

The Increasing Cost of Buying American*

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Abstract. The latest resurgence in the U.S. of policies aimed at reducing imports and bolstering domestic production has included the expansion of Buy American provisions. While some of these are new and untested, in this paper we evaluate long-standing procurement limitations on the purchase of foreign products by the U.S. Federal Government. We use procurement micro-data to first map and measure the positive employment effects of government purchases. We then calibrate a quantitative trade model adapted to include features relevant to the Buy American Act: a government sector, policy barriers in final and intermediate goods, labor force participation, and external economies of scale. We show that current Buy American provisions on final goods purchase have created up to 100,000 jobs at a cost of between \$111,500 and \$137,700 per job. However, the recently announced tightening of the policy on the use of foreign inputs will create fewer jobs at a higher cost of \$154,000 to \$237,800 per job. We also find scant evidence of the use of Buy American rules as an effective industrial policy.

Keywords: Buy American, Public Procurement, Trade Restrictions, Domestic Content

JEL Codes: F10, F13, H41, H57

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1 Introduction

The Buy-American requirements of recent prominent U.S. policies like the Infrastructure Investment and Jobs Act and the Inflation Reduction Act have caused concern among policymakers and economists regarding the potential costs to the U.S. economy of effectively restricting the import of certain goods and violating established rules of the WTO. While the consequences of such new policies have not yet materialized and will certainly be the subject of future research, this paper aims at carefully quantifying the effects of the original “Buy American” policy, the Buy American Act of 1933,¹ which has regulated public procurement by the Federal government and provided the blueprint for the multitude of domestic-content provisions in various programs, like the Federal Highway Administration “Buy America” and the Infrastructure Investment and Jobs Act “Build America Buy America”.²

Understanding the impact of the Buy American Act (BAA) is important not only because it has been the model for subsequent domestic-content requirements in many other Federal programs, but also because both the Trump and the Biden administrations have introduced the biggest changes in the legislation “in almost 70 years,”³ which will make it substantially more restrictive by 2029. This paper shows that the increasing stringency of the Buy American Act will generate proportionally increasing costs: while the present version of the policy has created 50,000-100,000 jobs at the cost of \$111,500-\$137,700 per job, its future form will deliver additional jobs at an estimated higher cost of \$154,000-\$237,800.

The two key elements of the Buy American Act are the requirements that, unless specific waiver conditions are met, i) goods purchased by the U.S. Federal government are manufactured in the U.S., and ii) at least 50% of the cost of components is spent on U.S.-produced inputs.⁴

These provisions of the BAA are essentially a barrier to imports of goods, which produces welfare costs due to lower import shares compared to free trade. When the Federal government is forced by law to purchase relatively more expensive supplies from producers in the U.S., taxpayers end up paying more for the goods that the government buys. What benefits, then, can such policies produce? The narrative that has accompanied the original Buy American Act and the subsequent similar provisions is that by purchasing certain goods in the U.S., the government would support “workers and manufacturing across America”.⁵ We take this goal of creating jobs, and in particular manufacturing jobs, from disappearing as a benefit that the policymaker values. This is particularly important in regions where such jobs are concentrated and essential to the local economy.

¹For Federal statute, see 41 U.S.C. §83

²For Federal statute, see, respectively, 23 U.S.C. §313 and 41 U.S.C. §70901 (Pub. L. No. 117-58, §§ 70901-52).

³See [White House \(2024\)](#) and Appendix Section

⁴See Section 2 for details.

⁵See [White House \(2024\)](#) and Section A.1

Another, less explicitly stated benefit of these policies is closer to what is often referred to as “industrial policy”. This involves boosting demand in industries characterized by learning-by-doing or other positive externalities, which could enhance industry productivity if a larger demand for their products is sustained through guaranteed government purchases.

Modeling and measuring these costs and benefits is the ultimate goal of this paper. Despite the limited academic literature on this topic, the economic impact of Buy American provisions has been a central issue in public debate and policy discussions, receiving attention in policy reports. For instance, in a PIIE policy report, [Hufbauer and Jung \(2020\)](#) employ a partial equilibrium model to estimate the stringency of Buy American provisions.⁶ As we describe in the next paragraphs, compared to these earlier efforts, our study makes significant contributions both in terms of measurement and modeling approach.

