Censuses. Of particular concern, we only observe domestic purchases of inputs in aggregate, and cannot identify the share of these purchases that are applied to our critical sectors. To address this, we rely on our nested CES production function outlined in section 3.1 .

We begin by taking the ratio of country-sector specific expenditure to total domestic expenditure by a particular firm. After some derivations we can express the following:

$$\log\left[x^s_{jt}(\varphi)/E_t(\varphi)\right] - \log[E^{\mathcal{D}}_t(\varphi)/E_t(\varphi)] = \log\left(\frac{T^s_{jt}\left(w^s_{jt}\tau^s_{\varphi jt}\right)^{-\theta_s}}{\Phi^s_t(\varphi)}\right) + \log\left(\frac{E^s_t(\varphi)}{E_t(\varphi)}\right) + \log\left(1+\frac{E^{\mathcal{J}}_t(\varphi)}{E^{\mathcal{D}}_t(\varphi)}\right)$$

Where $x^s_{jt}(\varphi)$ is the value of the firm's inputs from country-*j*. The terms $E^s_t(\varphi)/E_t(\varphi)$ and $E^{\mathcal{J}}_t(\varphi)/E^{\mathcal{D}}_t(\varphi)$ capture any nonlinearities in the firm's response to shocks that might arise due to the inability for the firm to substitute inputs across different classes of critical products. We measure these in our data. The former represents the share of a firm's inputs that are spent on sector-s imports. While the latter represents the ratio of total import expenditure to domestic expenditure.

We estimate part of this equation (excluding the first term in the left-hand side) using a sector-year fixed effect to control for domestic sourcing potential and our observed values for the latter two terms. This implicitly assumes that we allow all firms to source sector-s inputs from domestic suppliers without paying a fixed cost to do so. Specifically, we regress:

$$\log\left[x^s_{jt}(\varphi)/E_t(\varphi)\right] - \log\left[E^{\mathcal{D}}_t(\varphi)/E_t(\varphi)\right] = \zeta_{st} + \log\left(\frac{E^s_t(\varphi)}{E_t(\varphi)}\right) + \log\left(1+\frac{E^{\mathcal{J}}_t(\varphi)}{E^{\mathcal{D}}_t(\varphi)}\right) + \xi^s_{j\varphi t} \quad \text{3-14}$$

Running this regression obviously conflates the econometric error with the sourcing potential term that we are interested in recovering: $\log\left(T^s_{jt}\left(w^s_{jt}\tau^s_{\varphi jt}\right)^{-\theta_s}/\Phi^s_t(\varphi)\right)$. In what follows we discuss how we isolate the country-sector specific sourcing potential from the error and simultaneously recover the import elasticity, θ_s.

3.2.3.2 Estimating Sourcing Potential

After estimating equation 3-14 we still need to recover the sector-specific sourcing potential estimates for each country. We also need to estimate a sector import elasticity for U.S. firms. To do this we note that the error $\xi^s_{j\varphi t}$ contains a true error (denote this by $\varepsilon^s_{j\varphi t}$) and the set of parameters of sourcing potentials $\Theta^s_{jt}(\varphi)$. We take the estimated error terms from equation 3-14, denoted by $\widehat{\xi^s_{j\varphi t}}$, and express the following relationship:

$$\widehat{\xi^s_{j\varphi t}} = \log\left(T^s_{jt}\right) - \theta_s\log\left(w^s_{jt}\right) - \theta_s\log\left(\tau^s_{\varphi jt}\right) - \log\left(\Phi^s_t(\varphi)\right) + \varepsilon^s_{j\varphi t}$$

We estimate the above equation using our estimates of firm-country-sector specific trade costs (the predicted values from equation 3-13), a firm-sector-year fixed effect to capture $\log\left(\Phi^s_t(\varphi)\right)$, and a country-sector-year fixed effect to capture the terms $\log\left(T^s_{jt}\right)$ and $\theta_s\log\left(w^s_{jt}\right)$. Using the variation in our estimated trade costs we are able to identify θ_s for each DL sector by estimating the following regression.

$$\widehat{\xi^s_{j\varphi t}} = -\theta_s\log\left(\tau^s_{\varphi jt}\right) + \gamma^s_{jt} + \iota^s_{\varphi t} + \varepsilon^s_{j\varphi t} \quad \text{3-15}$$

In prior papers this equation, or similar equations have been estimated using variation in country specific wages, that is w_{jt}, to identify the import elasticity θ_s. Note that we allow for wages, transport costs, and technology to vary by sector and country. This assumes that these sectors are different enough to require different treatment in production and transportation across source countries. For example, Canada may be efficient at transporting hazardous materials into the United States since it can ship goods via land or sea, while U.S. hazardous imports from China may be restricted to maritime shipments only. Alternatively, Canada may produce higher cost hazardous materials because it has stronger environmental regulations that might drive up its costs of production, compared to China.

We present our estimates of the import elasticity in Table 3-2. Note that there is variation in the estimates across sectors, however all elasticity estimates are feasible and statistically significant despite strong fixed effect controls. The estimates also seem reasonable in magnitude.[19]

Table 3-2: Import Elasticity Estimates

	Import Elasticity
Critical Minerals and Materials	-1.839***
	(0.0634)
Energy	-3.514**
	(1.446)
ICT	-6.048**
	(2.403)
Public Health	-2.569***
	(0.8028)
Fixed-Effects:	Country-Sector-Year Triplet
S.E.: Clustered	by: Country & Sector
R2	0.1129

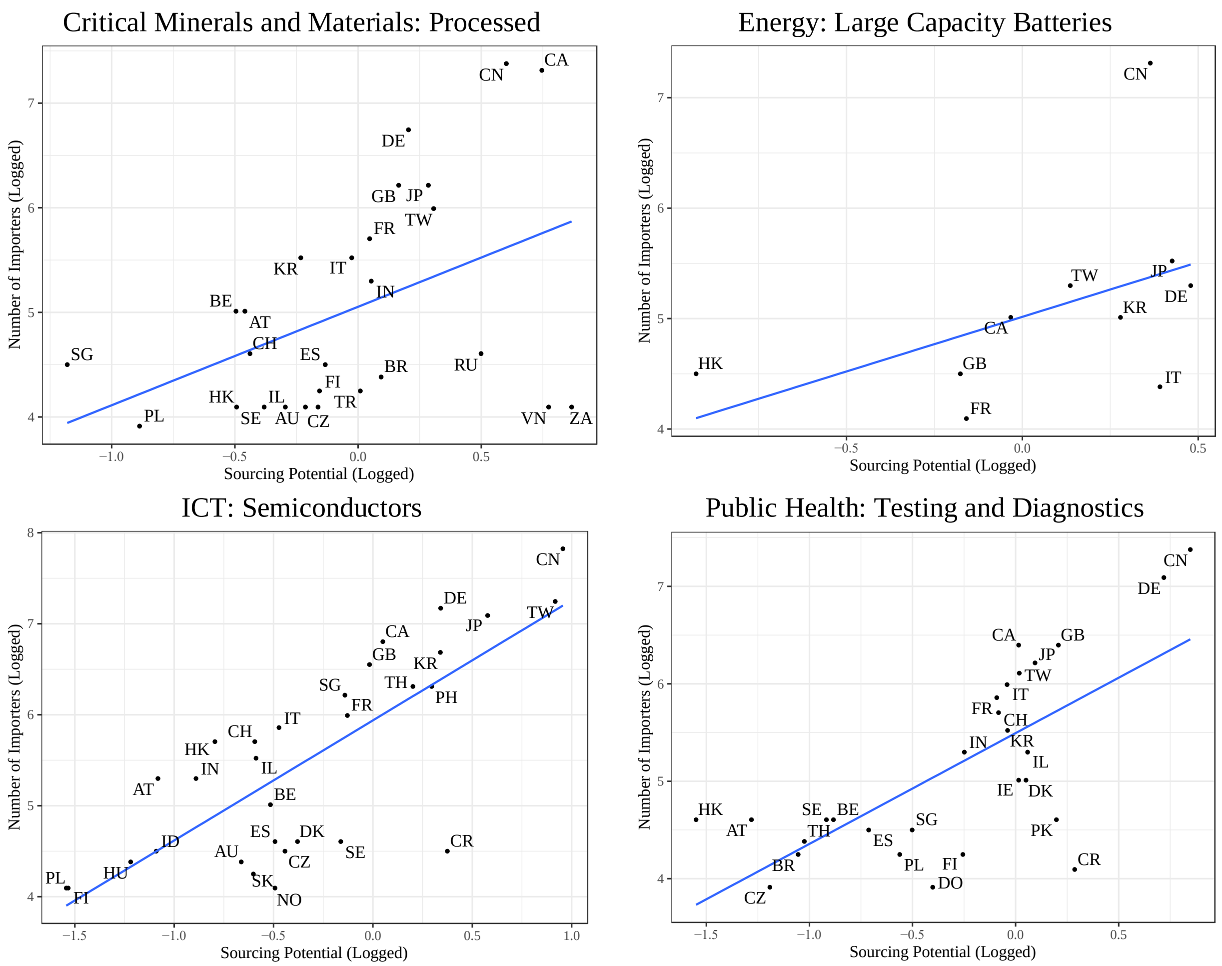
Notes: Standard errors are clustered by sector and country. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

The import elasticity for Critical Minerals and Materials is the smallest in absolute value across the four aggregate sectors, suggesting that U.S. firms are not able to easily adjust their demand for these products in response to price shocks. ICT products have the highest import elasticity, implying that U.S. imports of these products can be more easily substituted across countries.

[19] For example Allen and Arkolakis (2014) [9] estimate a mode choice of -14.2 across all industries using domestic U.S. domestic data, whereas Li and Wu (2019) [13] estimate a mode choice elasticity of -2.6 for international shipments. Our estimates are closer to the latter value for sectors besides the ICT sector. Our ICT estimates are in the middle of this range. The ICT is composed of lighter weight products that can be shipped via multiple methods, including air shipments. Heavy or products that must be shipped via bulk methods are unable to be feasibly shipped to the U.S. via any mode other than maritime shipments for international suppliers (other than Canada and Mexico which can access U.S. markets via rail and truck in addition to maritime shipments). The additional shipping options available to lightweight ICT products likely makes the international shipping mode elasticity estimated in this paper closer to the estimates that were recovered using domestic data where there are more shipping modes available to shippers.

To estimate sourcing potential by sector and country we can predict equation 3-15 to get $\widehat{\Theta^{s}_{jt}(\varphi)}$.[20] We plot the median sourcing potential, taken across firms for each country, for four DL subsectors in Figure 3-1.[21] The horizontal axis of each figure plots the median sourcing potential for each country, while the vertical axis plots the number of U.S. firms that source a DL commodity from the country. Sourcing potential captures the value of the foreign country as a supplier along the extensive-margin of trade. The greater a country's sourcing potential is the greater the extensive margin of trade is for U.S. firms that import from that country. The number of firms that import a product from a particular country is a direct measure of the importance of the extensive margin of trade.

Figure 3-1: Sourcing Potential and the Extensive Margin of Trade



Notes: The horizontal axis presents the logged value of the sourcring potential of importing from each country. A firm-country-subsector spefic sourcing potential is estimated and the point represented in this figure is the median value, taken across firms. The veritical axis plots the logged number of U.S. manufacturing or wholesale firms that import subsector-specific products from each country. The blue line represents the average relationship between the logged median sourcing potential and the logged number of firms that import from a country.

[20] Assuming that the true error term is uncorrelated with the structural regressors.

[21] We again present results for Processed Critical Minerals and Materials, Large Capacity Batteries, Semiconductors, and Testing and Diagnostic Equipment for Public Health and present similar figures for all subsectors in the Appendix.