First, by leveraging micro-data on each Federal government procurement contract in the Federal Procurement Data System, we can measure at a very granular level (*industry by industry*) the share of government consumption supplied by foreign firms, and compare it to the import penetration ratio of private consumption. This key metric reveals how much more constrained the government is when buying goods, relative to the private sector.

At first, it may appear easy to generate this key metric using readily available international input-output tables, such as the WIOT (World Input-Output Tables) or the OECD Inter-Country Input-Output (ICIO) tables⁷, which report a measure of government consumption of both domestic and imported goods. This is the data that, for example, [Hufbauer and Jung \(2020\)](#) and [Mulabdic and Rotunno \(2022\)](#) employ.⁸ However, comparing the government import penetration to the private import penetration ratio obtained from these data cannot, *by construction*, reveal government-specific import restrictions: it only captures differences in the sectoral composition of government consumption. This is because, in general, the trade data collected by customs does not record the final user of the product. In the absence of other information, a proportionality rule is applied: this dictates that, industry by industry, the import share *must* be the same for government and private consumption.⁹ In Section 3, our first finding shows that such aggregate data largely overestimates the government import penetration ratio, compared to those derived using micro-data. For example, while the government import penetration of 7.5% employed in [Hufbauer and Jung \(2020\)](#) is roughly half of the aggregate U.S. import share of GDP of 15%, the

⁶[Hufbauer and Jung \(2020\)](#) conclude that Buy American provisions are equivalent to a 26% ad valorem tariff and that the “taxpayer cost was over \$250,000 for each job “saved”. Other policy reports like [Bacchus \(2023\)](#) mention the “high price” of the policy, but do not provide a specific figure.

⁷See <https://www.oecd.org/en/data/datasets/inter-country-input-output-tables.html>

⁸While [Hufbauer and Jung \(2020\)](#) focus on the Buy American provisions, [Mulabdic and Rotunno \(2022\)](#) infer from the data a measure of ‘home bias’ in government purchases for several countries, including the U.S. See also earlier papers by [Trionfetti \(2000\)](#) and [Messerlin and Miroudot \(2012\)](#).

⁹This is clearly explained for example in the documentation of the World Input-Output Database in [Dietzenbacher et al. \(2013\)](#) and [Timmer et al. \(2015\)](#) and noted by [United States Government Accountability Office \(2019\)](#).

micro-data reveal that in 83.7% of industries, the government import penetration ratio is 10 times smaller than its aggregate counterpart. Hence, relying on the proportionality assumption and aggregate data not only masks sectoral heterogeneity but also leads to inaccurate estimates of the differences between government and aggregate import penetration ratios.

The second empirical contribution of the paper is twofold: first, we use data on individual contracts to produce a detailed map of Federal government purchases, tracing both the location of the buying government agency and the supplier of each product. This allows us to obtain a trade matrix that maps the flows of government-procured goods between all commuting zones in the United States. Armed with this map, we then conduct an empirical exercise to measure the impact of government purchases for local employment - a crucial elasticity in our exercise and a significant metric per se, akin to estimates of the fiscal multiplier in [Nakamura and Steinsson \(2014\)](#).¹⁰ Employing a shift-share instrument, we show that over a 5-year period, an additional \$2,947 per worker (one equal to one standard deviation) in government spending on goods produced in a commuting zone increases the manufacturing employment as a share of the working-age population by 0.47 percentage points.¹¹

On the modeling front, we contribute to the existing literature by developing a framework that allows us to quantify the policy's costs and assess its potential benefits in terms of employment and industrial policy. As the main building block, we adopt the quantitative trade model of [Caliendo and Parro \(2015\)](#), which extends the workhorse [Eaton and Kortum \(2002\)](#) model to incorporate trade in both final and intermediate goods, a necessary feature to capture BAA restrictions placed on the import of both final products and the components to produce them.