From Figure 3-1 there is a positive relationship between the extensive and intensive margins of trade across sectors and countries. However, it is also clear that this relation is not smooth; there are some significant outliers that buck this pattern. These differences are likely explained by the presence of frictions that exist in the extensive margin of trade.

As an example, consider South Africa (ZA) and Canada (CA) as suppliers of processed critical minerals and materials. Canada and South Africa have similar estimated levels of sourcing potential, with South Africa having a slightly higher value. This means that the total price paid by U.S. firms to import processed critical minerals from South Africa, including transportation costs, is slightly lower than it is from Canada. Despite this fact, nearly 7,500 more U.S. firms source their critical minerals from Canada.[22] We explain this difference in our model with a fixed and sunk cost that firms must pay before they can actively import from a country.[23]

It is also clear from the figures that a country's relative position varies across the four subsectors. This implies that different countries are specialized in their ability to supply U.S. firms across different critical subsectors. For example, Japan ranks as an efficient supplier of semiconductors and large capacity batteries. However, Japan is less efficient at supplying testing and diagnostics public health equipment, or processed critical minerals.

3.2.4 Sunk and Fixed Costs

Following Hoang, instead of estimating a single estimate for fixed and sunk costs we estimate bounds for fixed and sunk costs by sector-s. Bounds are estimated using a revealed preferences approach. This approach is leveraged because it is less computationally burdensome than the approach to estimate a single parameter and requires making additional assumptions about firms expectations. Because sunk costs are only applied once, when a firm decides to source from a new country and pay the sunk cost, it weighs the sunk cost versus its expected returns from sourcing from the country in the future. Because of this, estimating a single parameter for fixed and sunk costs requires considering a full dynamic equilibrium firm decision, which requires making additional assumptions regarding firm's future expectations. Rather than make these assumptions we choose a revealed preference approach, however this approach only allows us to bound these costs.

The first step to estimating fixed and sunk costs is calculating each firm φ's marginal revenue $r^{m}_{\varphi jt}$ of importing from each country j. Based on the production function described in 3.1.1 , this revenue can be expressed as:

[22] $7{,}500 \approx \exp(7.5) - \exp(4)$

[23] In the current version of the model, we allow our sunk and fixed costs to only vary by sector. In future work we will expand these to vary by country and sector.

$$r^{m}_{\varphi jt}\left(o^{m}_{\varphi t}\right) = f(x) = \begin{cases} \left[\left(\frac{\left(\sum_{k\in o^{m}_{\varphi t}} S_{\varphi kt} + S_{\varphi jt}\right)}{\left(\sum_{k\in o^{m}_{\varphi t}} S_{\varphi kt}\right)}\right)^{\frac{\sigma-1}{\theta}} - 1\right] r^{m}_{\varphi ht}\left(o^{m}_{\varphi t}\right), & if\ j \notin o^{m}_{\varphi t} \\ \left[1-\left(\frac{\left(\sum_{k\in o^{m}_{\varphi t}} S_{\varphi kt} - S_{\varphi jt}\right)}{\left(\sum_{k\in o^{m}_{\varphi t}} S_{\varphi kt}\right)}\right)^{\frac{\sigma-1}{\theta}}\right] r^{m}_{\varphi ht}\left(o^{m}_{\varphi t}\right), & if\ j \in o^{m}_{\varphi t} \end{cases} \quad \text{3-16}$$

Firm marginal revenue is calculated by adding a country j's sourcing potential $S_{\varphi jt}$ to the Firms sourcing capacity when j is not in the set of observed sourcing countries $o^{m}_{\varphi t}$. When country j is in the observed set $o^{m}_{\varphi t}$ the marginal revenue is calculated by subtracting j's sourcing potential from the firm's sourcing capacity. Additionally, we use estimated elasticities σ, θ, and the firm's observed revenue in the home country $r^{m}_{\varphi ht}\left(o^{m}_{\varphi t}\right)$ given the observed sourcing set. If country j's sourcing potential is large it will have a greater effect on firm marginal revenue than a country with a small sourcing potential.

Firm marginal revenue is used to estimate Fixed and sunk costs bounds using variation in observed country imports in year $t-1$ and year t. There are four possible deviations of firm import status from country j in year t. We discuss each scenario below. We assume a linear functional form for fixed costs: $f_{\varphi jt} = \gamma^{f} + \epsilon^{f}_{\varphi jt}$ and sunk costs: $s_{\varphi jt} = \gamma^{s} + \epsilon^{s}_{\varphi jt}$. Intuitively, each deviation will be used to identify a bound for either fixed or sunk costs.

Deviation 1: A firm imports from country j in both t and $t-1$. In this case the firm will only incur fixed costs in year t. This provides the upper bound for the fixed cost parameter. The firm profit equation is:

$$\pi_{\varphi dt} = \sigma^{-1} r^{m}_{\varphi jt}\left(o^{m}_{\varphi t}\right) - \gamma^{f} - \epsilon^{f}_{\varphi jt}$$

Deviation 2: A firm does not import from country j in year $t-1$ but does in year t. In this case, the firm will incur both sunk and fixed costs in year the t. This provides the upper bound for the sunk cost parameter. The firm profit equation is:

$$\pi_{\varphi dt} = \sigma^{-1} r^{m}_{\varphi jt}\left(o^{m}_{\varphi t}\right) - \gamma^{f} - \epsilon^{f}_{\varphi jt} - \gamma^{s} - \epsilon^{s}_{\varphi jt}$$

Deviation 3: A firm imports from country j in year $t-1$ but does no import in year t. In this case, the firm will gain back fixed costs from their expenses. This provides the lower bound for the fixed cost parameter. The firm profit equation is:

$$\pi_{\varphi dt} = \sigma^{-1} r^{m}_{\varphi jt}\left(o^{m}_{\varphi t}\right) + \gamma^{f} + \epsilon^{f}_{\varphi jt}$$

Deviation 4: A firm imports from country j in year $t-1$ but does no import in year t. In this case, the firm will gain back fixed and sunk costs in year the t. This provides the lower bound for the sunk cost parameter. The firm profit equation is:

$$\pi_{\varphi dt} = \sigma^{-1} r^{m}_{\varphi jt}\left(o^{m}_{\varphi t}\right) + \gamma^{f} + \epsilon^{f}_{\varphi jt} + \gamma^{s} + \epsilon^{s}_{\varphi jt}$$

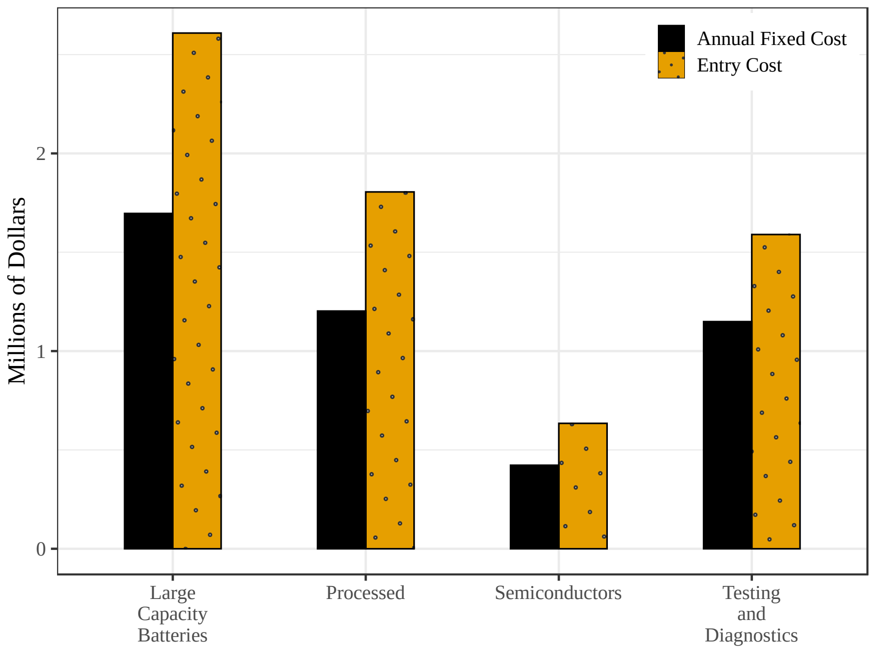
The four firm entry deviations can be used to construct upper and lower bounds for fixed costs and sunk costs. The parameters γ^{f} for fixed costs are estimated directly, but the estimates for sunk costs $\widetilde{\gamma^{s}} = \gamma^{f} + \gamma^{s}$ are estimates as both fixed costs and sunk costs together. This is done because these are the total fixed costs incurred by the firm for the first importing year. As in Hoang, the 95% confidence interval of the bounds is estimated using the test statistic specified in Andrews and Soares (2010).

We present the estimated upper bound estimates of fixed and sunk costs for four of the DL subsectors in Figure 3-2.[24] The black bars in the figure represent upper bound of the annual fixed cost that a firm must pay for each country that it sources DL commodities from. For example, a firm that sources large capacity batteries pays an annual cost of up to approximately 1.7 million dollars annually to maintain a sourcing relationship in each country that it imports from. If a firm sources large capacity batteries from two countries it would pay up to 3.4 million dollars annually to maintain sourcing operations in those two countries.

The patterned yellow bars represent the upper bounds of the total cost that a firm must pay when sourcing DL commodities in its first year of importing from a new location. The yellow bars include both the estimated sunk and annual fixed cost, and as such are always larger than the black bars, since the upper bound of the sunk costs of importing are always estimated to be larger than 0. These costs are non-trivial, we find that in the first year of importing from a particular country a firm's fixed costs can be anywhere from 125-175% of its annual fixed costs of sourcing depending on the DL subsector.

[24] We again present results for Processed Critical Minerals and Materials, Large Capacity Batteries, Semiconductors, and Public Health Testing and Diagnostic Equipment.

Figure 3-2: Fixed Costs of Importing



Notes: Bars represent the upper bounds of our fixed cost estimates in the first year that a firm sources from a country ($\widetilde{\gamma}^{s} = \gamma^{f} + \gamma^{s}$), and annually in all subsequent years (γ^{f}). The four DL subsectors represented are for Large Capacity Batteries, Processed Critical Minerals and Materials, Semiconductors, and Public Health Testing and Diagnostic Equipment.

The presence of higher fixed costs in the first year of importing limits the ability of firms to respond to trade shocks. Suppose a firm imports products related to Solar technologies from only China. If costs of importing from China were to rise unexpectedly, this firm would have a harder time finding Solar products comparted to a different firm that had experience importing from an additional location besides China. This example demonstrates how policies that reduce the sunk cost of importing from a new location can improve U.S. resiliency to supply shocks, by making it easier for U.S. firms to source from new markets. In the following section we explore how a supply shock to China would impact importers of DL commodities. We then estimate how the same shock would have impacted U.S. importers of DL commodities if the Indo Pacific Economic Framework (IPEF) had materialized into a trade agreement prior to the shock. The difference of the shock's impact across these two scenarios allows us to quantify the effect of the policy at reducing U.S. exposure to shocks in China. This increased resiliency to Chinese shocks will occur by lowering trade costs between the U.S. and IPEF partners, making it easier for more U.S. firms to source from IPEF countries. When the shock to China occurs in the IPEF scenario, more U.S. firms will have paid the sunk costs to source from an IPEF partner, allowing them to offset losses in imports from China with those from an alternative set of IPEF partners. This pair of counterfactuals demonstrates how policies can create opportunities for firms to overcome sourcing frictions and improve their resiliency to supply shocks.

4. Counterfactuals

Using the parameters estimated above, we perform two counterfactual scenarios of supply chain disruption. In our first counterfactual, we simulate a scenario where the U.S. and China “decouple” for DL critical sectors, reducing U.S. firms' sourcing potential from China by half where no preemptive trade policies are enacted. Then we adjust the counterfactual to include a preemptive Indo-Pacific Economic Framework (IPEF) trade agreement which includes a range of uniform tariff rate reductions. Our second counterfactual, we simulate a scenario where a conflict in the South China Sea disrupts the shipment of goods and raises the cost of importing from China, Vietnam, Japan, and the Philippines and assess the impact on U.S. importers' assuming a range of transportation cost increases for shipments from the region.