We introduce three key modifications to this model. First, we introduce a government sector that operates separately from the private market in terms of production and consumption. Firms producing for the government face different barriers (or "wedges" in the spirit of [Hsieh et al., 2019](#)) compared to those in the private market, regarding both final goods and intermediate goods. Consumers value public goods produced across different regions in the U.S. (e.g., national defense or national parks), and the government funds public goods production through labor taxes. Second, workers choose between working in one of several industries and "home production" as in [Galle et al. \(2022\)](#), a feature that introduces endogenous non-employment. Non-employment depends, among other factors, on wages, which in turn is affected by government demand. Finally, we allow each sector to be subject to (external) economies of scale, i.e. have productivity levels that depend on the total employment in the sector as in [Bartelme et al. \(2024\)](#). In this setup,

¹⁰It is reasonable to expect sizable effects of procurement spending, since its size is of the same order of magnitude as other shocks that have been shown to affect local employment, for example, the well-known China Shock documented in [Autor et al. \(2013\)](#) and [Autor et al. \(2021\)](#). Figure 1 shows that manufacturing procurement starts just below \$109 billion, the level of imports from China to the U.S. in 2001, the first year of our data. While those imports grew faster than procurement during the 2000s, the order of magnitude is comparable.

¹¹For comparison, a \$1,000 increase in import per worker in [Autor et al. \(2013\)](#) over a 10-year period was associated with a decline in the manufacturing employment share of 0.75 percentage points.

the government can, in principle, improve welfare by placing stronger restrictions on sectors characterized by stronger economies of scale.

Equipped with this model, we can infer the stringency of the BAA by comparing normalized shares of imports in government purchases to those in the private market. Similarly, we can infer BAA-related “wedges” on imports of intermediate goods used in the production of government goods. As suppliers might encounter general difficulties in doing business with the U.S. government— such as navigating procurement auction procedures and other complexities— these challenges could contribute to increased government wedges. We carefully account for these factors by leveraging an institutional detail of the BAA: the exemption of BAA requirements for the procurement of goods or services intended for use outside of the U.S. We consider the normalized EU-produced to the U.S.-produced procurement shares for consumption in the EU to infer these overall costs of dealing with US procurement. In our most conservative scenario, this generic “home bias” component accounts for about half of the overall wedges we calculate using only U.S. import shares, with the remaining half representing our “narrow” measure of BAA stringency.

What would happen if the BAA were removed or tightened, as recent policy changes suggest? How would changes in government spending on public procurement affect the economy? To what extent does BAA protection align with and capitalize on external economies of scale? The final part of this article seeks to answer these questions by employing our quantitative model to conduct several counterfactual exercises, utilizing the exact-hat algebra method as outlined in [Dekle *et al.* \(2007\)](#). First, we revisit our reduced-form results linking government spending and jobs, and we simulate the effect of halving government spending from its 2014 level, effectively resetting total federal spending to its 2001 level. Our findings indicate that this produces employment losses that closely match those predicted by our reduced-form analysis, lending credibility to the empirical predictions of the quantitative model.

The second, and key, exercise is to simulate the effects of removing BAA-induced import restrictions. We also recognize that it is implausible to remove BAA restrictions in critical sectors for national security. Therefore, we exploit a special clause in the Federal Acquisition Regulation (FAR) that indirectly identifies which industries are subject to national security concerns. In our preferred counterfactual, removing Buy American provisions results in a loss of roughly 100,000 manufacturing jobs, at a cost of between \$132,100 and \$137,700 per job in terms of equivalent variation. When we remove the more conservative and smaller ‘narrow’ BAA wedges, the resulting employment loss is just above 50,000 manufacturing jobs, at a cost of between \$111,500 to \$132,300 per job.

We next turn to restrictions on the use of foreign intermediate inputs, which are expected to tighten substantially under both President Trump and President Biden, with the minimum required share of U.S. components increasing from 50% to 75% by 2029. Interestingly, we find that in the baseline period of 2014, restrictions on the imports of intermediate inputs were only binding

for one sector: Computer and Electronic Product Manufacturing. However, the announced change will make it binding for several additional sectors. The model predicts that the employment effect of such tightening is to increase domestic employment by 41,300 manufacturing jobs. However, this comes at a considerably higher cost in terms of welfare, ranging from \$154,000 to \$237,800 per job. The higher cost arises from two main factors: first, the newly protected sectors that compete with foreign intermediate inputs tend to have a lower labor share relative to sectors protected by final goods restrictions. Second, the regions most affected by the rise in input costs are those with a high concentration of government procurement, leading to increased public goods procurement costs.

Regarding external economies of scale, we find two relevant results. First, when we conduct these counterfactuals in two versions of the model- one with and one without external economies of scale- almost all the results we have discussed so far remain largely unchanged. This is because, at present, the stringency of BAA seems to be unrelated to the strength of external economies of scale. In other words, the BAA provisions are not effectively targeting the sectors where industrial policy could have the greatest impact. Motivated by this result, we perform an exercise in which we rearrange BAA wedges across sectors to be perfectly correlated with the strength of economies of scale. This adjustment produces a modest increase in welfare of \$3.69 per capita and a loss of employment of 13,700 jobs.

Our article is closely related to the literature that estimates trade frictions in government procurement. While the academic literature on Buy American provisions and government domestic content requirements is generally sparse¹², some studies investigating trade frictions in government procurement rely on aggregate international input-output tables (Mulabdic and Rotunno, 2022; Trionfetti, 2000), with the caveats mentioned above. Our study, on the other hand, is more aligned with the handful of papers that use large datasets of individual procurement contracts to assess the extent of foreign sourcing as a share of government procurement. These papers primarily focus on procurement within the European Union.¹³ An example is the work by Herz and Varela-Irimia (2020), which documents border effects in the award of public contracts in the European Union. Their micro-data estimates also reveal much smaller import shares than the aggregate data from I-O tables, consistent with our findings. Another example is the recent paper by Garcia Santana and Santamaría (2023), which documents high levels of “home bias” even at the sub-national level, and in the European context, where barriers to cross-national procurement contracts are, in principle, absent. This is an important consideration that we address when attributing the low government import penetration to Buy American provisions, as opposed to all the other

¹²The only estimate, to the best of our knowledge, of the costs of the BAA provisions is the policy piece by Hufbauer and Jung (2020), which we previously discussed.

¹³Up to our knowledge, the United States Government Accountability Office (2019) report is the only policy paper that uses FPDS data to document the extent of U.S. government’s imports.

unobservable factors that might lead governments to disproportionately purchase domestically produced goods.

Our analysis of the employment effects of government purchases at a geographic level is related to the literature on the fiscal multiplier that leverages differences over time and across locations of government spending. Examples include [Nakamura and Steinsson \(2014\)](#), [Serrato and Wingender \(2016\)](#), [Wilson \(2012\)](#), [Garin \(2019\)](#), [Chen *et al.* \(2021\)](#), while earlier work on the local impact of defense spending is surveyed in [Braddon \(1995\)](#). Unlike these studies, however, our focus is on the impact of the universe of federal procurement contract spending, with our counterfactuals specifically addressing changes in BAA restrictions. Moreover, by incorporating the BAA features in our model, we quantify the cost per job connected to BAA restrictions in an internally consistent manner.

Our research connects to the existing literature in procurement that examines policies designed to restrict competition for contracts to favor specific groups of firms ([Krasnokutskaya and Seim, 2011](#); [Athey, Coey and Levin, 2013](#); [Carril, Gonzalez-Lira and Walker, 2022](#)). Most of these papers build upon industrial organization tools to evaluate the consequences of these policies at the contract level, emphasizing effects on revenue and performance. Our work extends this discussion by highlighting the broader industry-level effects, including impacts on employment. Moreover, the procurement database that we use in this paper, the Federal Procurement Data System (FPDS), has been used in the industrial organization and the public finance literature to tackle a variety of research questions (e.g., [Decarolis, Giuffrida, Iossa, Mollisi and Spagnolo, 2020](#); [Kang and Miller, 2022](#); [MacKay, 2022](#)). In contrast, the use of the FPDS database in a macro context is rather new. The only exception is [Cox *et al.* \(2024\)](#), which uses FPDS to understand the composition of government consumption and study fiscal transmission mechanisms.

The paper is also related to the broader literature on local content requirements and rules of origin (ROOs) in regional trade agreements (RTAs) that condition lower tariffs within the RTA on the share of local inputs. Similar to the effect demonstrated by [Conconi *et al.* \(2018\)](#), we can expect BAA restrictions to limit the imports of intermediate inputs by firms serving the government. However, unlike ROOs, which can be bypassed if final-good producing firms choose to pay the MFN tariffs,¹⁴ firms can only avoid BAA requirements by not selling to the government. Our model and counterfactuals reflect these restrictions, capturing the distinct impact of BAA provisions on the sourcing decisions of firms.