4.1 Decoupling and IPEF

In the first counterfactual, we simulate a scenario where the U.S. and China “decouple” for DL critical sectors and then explore how a preemptive Indo-Pacific Economic Framework (IPEF) would blunt the effects of decoupling. We model this decoupling as a reduction of U.S. firm's sourcing potential from China for all DL sectors by reducing Chinese sourcing potential for U.S. firms by half.[25] While this reduction is arbitrary it is not inconceivable given the stated goals of both the Chinese Communist Party and the United States Government.[26] This reduction in sourcing potential will cause the sourcing capacity of U.S. firms to fall across all DL sectors as China is often one of the most important suppliers to U.S. firms in these categories.

We then estimate how a proposed Indo-Pacific Economic Framework (IPEF) agreement would offset these losses across the DL sectors through a reduction in tariff rates or variable import costs.[27] We consider a range of uniform tariff rate reductions across the DL to account for different changes that might be feasible tariff reductions. We use a range of simulated values to simulate the policy since, as of this report, an IPEF trade agreement has not been negotiated. The estimates in this section are meant to demonstrate how changes in trade policy can reduce the effects of future shocks. Given the potential policy implications and the importance of IPEF members in supplying DL commodities to the U.S, we opted to simulate a trade agreement based on IPEF to demonstrate how similar trade policy may help in buffering against future economic shocks.

4.1.1 Modelling Decoupling

This section describe how we chose to model decoupling from China and present our estimates for how it will impact U.S. importers of DL commodities. Concerns have been voiced by policy makers, through media outlets and occasionally directly in policy documents, about the dependence of U.S. businesses on Chinese inputs from all sectors listed in the DL.[26] Summary statistics presented in Appendix Table C-1 provide some justification for these concerns; in 2017, China was the top supplier to the U.S. for the majority of the subsectors in the DL, as

[25] Given our estimates of import elasticities across DL sectors this reduction is equivalent to a percentage increase in U.S. import tariff on Chinese imports of 27.3% in Critical Minerals and Materials, 14.3% for Energy products, 8.3% for ICT products, and 19.5% for Public Health products. Note that these numbers reflect the percentage change in multiplicative tariffs (one plus the tariff rates).

[26] **Critical Minerals:** https://oversight.house.gov/release/hearing-wrap-up-reliance-on-non-allied-foreign-sources-for-critical-minerals-is-neither-sustainable-nor-secure/
Semiconductors (ICT): https://www.nytimes.com/2023/07/08/business/economy/us-china-chips-janet-yellen.html
Solar Panels (Energy): https://www.energy.gov/policy/articles/americas-strategy-secure-supply-chain-robust-clean-energy-transition
Biotech (Public Health): https://www.bloomberg.com/news/newsletters/2024-02-17/bloomberg-new-economy-cutting-china-out-of-biotech-unifies-us-parties

[27] In future work we could alternatively consider modeling IPEF as a reduction in the sunk cost of entering one of these markets. Doing so would however require some parameterization of our fixed and sunk cost estimates as a function of the non-tariff barriers outlined in deep trade agreements.

measured by the number of firms that source from China. In subsectors where China was not the top supplier, China was always ranked in the top three. This suggests that simply breaking away from China will impose large costs on U.S. importers. However, it leaves many questions unanswered, notably, "In what DL sectors will these costs be felt the most?" The answer most directly depends on how costly it is for firms to find new alternatives to China.
This counterfactual formally models decoupling within the context of the model we defined and estimated in Section 3, considering our estimated variable, sunk and fixed costs facing U.S. importers. We model decoupling as a halving of Chinese sourcing potential across the DL commodities which could reflect trade restrictions imposed by either the U.S. or China that raise the variable cost of importing DL products from China. An example of the former could be the U.S. imposing tariffs on Chinese products belonging to DL sector. An example of the latter could reflect an export restriction policy imposed by China targeting strategically important commodities. The way we have modelled a decoupling shock here could also be representative of productivity slumps, shipping delays, or natural disasters that only affect trade between the U.S. and China but do not affect neighboring countries.

Mechanically, our decoupling shock affects the variable costs facing U.S. importers actively importing from China. Higher variable costs of importing, reduces U.S. import demand from China, potentially lowering firm revenues for those firms that source inputs from China. Facing potential lower revenues, U.S. firms that had sourced from China face a decision. Do they try to offset their losses by importing from other countries or do they make do with what they can get from China?

The answer to this question depends on the type of importer. In particular, it depends on whether the U.S. importer sources exclusively from China, or if they source a particular DL commodity from multiple countries. The existence of the sunk costs of importing drives the difference in decoupling's impact on these two groups of importers. Firms that source a DL commodity exclusively from China are likely to be impacted by the shock more, because if they want to begin sourcing from a new supplier country they will have to pay sunk costs.[28] Firms that import from China and some other country will be able to offset some losses from decoupling by increasing their import demand from their other suppliers.[29] However, increasing import demand from the firm's existing set of suppliers may not be enough to offset the losses that the firm sees

[28] Implicit in this discussion is whether different countries' DL products are complements or substitutes. Following AFT and Hoang we have assumed that country-specific varieties are complements in production, requiring $\sigma - 1 > \theta_s$. Under this assumption, a reduction in sourcing potential from one country lowers the importer's demand for other varieties. In our setup we have assumed that firms pay a fixed cost to import any DL subsector commodity from a given country. Given the framework of AFT, a firm only sources a particular variety from one supplying country: the supplier of a variety from the set of countries it has searched that offers the total lowest cost. However, firms may source more than one variety of a commodity from the same DL subsector from a given country, and only has to pay the sunk cost once. This introduces complementarities in a firm's resiliency across varieties of particular DL sector commodities. To see the importance of these complementarities consider the following example. A firm imports low-end semiconductors from China and imports a high-end semiconductors from Taiwan. Both high-end and low-end semiconductors belong to the semiconductor DL subsector, and as such the firm has paid the sunk costs to source semiconductors from both Taiwan and China. Assume that Taiwan can also supply the firm with low-end semiconductors, but at a higher variable cost to the firm than what China offers. In response to a shock to China, the firm can substitute away from the Chinese low-end semiconductor it purchases and buy low-end semiconductors from Taiwan instead. Since the firm already imports high-end semiconductors from Taiwan, it likely has a good understanding of how to source different types of semiconductors in Taiwan. Therefore, we have implicitly assumed that the firm can begin importing low-end semiconductors from Taiwan without paying an additional sunk cost.

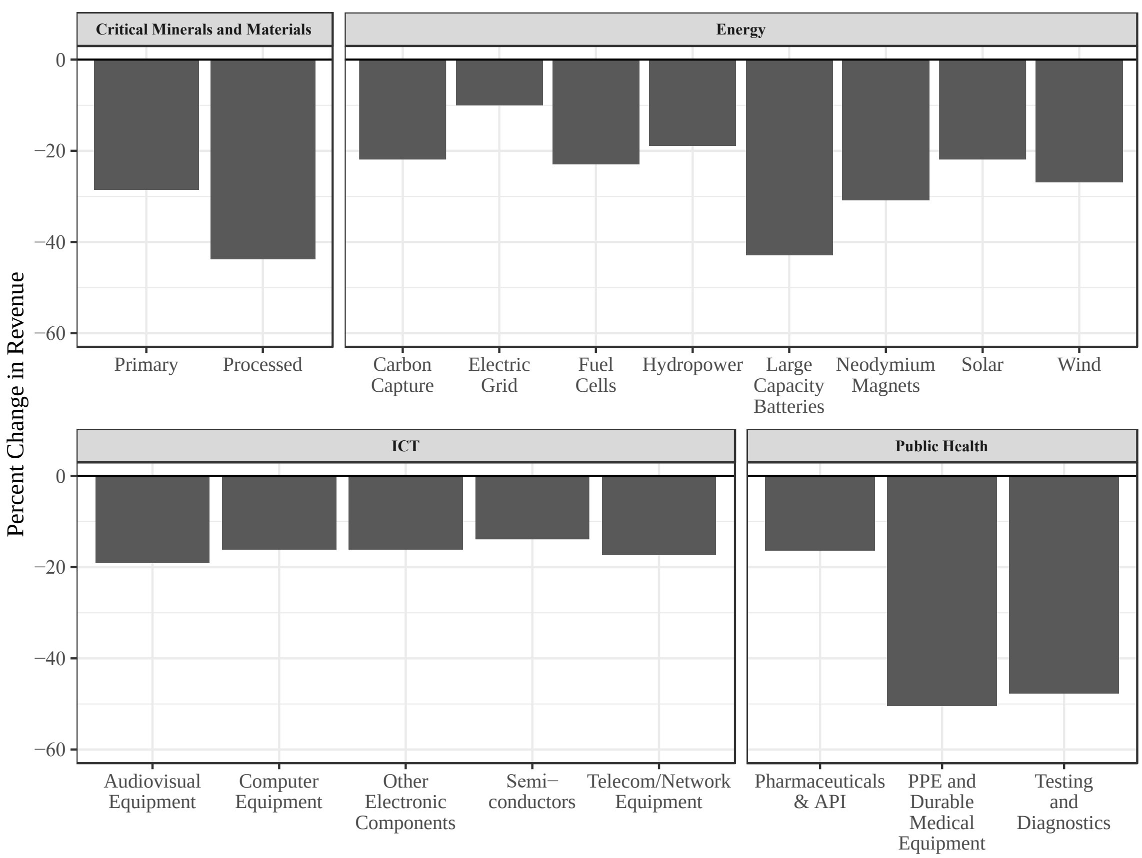
[29] To see this in the model, revisit equation **3-7** along with equations **3-4** and **3-5** to see that operating profits are increasing in a firm's sourcing capacity. A firm's sourcing capacity is the sum of the country sourcing potentials from the set of countries that the firm imports from. If a firm only sources from China, and China's sourcing potential is halved then the firm's sourcing capacity is halved, and its revenue falls. If the firm sources from China and other countries, this effect is lessened.

due to decoupling, and the firm may still find it worthwhile to search for suppliers in new countries.

The firm's decision to add a supplier in response to decoupling comes down to a comparison of the increase in its operating profits from adding the new supplier, against the sunk costs it would have to pay to begin importing from the new supplier. Figure 4-1 shows how our decoupling shock will impact U.S. revenues for firms that import DL commodities from China. Figure 4-1 shows losses in revenues of 10-50% with critical minerals, medical equipment, and testing diagnostics being affected the most and ICT subsectors be affecting the least.

These are the estimated changes in revenue among firms that actively sourced from China. Not all firms import from China and as such these estimates do not reflect to total impact that decoupling would likely have on the U.S. economy. Likewise, some U.S. firm will stop importing from China all together in response to the shock. Decoupling will have consequences for U.S. import demands from exporters outside of China, since input varieties are complements in production.

Figure 4-1: Change in Importer Revenues from Decoupling



Notes: Figure represents the estimated decreas in U.S. firm revenues that would occur in response to China's sourcing potential being halved for each critical subsector. The estimated impacts are only relevant for U.S. firms actively source from China, and currently assume that firms cannot enter new countries in response to the shock. Future versions of this report will allow for these adjustments.

4.1.2 Proactive Trade Policy and Resiliency: An Indo-Pacific Economic Framework Example

Here we further explore this example of decoupling from China, but this time assume that prior to decoupling the United States has joined a formal trade agreement with Indo-Pacific Economic Framework (IPEF) partner countries.[30] The difference in outcomes for U.S. firms across the two scenarios measures IPEF's impact on reducing U.S. firms' exposure to decoupling shocks.