On the methodology front, our paper is related to the broad category of gravity models, often used to quantify the welfare effects of policy or other parameter changes. These models, some of which are surveyed in [Costinot and Rodríguez-Clare \(2014\)](#), frequently employ the exact hat algebra method introduced by [Dekle *et al.* \(2007\)](#) for conducting counterfactual analyses. Examples

¹⁴See [Grossman \(1981\)](#) and more recently [Head *et al.* \(2024\)](#).

include Di Giovanni *et al.* (2014), Caliendo and Parro (2015), Eaton *et al.* (2016), Caliendo *et al.* (2023) and Bonadio *et al.* (2021). We build on these studies by incorporating specific features of the BAA, such as differential restrictions on the purchase of both final and intermediate goods when selling to the government versus the private market. This approach allows us to evaluate the policy's impact on both local employment and productivity.

Finally, our findings call into question the effectiveness and welfare costs of using public procurement as a tool for industrial policy. This issue is particularly relevant today, as the need for industrial policy is increasingly recognized across the political spectrum (Rodrik, 2022). But while the literature on industrial policy has been growing recently (among others, Aghion, Cai, Dewatripont, Du, Harrison and Legros, 2015; Juhász, 2018; Kalouptsidi, 2018; Criscuolo, Martin, Overman and Van Reenen, 2019; Hanlon, 2020; Giorcelli and Li, 2021; Choi and Levchenko, 2021; Lane, 2022)¹⁵, the role of non-tariff import restrictions on government purchases is rarely studied in this context. In our study, we fill this gap, and we incorporate industry-level external economies of scale (as in Kucheryavyy *et al.* (2023) and Bartelme *et al.* (2024)), which are often considered a key rationale for import protection in industrial policy. Additionally, the geographic concentration of federal procurement and varying sectoral exposure to BAA restrictions lead to significant regional disparities in the welfare and employment impacts of BAA and its future reforms. Public procurement, therefore, emerges as a form of government intervention that can shape wages, employment, and industry composition across regions, adding to a broader set of place-based policies aimed at addressing regional disparities through targeted public investments and subsidies (Busso *et al.*, 2013; Neumark and Simpson, 2015; Fajgelbaum and Gaubert, 2020).

The rest of the article is organized as follows. Section 2 describes the policy rules. Section 3 details the federal procurement contract data and provides an overview of the geography of public procurement. Section 4 presents the quantitative model, Section 5 discusses the additional datasets used and explains how we bridge the model with the data, including our reduced-form evidence on the impact of federal procurement spending on employment. Section 7 shows our counterfactual analyses and Section 8 concludes.

2 Buy American Act

The Buy American Act of 1933 (BAA) was enacted during the Great Depression with the intention of preserving jobs for American workers.¹⁶ While Congress has often discussed expanding the scope of domestic preferences in federal procurement, the Act itself has rarely been changed until very recently.

¹⁵For a review of the industrial policy literature, please see Harrison and Rodríguez-Clare (2010) and Juhász *et al.* (2023).

¹⁶See Appendix A.1 for more details on the origins of the policy.

2.1 The Content of the BAA

The BAA mandates that federal agencies conducting procurement for public use in the U.S. purchase “[o]nly unmanufactured articles, materials, and supplies that have been mined or produced in the United States, and only manufactured articles, materials, and supplies that have been manufactured in the United States substantially all from articles, materials, or supplies mined, produced, or manufactured in the United States”.¹⁷ Similarly, these requirements extend to construction materials used by contractors working on government construction contracts within the United States.

The Federal Acquisition Regulation (FAR) implements this mandate by requiring federal agencies to apply a price preference to domestic “end products”, defined as “articles, materials, and supplies to be acquired for public use” (48 CFR § 52.225-1). An end product comprises several “components”.¹⁸ Depending on whether an end product is manufactured or unmanufactured, the BAA delineates distinct criteria for items to qualify as domestic and therefore adhere to its regulation.

For an unmanufactured construction material or end product to be considered domestic, it must be mined or produced in the U.S. For instance, sand mined in the U.S. is compliant with BAA. For a manufactured construction material or end product, BAA uses a two-part test to determine if it qualifies as domestic: first, the article must be manufactured in the U.S.; second, the cost of all its domestic components must exceed 50% of the cost of all the components, where components are considered domestic if they are manufactured in the U.S.. For example, an automobile manufactured in France is non-compliant with BAA; instead, an automobile manufactured in Ohio, which includes components made in France, is compliant with BAA as long as it consists of more than 50% US components by cost.^{19,20}

¹⁷Although neither the BAA nor any of the Executive Orders implement it contain an explicit definition, an unmanufactured product or material is considered one that is not processed into a specific form or combined, in advance, with other raw materials to create a new material (for instance, sand or unmodified gravel). On the other hand, a manufactured product has undergone substantial changes in physical character and into the required form for public use (for instance, concrete mix or an automobile).

¹⁸The FAR defines a component as an article, material, or supply incorporated directly into an end product or construction material. For instance, in a procurement contract for an automobile, the automobile itself is considered an end product, whereas the engine is considered its component.

¹⁹In 2009, an exception was introduced for a set of manufactured end products considered commercially available off-the-shelf (COTS) items: they only have to be manufactured in the U.S. without any restriction on the cost of their components. An example of a COTS item is Microsoft Office.

²⁰The costs of components are calculated by considering the specific expenses the contractor encounters when procuring or producing those components, excluding labor costs.

2.2 Applicability, Waivers, and Enforcement

The BAA applies to all procurement contracts made directly by U.S. federal government agencies and valued over the micro-purchase threshold.²¹ The procurement contract must be for intended use or performance within the U.S.. This does not encompass locations where the U.S. lacks complete sovereign jurisdiction, such as overseas military bases leased from foreign governments. Moreover, the BAA does not apply to contracts procuring services or to contracts awarded by state and local authorities under federal grant programs, where other domestic-content requirements are often in place.

Federal law delineates exemptions (“waivers”) under which a federal agency can procure foreign end products or permit the use of foreign construction materials without violating the BAA.²² A waiver can be granted if (i) domestic end products are “unavailable in sufficient and reasonably available commercial quantities and of a satisfactory quality,” (ii) the cost of acquiring the domestic product is deemed unreasonable, or (iii) the agency is purchasing foreign eligible products from designated countries under the Trade Agreements Act of 1979. The presence of these waivers makes it possible for the government’s import share to be positive, and the ease of obtaining waivers has often been at the core of calls to reform and tighten the BAA.²³

For compliance with the BAA, vendors supplying products to federal agencies must certify the origin and place of manufacture of their goods. For unmanufactured products, the origin is determined by the sourcing country. For manufactured products, the origin is based on where the majority of the components, by cost, are produced. Vendors can certify annually through the System for Award Management (SAM) or provide origin information in individual contract offers. Each bid requires a Buy American Certificate, which confirms whether the products are domestic or lists any foreign products and their origins.

Prospective or current bidders can contest an agency’s implementation of the BAA or another vendor’s compliance before a contract is awarded, typically through a bid protest. Furthermore, civil litigation can be instigated by whistle-blowers, often competitors, employees, or private citizens, if they suspect violations of the BAA. Finally, the Government Accountability Office (GAO), Inspector General, and Department of Justice (DOJ) also conduct audits to ensure compliance with the BAA.

Further details about the BAA and other Buy American provisions are reported in Section A. We now turn to the description of the federal procurement micro-data that we employ to construct flows of products produced for and consumed by the federal government.

²¹In the period of our study, the micro-purchase threshold was increased twice: from \$2,500 to \$3,000 on September 28, 2006, and to \$3,500 on October 1, 2015. Effective August 31, 2020, the micro-purchase threshold has been increased to \$10,000.

²²See Section A.3.2 in the Appendix for further details on BAA waivers.

²³For example, President Biden instituted an office to monitor and publicize waivers. See Exec. Order 14,005.

3 The Data: The Size and Geography of Federal Public Procurement

In this section, we describe the data on federal procurement that we will subsequently employ to quantify the employment and welfare effects of BAA. Our primary goal is to give the reader a sense of the geography of government purchases, where the products are consumed, where they are produced, and whether they come from abroad. The import share of government consumption will be our key variable for estimating the stringency of BAA, and knowing where government demand is strong allows us to determine the biggest geographical and sectoral winners and losers from modifying the BAA provisions.