Policy actions undertaken prior to a negative shock improve resiliency by providing U.S. firms with an expanded set of alternative sources of DL commodities. Our model suggests that proactive policies are more effective than reactive policies. To see this, consider the fact that firm revenues are greater prior to negative economic shocks.[31] Sunk costs are more easily overcome when firm revenues are higher. Therefore, policy changes made prior to the realization of a negative shock (when firm revenues are greater) will likely induce more firms to pay sunk costs to search for suppliers. Since the sunk costs must only be paid one time, this effectively creates a time varying effect of policy actions.

To demonstrate this effect, we use a hypothetical trade agreement between IPEF partners that formalizes market access provisions in the form of tariff reductions. We first simulate IPEF, inducing firms to increase their sourcing strategies. We then simulate decoupling again, assuming that the IPEF agreement is in place. We then compare this simulation to the results generated in section 4.1.1 .

Figure 4-2 presents estimates of how hypothetical tariff reductions applied to IPEF partners would impact firm revenues for firms that already source from an IPEF country. The solid-black line represents this relationship. The horizontal axis represents a percentage decrease in tariff rates between the United States and IPEF partners. The impact of tariff reductions on the revenues of active importers varies across DL sectors. For example, tariff reductions targeting IPEF partners are predicted to increase revenue more for importers of processed critical minerals and materials and semiconductors, than in large capacity batteries and public health testing and diagnostic equipment.

The size of the tariff reduction also has implications for importer revenue changes as well. For example, tariff reductions in processed critical minerals and materials will move with tariff reductions in a near linear fashion, while small tariff reductions in semiconductors are estimated to lead to large gains firm revenues before plateauing after tariff rates decrease by a fifth.

The dotted lines in Figure 4-2 show the estimated revenue losses from our baseline decoupling scenario shown in Section 4.1.1 , along with including information on the total number of firms that currently import from China and IPEF partners. The revenue gains from cutting tariffs on IPEF partners are greater for semiconductors, than the estimated losses from decoupling. The revenue gains in processed critical minerals and materials from IPEF tariff reductions begin to approach the revenue losses in decoupling if tariff rates are cut in half. For large capacity batteries and public health testing and diagnostic equipment, the revenue gains from IPEF tariff reductions do not approach the revenue losses from decoupling for active importers.

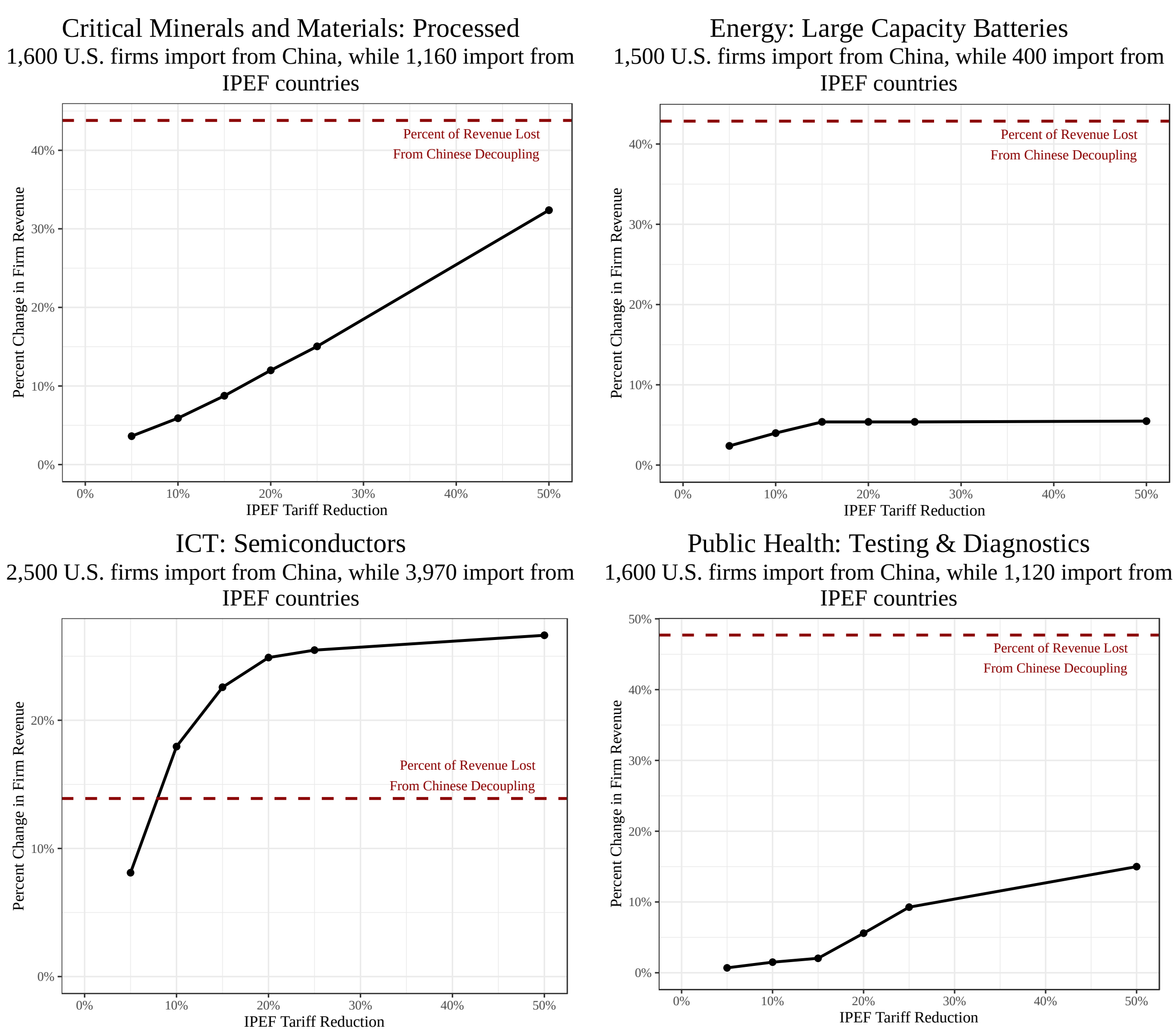
[30] Specifically, Australia, Brunei Darussalam, Fiji, India, Indonesia, Japan, the Republic of Korea, Malaysia, New Zealand, Philippines, Singapore, Thailand, and Vietnam.

[31] Put differently and more succinctly, negative economic shocks lower firm revenues.

It is worth emphasizing that these are preliminary results that do not allow firms to shift their sourcing strategies in response to the decoupling shocks. We expect these estimates to be lower bounds for firms that actively source from IPEF partners or China, since firm's sourcing strategies are assumed to be fixed. These simulations also ignore the fact that new firms will likely begin sourcing from IPEF partners in response to tariff reductions. Despite this, the simulations provide an intuitive guide for motivating our results.

Future work will quantify the full cost of our decoupling shock to U.S. firms, considering the fixed costs that firms must pay to continue sourcing from China, and the additional sunk costs they must pay when searching for suppliers in new countries. We will follow AFT and use the algorithm developed in Jia (2008) [14] to estimate firm's optimal decisions, given the changes in Chinese sourcing potential that we simulate. Intuitively we should expect that the industries with the largest sunk costs, where many firms source from China, and, where China has a disproportionately high sourcing potential will see the largest impacts from decoupling. Testing and Diagnostics Equipment related to Public Health and Large Capacity Batteries are an example of two such sectors.

Figure 4-2: Importer Revenues Changes under IPEF and Decoupling



Notes: The horizontal axis represents a percentage reduction in tariff rates, for example if a tariff is 7% and is reduced by 10%, the 10% would reflect a reduction in the tariff rate of 0.7%. The vertical axis plots the percent change in firm revenues for firms that actively source from IPEF countries, for the black line, or China in the case of the dashed red line. These estimates do not allow for adjustments in the number of firms that import from a particular supplier, future versions will incorporate these changes.

There are other DL subsectors where U.S. firms disproportionately source Chinese products despite other countries having similar sourcing potentials. In Processed Critical Minerals and Materials, for example, South Africa has a similar sourcing potential to China however many more firms source from China. In instances like this, policy actions taken today can possibly encourage firms to diversify their sourcing by raising sourcing potential in these countries or by lowering the sunk cost to enter these countries. Diversifying the set of suppliers today can reduce the effects supply shocks such as decoupling in the future. In the next section we discuss this further and present a hypothetical policy change prior to our decoupling shock to estimate the effect it can have on mitigating the negative impact of the decoupling across the DL.

4.2 South China Sea Scenario

In this section we present a counterfactual scenario motivated around a conflict in the South China Sea that prevents the shipment of goods through the area, effectively raising the cost of importing via maritime shipping modes. The South China Sea serves as a crucial shipping route, accommodating virtually all traffic that traverses the Strait of Malacca. The United Nation's Conference on Trade and Development estimated in 2016 that nearly a third of global trade passed through the South China Sea.[32]

China has aggressively asserted its claims over the South China Sea in recent years.[33] Vietnam, Japan and the Philippines have actively contested these claims, leading to present day skirmishes that have seen Chinese Coast Guard vessels targeting Philippines vessels with water cannons.[34] If these conflicts escalate there is a risk that shipping vessels through the region could be attacked. In such an instance, the price of shipping and insurance rates would rise for any vessel that needed to pass through the region.

In this section we simulate such a conflict's impact on U.S. importers' ability to source DL commodities from South-East Asia. In this version, we simulate a range of transportation cost increases for shipments that arrive in the United States from the region.[35] One major caveat of this version of the analysis is that we assume that sourcing potential in third party countries remains unchanged. If a conflict were to break out in the South-China Sea it would likely impact the shipment of intermediate goods between countries such as Taiwan and India. This would impact the ability of those countries to produce goods efficiently. As such, sourcing potential of India and Taiwan would be impacted by a disruption in the South-China Sea. In a future version we will calibrate how sourcing potential in third-party countries would be impacted by a shipping disruption in the South-China Sea.

[32] https://unctad.org/system/files/official-document/rmt2016_en.pdf

[33] https://www.cfr.org/global-conflict-tracker/conflict/territorial-disputes-south-china-sea

[34] https://www.reuters.com/world/asia-pacific/china-coast-guard-says-it-took-measures-against-philippine-vessels-south-china-2024-03-23/

[35]

We apply our South-China Sea shock to imports that originate from the following South-East Asian Countries: Vietnam, Singapore, Thailand, Indonesia, Philippines and Cambodia. Based on their geography, these countries are the most likely to be severely impacted in their ability to export to the United States. Other countries, such as Brunei Darussalam, would likely be impacted based on their geography. However, in 2017, the United States only sourced DL commodities from the countries listed.

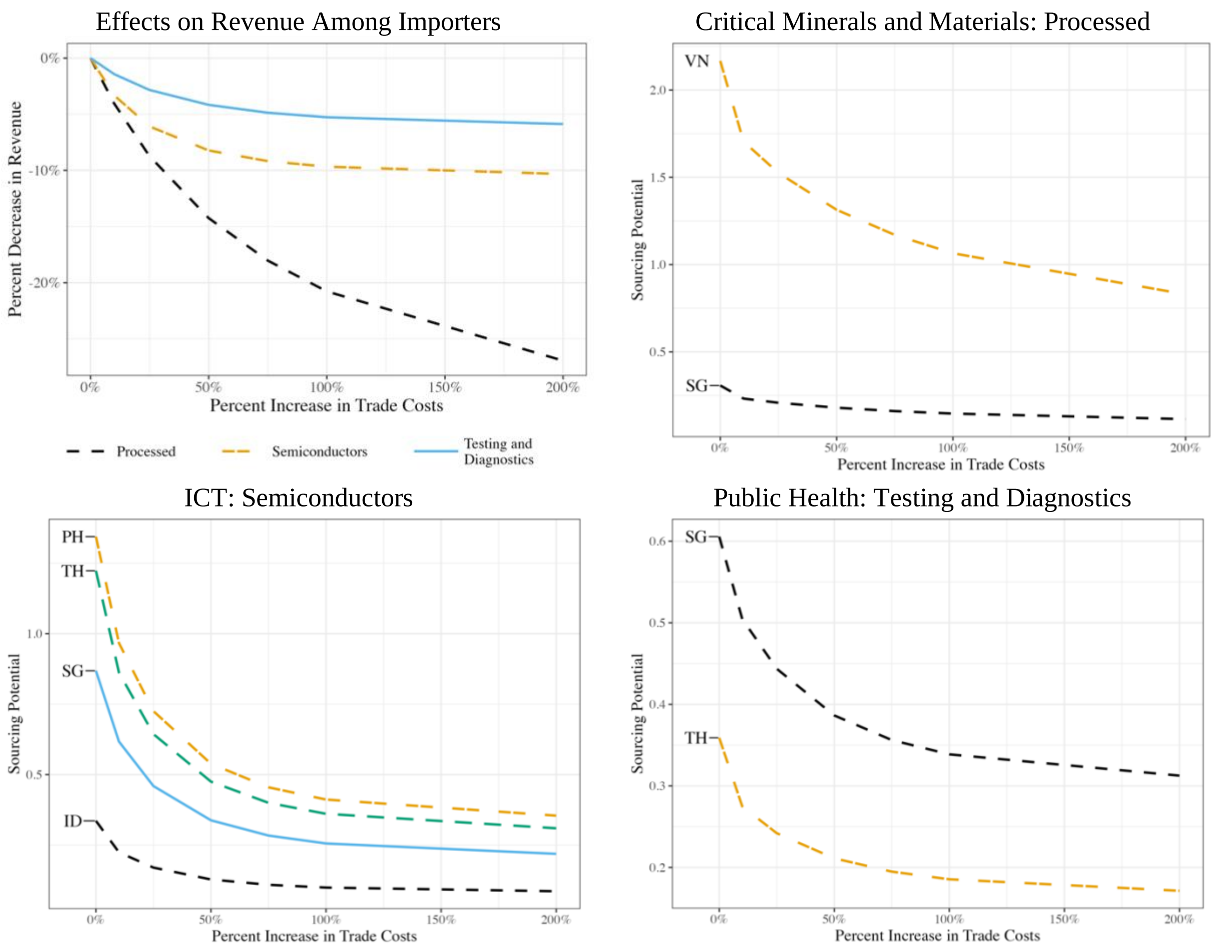
Since it is uncertain how long a conflict in the South China Sea might last, we simulate how a range of trade cost increases would impact U.S. firms that source from the region. We allow imports to be substituted across various mode choices in response to the disruption by applying the model of transportation costs outlined in section 3.2.1 . Using the sector-specific estimates of mode choice elasticities, firms can respond to the higher transportation cost via maritime shipments by using alternative transport modes, such as air shipments. However, it still may be prohibitively costly to source products by air if they are too weighty. The ability to substitute across modes varies by product and is reflected in our DL subsector specific transport costs and sector specific mode choice elasticity estimates.

Figure 4-3 presents the estimated effects of the South China Sea disruption. The top-left panel estimates how revenues would be affected for U.S. firms that source from the set of relevant countries. This shows that a doubling or tripling of trade costs in the South China Sea would impact firm revenues of a firm that imports from any of the impacted countries for processed critical minerals and materials, semiconductors, and public health testing and diagnostic equipment.

The remaining three panels show how estimates of sourcing potential would change across the effected countries. The top right shows that Processed Critical Mineral and Materials from Vietnam would see a large decline, falling by more than half. The bottom-left panel shows the Philippines, Thailand, and Indonesia Semiconductor sourcing potential would fall quickly as trade costs rose do to the disruption. The bottom-right panel shows that Singapore's sourcing potential for public health would be more negatively impacted than Vietnam's. From the three panels it is also clear that across the three sectors presented here, Vietnam and Singapore are exposed across more industries than other countries.

This counterfactual, like the decoupling counterfactual presented above, is currently incomplete. Figure 4-3 shows how active importer revenue would likely be impacted, assuming those importers cannot look for alternative suppliers in the case of the disruption. The likely response to the disruption will be that some importers will exit the region and begin looking for suppliers in other countries.

Figure 4-3: South China Sea Disruption



Notes: The horizontal axis represents a percentage increase in trade costs for U.S. imports form Southeast Asia. The vertical axis in the top-left panel plots the percent change in firm revenues for firms that actively source from Southeast Asian countries. In the remaining panels, the vertical axis shows the impact that the change in trade costs will have on each country's sourcing potential. These estimates do not allow for adjustments in the number of firms that import from a particular supplier, future versions will incorporate these changes. Future verions will also allow for the shipping disruption to impact more countries.

5. Conclusion and Policy Takeaways

This report presents new stylized facts about the international sourcing strategies of U.S. firms for DL products, develops a model of U.S. production and firm imports, and performs two counterfactual scenarios. First, this effort finds that firm that import critical products tend to have greater revenues and employment than other importing firms which highlights the importance of these firms to the U.S. economy. Second, China is a major supplier across all critical products. Third, there are outlier countries which vary across sectors where one country may provide a significant number of essential products to a few U.S. companies which could be leveraged by more U.S. firms.

Given the status of U.S. reliance on China in these critical DL sector we estimate a model of endogenous sourcing for U.S. imports of commodities identified across the DL. In the model, U.S. firms can source DL commodities from foreign suppliers at a country-subsector specific price that incorporates the cost of manufacturing, shipping, and any applicable tariffs. However, the importer must pay a sunk cost to search for a supplier within a country in its first year of importing from that country. Once this sunk cost has been paid in the first year the firm imports from a particular supplier, the importer no longer must pay to look for suppliers in that country.

We estimate the parameters of the model using confidential Census data for U.S. firms and apply the model to two counterfactual scenarios. The first scenario considers how a formalized trade agreement featuring market access provision centered around Indo-Pacific Economic Framework partners, can reduce U.S. exposure to decoupling scenarios. The second scenario simulates how a disruption in the South China Sea would impact the ability of U.S. firms to source DL commodities from southeast Asia. In both scenarios, we breakdown our estimated effects across the DL subsectors.

If the first scenario, the effects of decoupling from China will be the greatest in Critical Minerals and Materials, Advanced Capacity Batteries, PPE and Durable Medical Equipment, and Testing and Diagnostics Equipment related to Public Health. However, we show that an IPEF agreement featuring tariff cuts can potentially offset some of the losses that would be seen in Critical Minerals and Materials. We also show that an IPEF agreement featuring tariff cuts could also likely offset any losses in U.S. sourcing of semiconductors due to a decoupling shock.

The second South China Sea scenario shows that the U.S. capacity to source inputs from our southeast Asian trading partners would fall across all subsectors of the DL. These decreases would largely be concentrated in Processed Critical Minerals and Materials. These products are heavy and are the most reliant on maritime shipping and are therefore less easily shipped via air - the only other viable shipping mode for products that arrive in the U.S. and originate from southeast Asia. The disruption would also impact Semiconductors, PPE and Durable Medical Equipment, and Solar Panel products. While these industries can be shipped via air as an alternative, the scale of the products sourced by the U.S. means that trade would still be impacted by a disruption in maritime shipments.

Future work will feature technical refinements to the estimation of the model and the counterfactual scenarios. The largest refinements will be applied to our estimation of the fixed and sunk costs that firms must pay to source products from abroad. Current estimates do not allow these costs to be country specific, they only vary across DL subsectors. MITRE researchers are currently working to estimate country-subsector specific estimates for these costs. These costs will be estimated in multiple ways to explore various policy levers that could be potentially leveraged to reduce the costs. For example, the fixed and sunk costs could vary depending on whether a deep trade agreement was in place between the U.S. and the supplying country. Likewise, lower levels of corruption or stronger institutions could reduce these costs as well.

MITRE is actively working to complete the counterfactual analysis outlined in this report. This involves allowing U.S. firms to change their global sourcing strategies in response to the counterfactual scenarios. This will allow for the calculation of a richer set of counterfactual statistics, such as aggregate GDP losses, changes in the number of firms that import a particular good from a particular country, or losses in revenue for U.S. importers.

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Appendix B Technical Model Descriptions

Appendix B-1 Technical Description of Value of Firm's Intermediate Source

We insert specific marginal cost shifter $a_j^s(\nu, \varphi)$ for each firm, sector, country triplet. This implies the firm's variable cost of importing variety ν in DL subsector s is:

$$z^s\big(\nu, \varphi; \mathcal{J}_J(\varphi)\big) = \min_{j \in \mathcal{J}_J(\varphi)} \tau_{j\varphi}^s \cdot a_j^s(\nu, \varphi) \cdot w_j^s$$

Where $\mathcal{J}_J(\varphi)$ denotes the set of countries that firm φ has chosen to search. The firm's variable cost of importing one more unit of can be taken as:

$$c^s(\varphi) = \left(\int \left[z^s\big(\nu, \varphi; \mathcal{J}_J(\varphi)\big)\right]^{1-\rho_s} d\nu\right)^{\frac{1}{1-\rho_s}}$$

Where ρ_s is an elasticity of substitution parameter across the varieties within a subsector.[36] The match specific marginal costs shifters are distributed randomly and follow a Fréchet distribution as in Eaton and Kortum (2002) [7]. That is these parameters are distributed according to a cumulative distribution function given by:

$$\Pr\big(a_j^s(\nu, \varphi) \geq a\big) = e^{-T_j^s a^{\theta_s}} \text{ with } T_j^s > 0$$

In Eaton and Kortum this distribution of technologies, denoted by θ_s, governs global trade patterns for each sector.

Appendix B-2 Technical Description of Optimal Prices and the Market Setting

We assume that U.S. manufacturing firms sell directly to U.S. households and do not export. We follow AFT and assume that households do not import and must purchase from a U.S. manufacturer. Furthermore, we assume that the U.S. market for manufacturing output is monopolistically competitive. Under these assumptions the demand for a specific firm's variety is given by:

$$q_{US,t}(\omega) = E_{US,t} P_{US,t}^{\sigma-1} p_{US,t}(\omega)^{-\sigma}$$

Where $q_{US,t}(\omega)$ and $p_{US,t}(\omega)$ are the quantity demanded by and the price facing (respectively) U.S. households for variety ω in year *t*.[37] The total expenditure of U.S. households on manufactured products in denoted as $E_{US,t}$. The price index facing households is given by the standard love of variety price index and is denoted as $P_{US,t}$.

[36] AFT and Hoang point out that this elasticity is relatively unimportant under the assumption of perfect competition in the model.

[37] We return to the use of time subscripts here to emphasize the specific role of dynamics in determining a firm's profits. Until this point, a firm's actions were conditional on its set of suppliers in a specific time period.