We use data from the Federal Procurement Data System (FPDS), which contains detailed information on the universe of contracts signed by the federal government. The data is available from 2001, and for every contract, we observe detailed information about the agency, sub-agency, and contracting office making the purchase, the identity (DUNS code²⁴) of the private vendor, the dollar amounts obligated, a four-digit code describing the product or service required, and a six-digit Industry (NAICS) code. Also, we observe the type of contract pricing, the extent of competition in the award, the characteristics of the solicitation procedure, the number of offers received, the applicability of a variety of laws and rules (including BAA), and the reason and the content of all contract modifications after the contract is awarded.

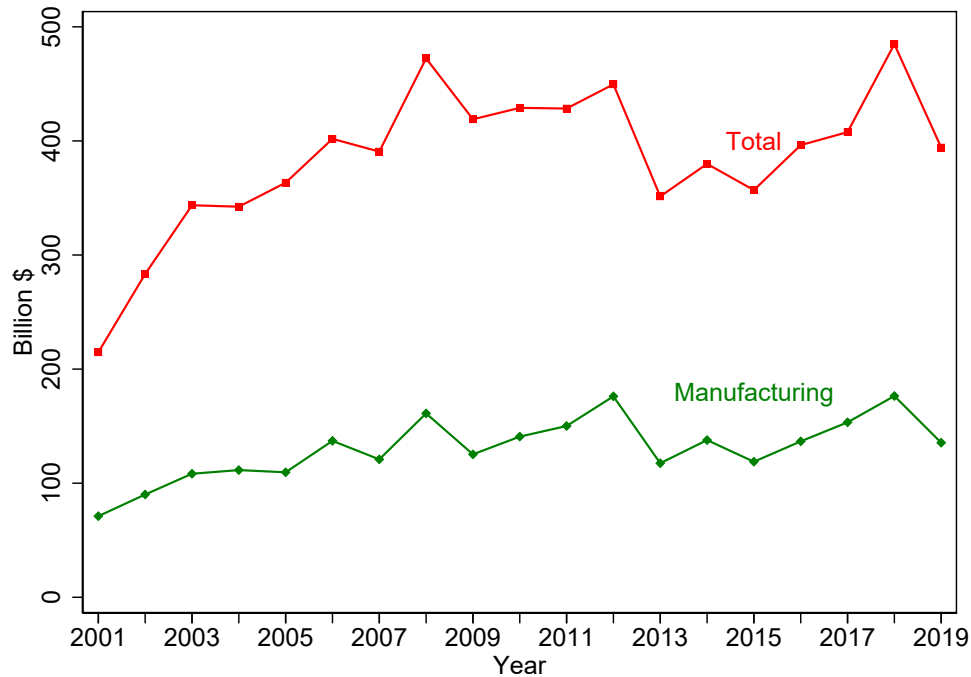
Given that large contracts span multiple years, we organized the dataset at the contract-year level to capture the contracts' per-year amounts. Also, we cleaned location variables; the dataset contains the zip codes of the buyers (procurement offices) and the vendors (DUNS). If the location is outside the U.S., we replace the zip code with the country name. The resulting dataset contains 32 million contract-year observations; these contracts were required by procurement offices located in 1,900 different U.S. zip codes across all fifty states (and DC) and were awarded to over 600,000 different vendors.²⁵ Appendix B.1 provides more details about the FPDS dataset.

Figure 1 describes the annual procurement spending recorded in FPDS. The red line shows the total expenditure in any category, while the green line focuses on contracts involving manufacturing industries. Overall, procurement spending doubled between 2001 and 2008 and then stabilized at around 400 billion dollars annually. Manufacturing industries represent roughly one-third of the total amount and span a wide range of industries. As a reference, the top six-digit NAICS in spending is 336411 (Aircraft Manufacturing). Appendix Table B.2 describes the top 20 six-digit NAICS industries.

²⁴The DUNS number is a nine-digit identifier for businesses. This identifier is proprietary as it is managed by Dun & Bradstreet. The identifier provides a distinct number for business branches relative to their headquarters, allowing for the separation of their locations.

²⁵Roughly 4% of contracts are required from an office located outside of the U.S.