Appendix C Additional Tables

Appendix Table C-1: The Extensive and Intensive Margin of Trade

		Country	Rank By: Firm	Rank By: Value	Number of Importers	Value of Imports
Critical Minerals	Primary	Canada	1	1	300	511,000
		China	2	2	150	242,000
		Germany	3	4	90	65500
	Processed	China	1	6	1,600	1,101,000
		Canada	2	1	1,500	7,472,000
		Germany	3	5	850	1,256,000
Energy	Carbon Capture	Canada	1	1	500	868,000
		Germany	2	7	450	56,000
		China	3	2	450	374,000
	Electric Grid	China	1	2	800	259,000
		Canada	2	1	700	763,000
		Germany	3	3	450	209,000
	Fuel Cells	China	1	1	10,500	9,683,000
		Canada	2	4	6,800	2,706,000
		Germany	3	3	5,200	3,670,000
	Hydropower	Germany	1	2	2,200	859,000
		China	2	1	1,900	1,949,000
		Canada	3	4	1,500	520,000
	Large Capacity Batteries	China	1	1	1,500	915,000
		Japan	2	2	250	736,000
		Germany	3	4	200	123,000
	Neodymium Magnets	China	1	2	1,100	265,000
		Canada	2	7	400	87,500
		Germany	3	3	350	244,000
	Nuclear Power	Canada	1	1	150	670,000
		China	2	3	80	134,000
		Germany	3	2	70	315,000
	Solar	China	1	1	4,100	1,235,000
		Canada	2	2	2,800	952,000
		Germany	3	3	1,600	495,000
	Wind	China	1	1	2,500	1,256,000
		Germany	2	5	1,500	328,000
		Canada	3	2	1,100	698,000

		Country	Rank By: Firm	Rank By: Value	Number of Importers	Value of Country
Information Communication Technology	Audiovisual Equipment	China	1	1	2,800	5,566,000
		Taiwan	2	7	600	192,000
		Germany	3	8	400	130,000
	Computer Equipment	China	1	1	4,700	41,230,000
		Taiwan	2	3	2,000	3,230,000
		Germany	3	8	1,800	488,000
	Other Electronics Equipment	China	1	1	5,800	4,123,000
		Germany	2	4	2,000	631,000
		Taiwan	3	3	1,900	640,000
	Semiconductors	China	1	2	2,500	3,933,000
		Taiwan	2	3	1,400	3,739,000
		Germany	3	7	1,300	1,105,000
	Telecom/Network Equipment	China	1	1	4,300	18,950,000
		Taiwan	2	3	1,400	1,660,000
		Canada	3	6	1,200	643,000
Public Health	PPE & Durable Medical Equipment	China	1	3	14,000	8,568,000
		Canada	2	4	5,500	6,165,000
		Germany	3	5	2,800	5,023,000
	Pharmaceuticals & API	China	1	3	2,300	5,723,000
		Canada	2	12	1,500	1,489,000
		Germany	3	2	1,200	7,736,000
	Testing and Diagnostics	China	1	4	1,600	2,397,000
		Germany	2	2	1,200	4,152,000
		Canada	3	10	600	719,000

Appendix D Reliance on China Decomposition

In this section we break down the U.S.'s reliance on China across the subsectors of the DL. We calculate the relative importance of the intensive and extensive margins of trade in driving changes in China's U.S. import share for DL goods. Our approach builds on Bernard et al. (2018) [15] by creating a variance covariance decomposition for a single country's share of imports along the various margins of imports.

To measure China's relative importance along the intensive margin, we define the average value of firm imports from China as $AV_{\mathrm{hs,s}}^{\mathrm{cn}} \equiv \mathrm{v}_{\mathrm{hs,s}}^{\mathrm{cn}} / \mathrm{N}_{\mathrm{hs,s}}^{\mathrm{cn}}$. Where $\mathrm{v}_{\mathrm{hs,s}}^{\mathrm{cn}}$ is the value of U.S. imports of product *hs*, which belong to subsector *s*, from China, and $\mathrm{N}_{\mathrm{hs,s}}^{\mathrm{cn}}$ is the number of U.S. firms that import *hs* from China. We compare the average value of firm imports from China to the average value of firm-level imports from all sources globally. To measure average U.S. firm-import values from across multiple countries we define $AV_{\mathrm{hs,s}} \equiv \sum_{\mathrm{j}} \mathrm{v}_{\mathrm{hs,s}}^{\mathrm{j}} / O_{\mathrm{hs,s}}$. Here, $\mathrm{v}_{\mathrm{hs,s}}^{\mathrm{j}}$ defines the value of U.S. imports of product *hs*, which belong to subsector *s*, from any country *j*, and $O_{\mathrm{hs,s}}$ is the number of firm-country pairs that import product *hs* from anywhere. Dividing total imports by $O_{\mathrm{hs,s}}$ gives the average value of U.S. firm-level imports from the average supplier of product *hs*. [38]

To measure China's relative importance along the extensive margin of trade, we take the number of firms that import from China ($\mathrm{N}_{\mathrm{hs,s}}^{\mathrm{cn}}$) and divide it by the number of firms that import product *hs* from anywhere ($\mathrm{N}_{\mathrm{hs,s}}$). We also include the number of countries that supply the U.S. with product *hs*, which we denote by $\mathrm{N}_{\mathrm{hs,s}}^{\mathrm{C}}$. We include this latter channel because the number of countries that can supply a particular product may drive U.S. reliance on China. For example, if the U.S. can only source a product from a handful of countries, and China is one of those countries, then China will likely account for a greater share of U.S. imports.

China's share of U.S. import value in product *hs*, by definition, equals $\mathrm{v}_{\mathrm{hs,s}}^{\mathrm{cn}} / \sum_{\mathrm{j}} \mathrm{v}_{\mathrm{hs,s}}^{\mathrm{j}}$. Multiplying and dividing this expression by $\mathrm{N}_{\mathrm{hs,s}}$, $\mathrm{N}_{\mathrm{hs,s}}^{\mathrm{cn}}$, $O_{\mathrm{hs,s}}$ and $\mathrm{N}_{\mathrm{hs,s}}^{\mathrm{C}}$ allows us to express the China's share of U.S imports as:

$$\frac{\mathrm{v}_{\mathrm{hs,s}}^{\mathrm{cn}}}{\sum_{\mathrm{j}} \mathrm{v}_{\mathrm{hs,s}}^{\mathrm{j}}} = \left(\frac{AV_{\mathrm{hs,s}}^{\mathrm{cn}}}{AV_{\mathrm{hs,s}}}\right) \cdot \left(\frac{\mathrm{N}_{\mathrm{hs,s}}^{\mathrm{cn}}}{\mathrm{N}_{\mathrm{hs,s}}}\right) \cdot \frac{1}{\mathrm{N}_{\mathrm{hs,s}}^{\mathrm{C}}} \cdot \left(\frac{\mathrm{N}_{\mathrm{hs,s}}^{\mathrm{C}} \cdot \mathrm{N}_{\mathrm{hs,s}}}{\mathrm{O}_{\mathrm{hs,s}}}\right)$$

The first right-hand-side term compares the average value of firm-level imports from China to those from the average country supplying the U.S. with product *hs*. Variation in this term is attributed to China's relative importance as a U.S. supplier along the intensive margin of trade. The second term is the share of U.S. importers of product *hs* that import the product from China and the third term captures the total number of source countries for the product. The final term is

[38] In the of looking at a single country j, $O_{hs,s}^{j}$ is simply equal to $N_{hs,s}^{j}$ since there is only one country to consider. As such $O_{hs,s}^{cn} = N_{hs,s}^{cn}$.

referred to as the density of trade and it captures how concentrated firm sourcing is across firm-country pairs.[39]

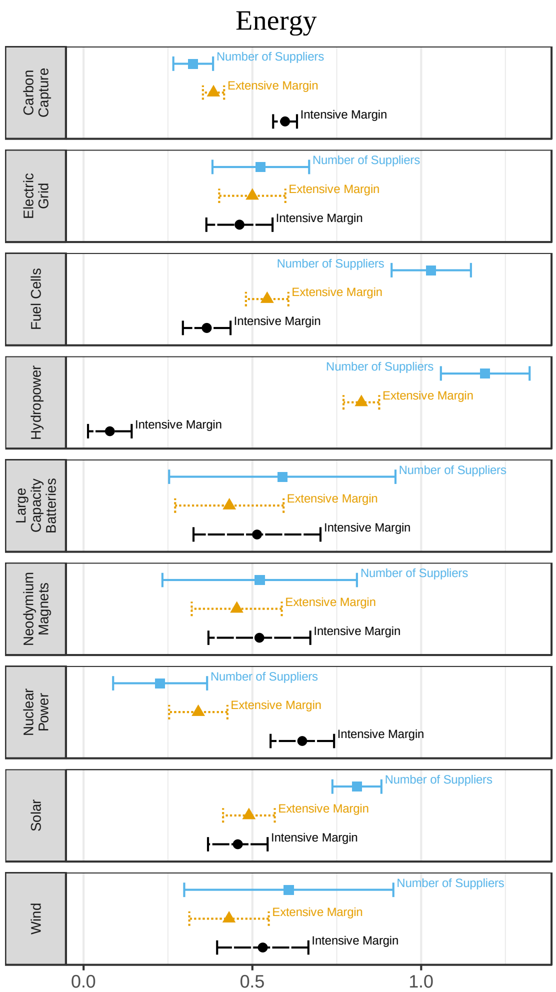
We measure each of the four term's share of the variation in U.S. imports that originate from China across each DL subsector *s*. We do this by regressing the log of Chinese import shares onto the log of each variable and allowing the estimated coefficients to vary by subsector *s*. For many products, the variation in China's share of US imports covaries most closely with the number of alternative source countries.

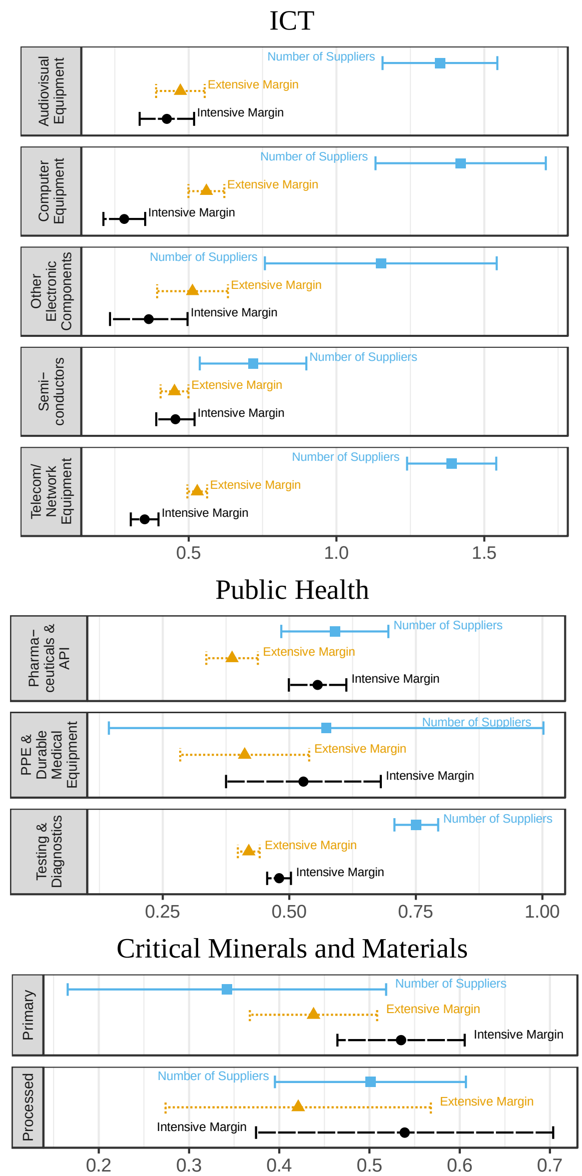
[39] For intuition, if all firms that source product *hs* at all source it from all possible locations, then this term equals 1. On the other hand if a firm that imports a product only sources it from one location then this term equals $N^{C}_{hs,s}$.

Appendix Table D-1: China Import Share Variance Decomposition Estimates

Sector	Subsector	Average import value ratio	Number of importers ratio	Number of countries	Density
Critical Minerals & Materials	Primary	0.535***	0.438***	0.342***	-0.314***
		(0.084)	(0.075)	(0.054)	(0.047)
	Processed	0.539***	0.421***	0.501***	-0.461***
		(0.018)	(0.016)	(0.030)	(0.027)
Energy	Carbon Capture	0.597***	0.385***	0.325***	-0.306***
		(0.050)	(0.050)	(0.073)	(0.067)
	Electric Grid	0.462***	0.500***	0.525***	-0.488***
		(0.036)	(0.032)	(0.060)	(0.055)
	Fuel Cells	0.365***	0.544***	1.03***	-0.941***
		(0.033)	(0.027)	(0.067)	(0.060)
	Hydropower	0.078	0.823***	1.19***	-1.09***
		(0.096)	(0.082)	(0.171)	(0.154)
	Large Capacity Batteries	0.514***	0.432***	0.589***	-0.535***
		(0.077)	(0.068)	(0.147)	(0.132)
	Neodymium Magnets	0.521***	0.454***	0.522***	-0.497***
		(0.048)	(0.044)	(0.071)	(0.066)
	Nuclear Power	0.648***	0.340***	0.227***	-0.215***
		(0.045)	(0.039)	(0.037)	(0.032)
	Solar	0.457***	0.490***	0.810***	-0.757***
		(0.069)	(0.060)	(0.158)	(0.149)
	Wind	0.531***	0.431***	0.608***	-0.569***
		(0.047)	(0.042)	(0.099)	(0.091)
ICT	Audiovisual Equipment	0.426***	0.472***	1.35***	-1.25***
		(0.036)	(0.031)	(0.147)	(0.136)
	Computer Equipment	0.282***	0.560***	1.42***	-1.27***
		(0.067)	(0.061)	(0.200)	(0.180)
	Other Electronic Components	0.365***	0.513***	1.15***	-1.02***
		(0.033)	(0.024)	(0.092)	(0.081)
	Semiconductors	0.455***	0.452***	0.718***	-0.625***
		(0.024)	(0.017)	(0.077)	(0.064)
	Telecom/Network Equipment	0.351***	0.529***	1.39***	-1.27***
		(0.078)	(0.065)	(0.219)	(0.204)
Public Health	PPE & Durable Medical Equipment	0.528***	0.412***	0.573***	-0.513***
		(0.029)	(0.026)	(0.054)	(0.050)
	Pharmaceuticals & API	0.556***	0.387***	0.590***	-0.533***
		(0.012)	(0.011)	(0.022)	(0.020)
	Testing & Diagnostics	0.480***	0.420***	0.751***	-0.651***
		(0.036)	(0.036)	(0.090)	(0.086)
R-Squared		0.752	0.27	-2.29	-3.23

Appendix Figure D-1: China's Import Share Decomposition Results

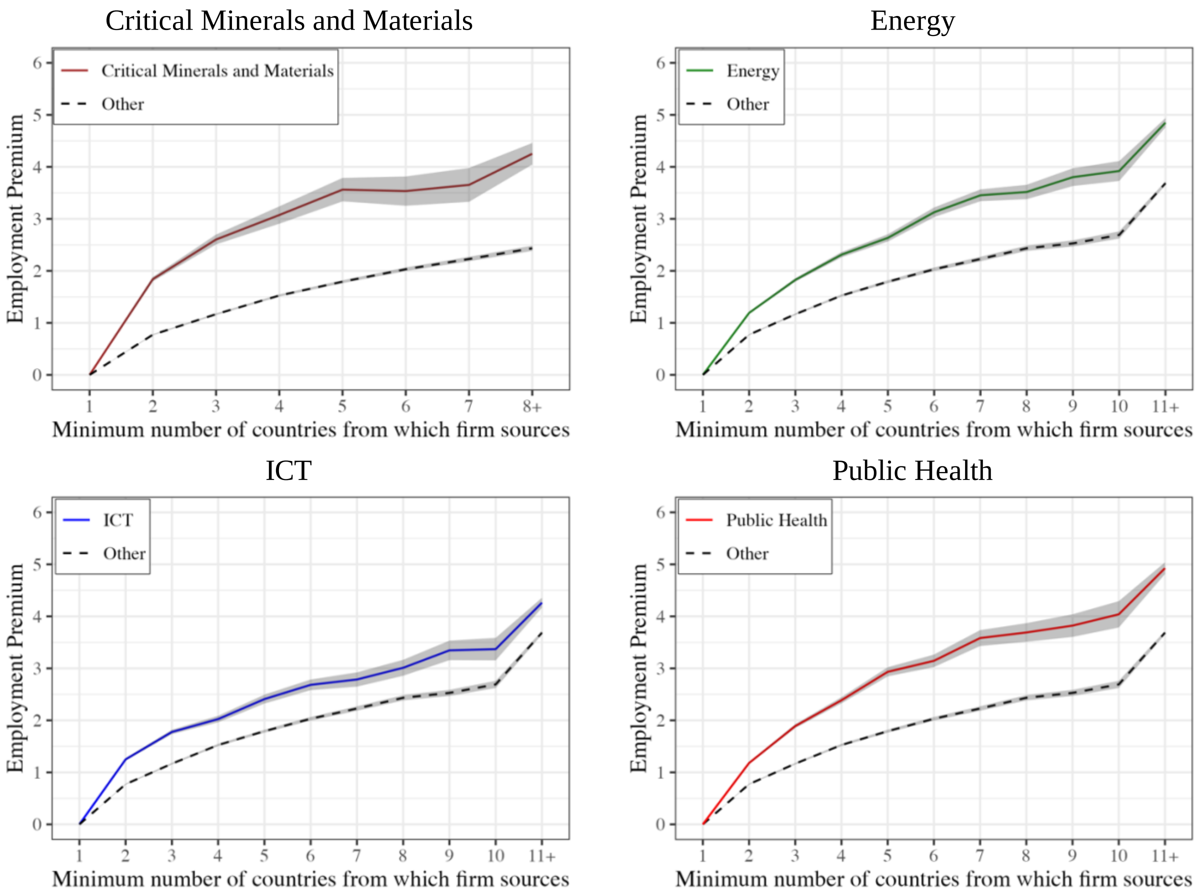




Notes: This figure presents an alternative presentation of the results summarized in Appendix Table D-1. The estimates of for the "Density" column are omitted. The error bars correspond to 95% confidence intervals.

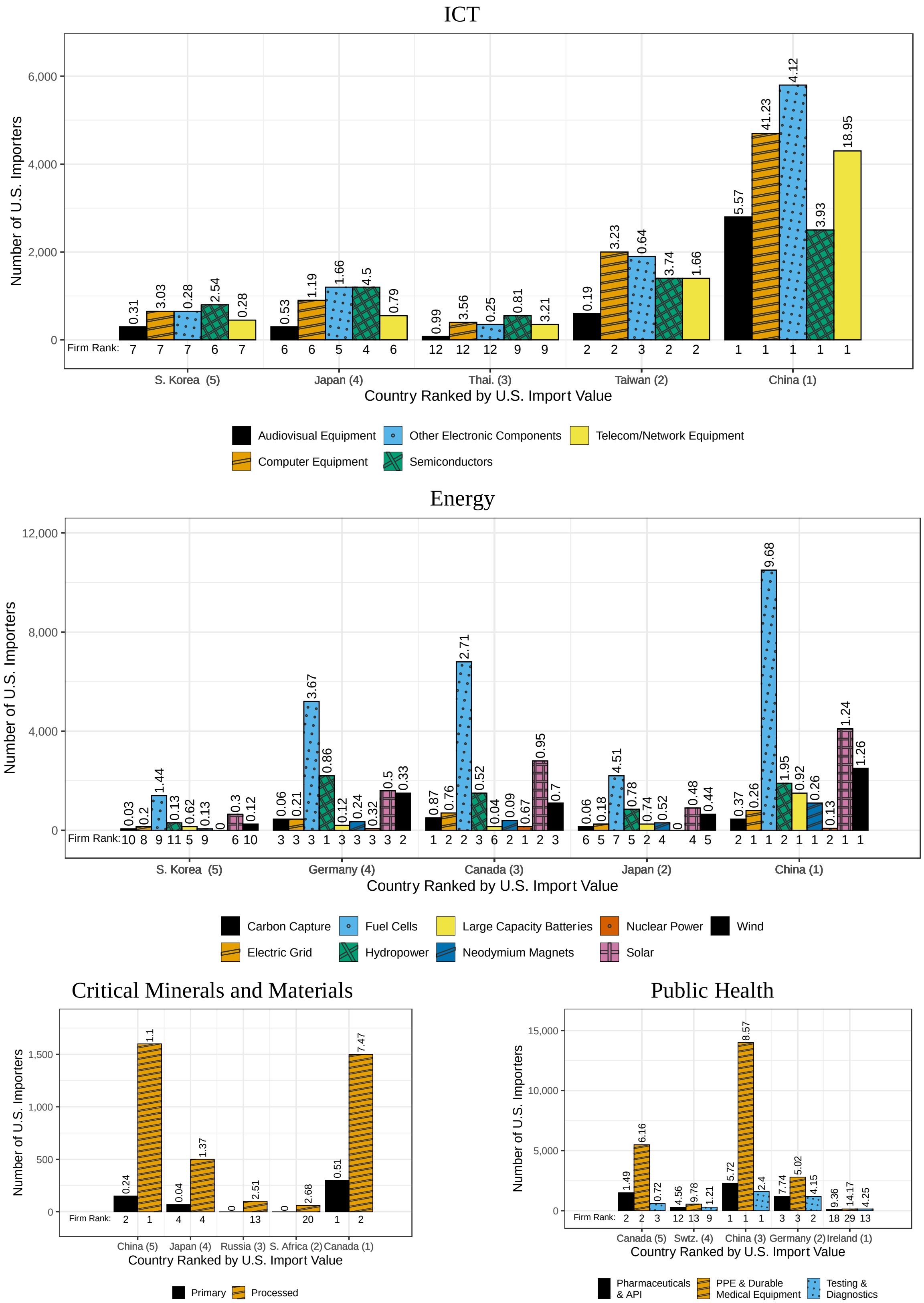
Appendix E Additional Figures

Appendix Figure E-1: Importer Employment Premium



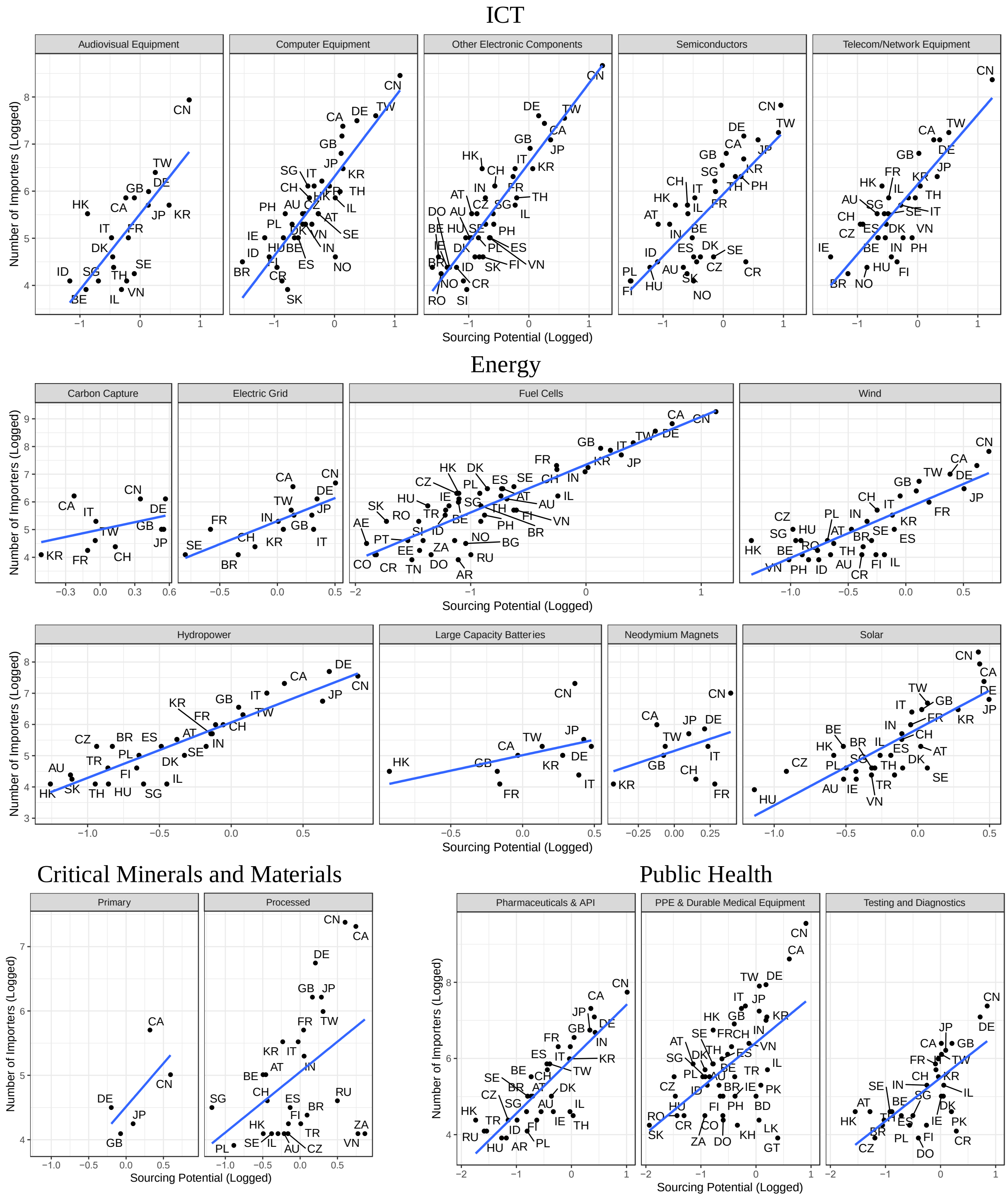
Notes: To construct the figure, we partition firms into groups based of their import activity across the DL sectors, with the "Other" Category reflecting importers of non-DL products. For each group we regress the log of firm employment on cumulative dummies for the number of countries from which a firm sources its DL products from, along with industry controls for the firm. The omitted category is non-importers, so the premia are interpreted as the difference in size between non-importers and firms that import from at least one country, at least two countries, etc. The horizontal axis denotes the number of countries from which a firm sources, with 1 corresponding to firms that use only domestic inputs. The grey shaded areas represent a 95% confidence interval.

Appendix Figure E-2: The Intensive and Extensive Margins of Trade



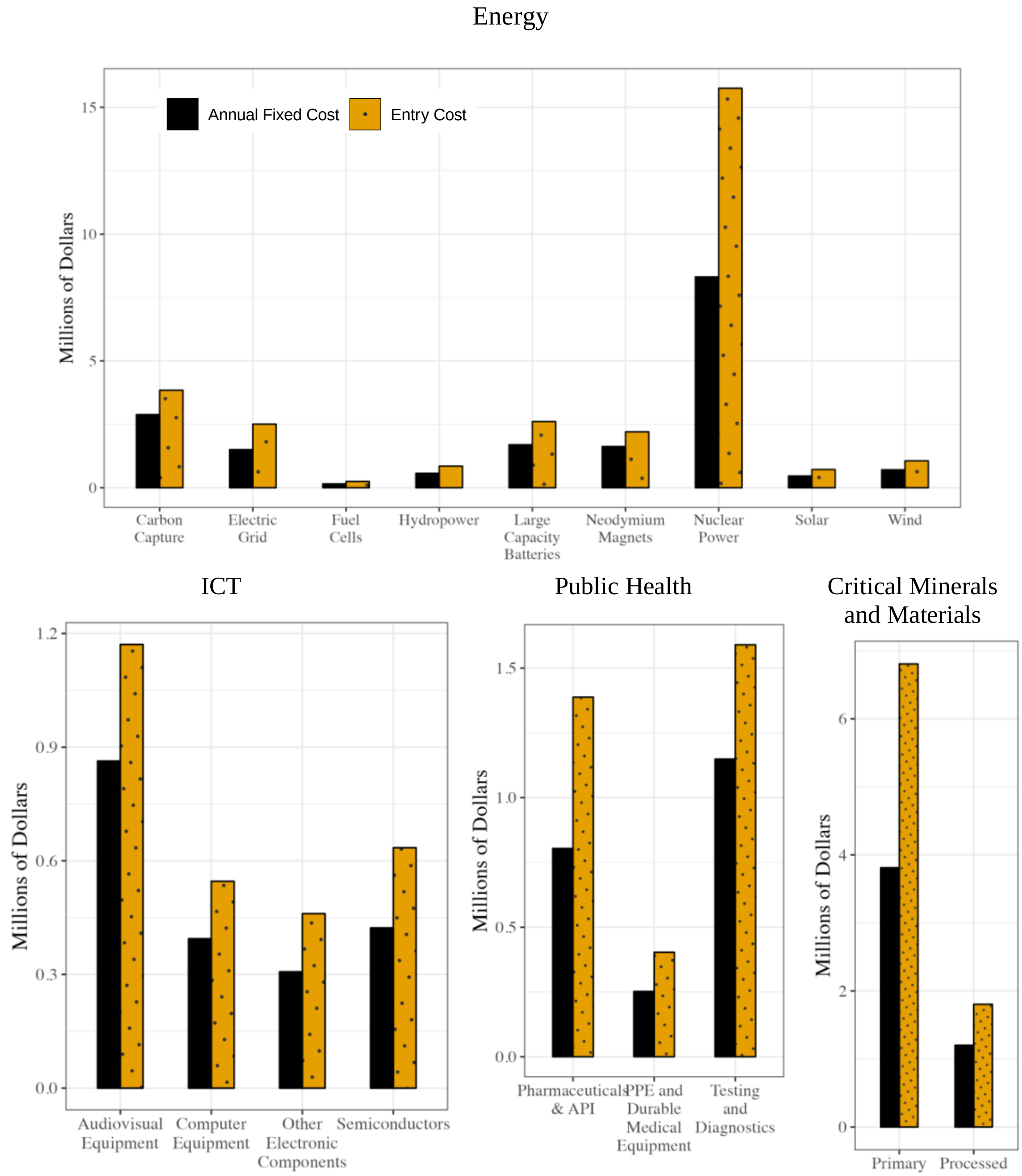
Notes: This figure summarizesthe summary statistics presented in Appendix Table C-1. Countries are ordered on the horizontal axis by their U.S. import value taken over the entire sector. The number in parenthesis next to each country name reflects the country rank. Country ranks are decreasing numerically from left to right so that the top-supplier by import value is labeled (1) and positioned to the left. The vertical axis measures the number of U.S. manufacturing or wholesale firms that source from each country. The bars represent the number of firms that import from each country, broken down by subsector. The number at the bottom of each bar represents the supplier country's rank as a supplier of each subsector. The number at the top of each bar represents the subsector import value sourced from each country in billions of USD. The data refers to values from 2017.

Appendix Figure E-3: Sourcing Potential and the Extensive Margin



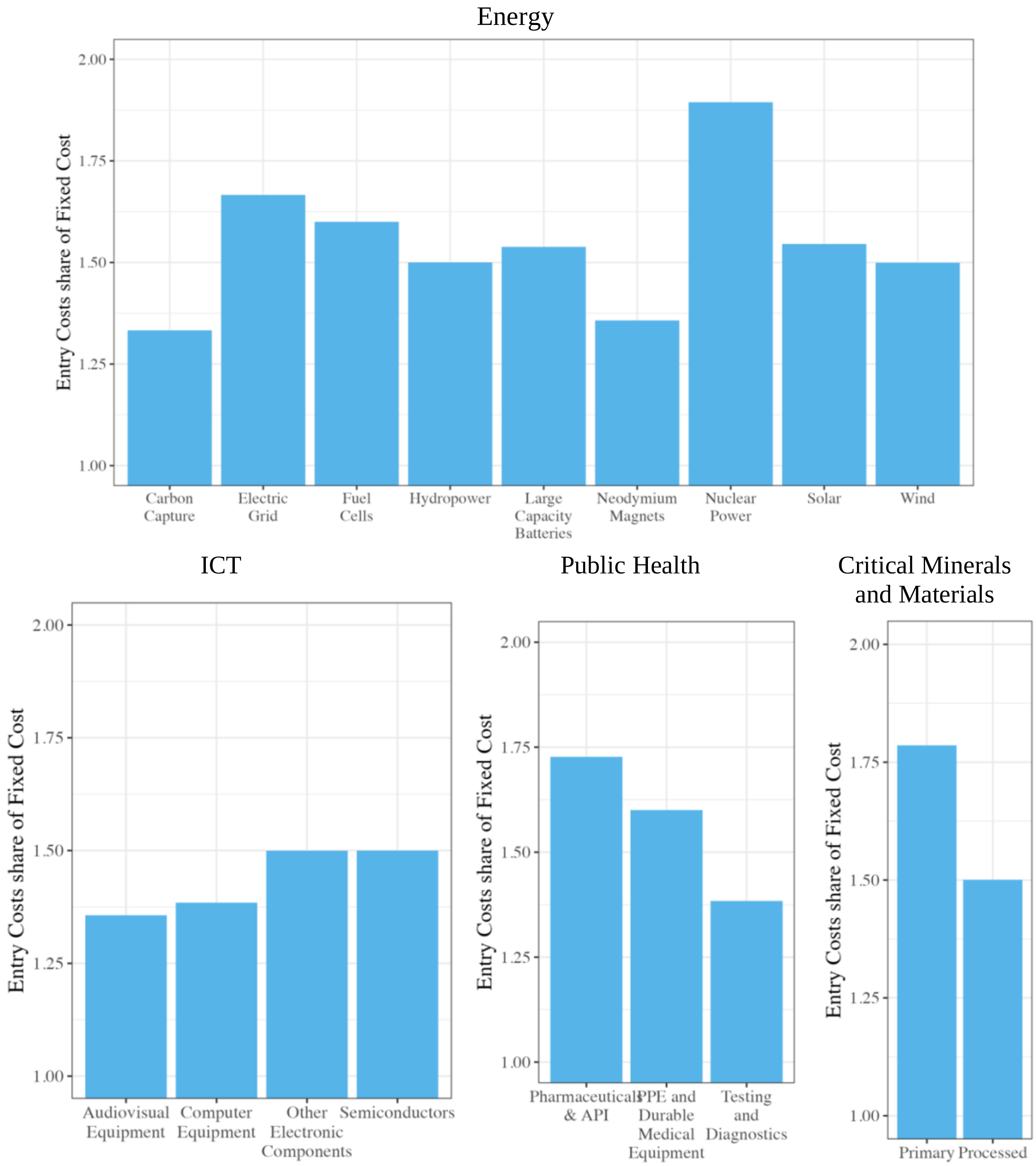
Notes: The horizontal axis presents the logged value of the sourcring potential of importing from each country. A firm-country-subsector spefic sourcing potential is estimated and the point represented in this figure is the median value, taken across firms. The veritical axis plots the logged number of U.S. manufacturing or wholesale firms that import subsector-specific products from each country. The blue line represents the average relationship between the logged median sourcing potential and the logged number of firms that import from a country.

Appendix Figure E-4: Fixed and Sunk Cost Estimates



Notes: Bars represent the upper bounds of our fixed cost estimates in the first year that a firm sources from a country ($\widetilde{\gamma}^{s} = \gamma^{f} + \gamma^{s}$), and annually in all subsequent years (γ^{f}).

Appendix Figure E-5: Sunk Cost's Share of Fixed Costs



Notes: Bars represent ratio of the upper bounds of our fixed cost estimates in the first year that a firm sources from a country ($\widetilde{\gamma^s} = \gamma^f + \gamma^s$), to the annual cost of importing in all subsequent years (γ^f). Put differently, each bar plots $\widetilde{\gamma^s}/\gamma^f$.