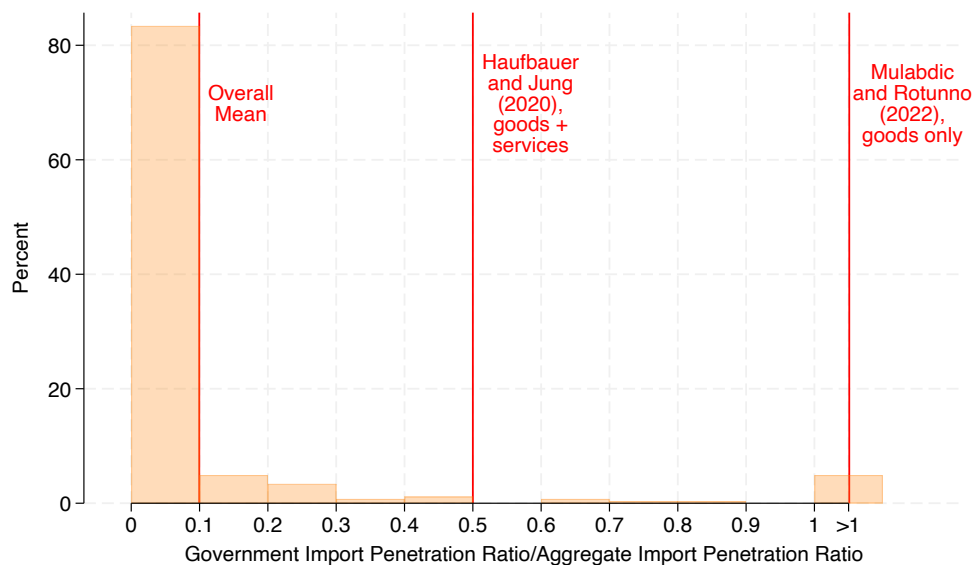
Figure 1: Federal Procurement Spending



Notes: This figure describes spending by the federal government between 2001 and 2019. The amount of expenditure is calculated by aggregating FPDS contract-year observations at the year level. Manufacturing contracts are those NAICS starting with 31, 32 or 33.

Comparing import penetration: government vs aggregate consumption. As we mentioned in the introduction, while other papers have adopted the import penetration ratio of the government relative to the aggregate (or non-government) import penetration ratio to measure the restrictiveness of domestic content provisions, we show here that using international input-output tables to build this metric cannot, *by construction*, reveal how much more constrained the government is compared to the private sector when importing. This is because imports are measured at the aggregate level for the entire economy and are not split by final consumer (government vs households etc). Within each sector, a proportionality rule is applied to apportion imports to the government vs other final consumers using the government consumption share of that good. Given this well-documented fact,²⁶ government import penetration ratio being lower than their aggregate counterparts only reveals that the government consumes goods that have a relatively low import

Figure 2: Histogram for Import Penetration Ratio for Government versus Aggregate



Notes: The histogram represents the frequency distribution of the ratio of government to aggregate import penetration ratios across manufacturing NAICS 6-digit industries in year 2014. The import penetration ratio for the government is calculated from FPDS data as the value of awards to firms located abroad relative to total awards in an industry. The aggregate import penetration ratio is obtained by dividing general imports and domestic absorption at the NAICS 6-digit level. Aggregate imports and exports are retrieved from US trade data built by Peter Schott, and domestic absorption is calculated as total shipment value (from NBER-CES) minus exports plus imports. We highlight the overall mean of 0.1 (calculated as the ratio of 0.028 import penetration ratio in FPDS and 0.276 import penetration for the aggregate economy) and two values from the literature: 0.5 is calculated as the ratio of *i*) goods and services imported by the government as a percent of government procurement (7.5%) and *ii*) imports of goods and services as a share of GDP in 2017 (15%) from [Hufbauer and Jung \(2020\)](#); 1.05 is reported in Table A.6 in [Mulabdic and Rotunno \(2022\)](#) and is defined as the ratio of government import penetration ratio to private import penetration ratio for goods (not services).

penetration ratio.²⁷

Figure 2 employs FPDS data to show that, when calculated industry by industry, government import penetration ratios are much lower than aggregate ones: 83.70% of NAICS 6-digit industries display a government import penetration ratio that is less than 10% of their aggregate counterpart. The vast majority of industries lie to the left of the two comparison values from [Hufbauer and Jung](#)

²⁶See equation (12) of page 87 in [Dietzenbacher et al. \(2013\)](#).

²⁷Consider an economy where the consumption of both goods A and B is 100 and A has a lower import penetration ratio.

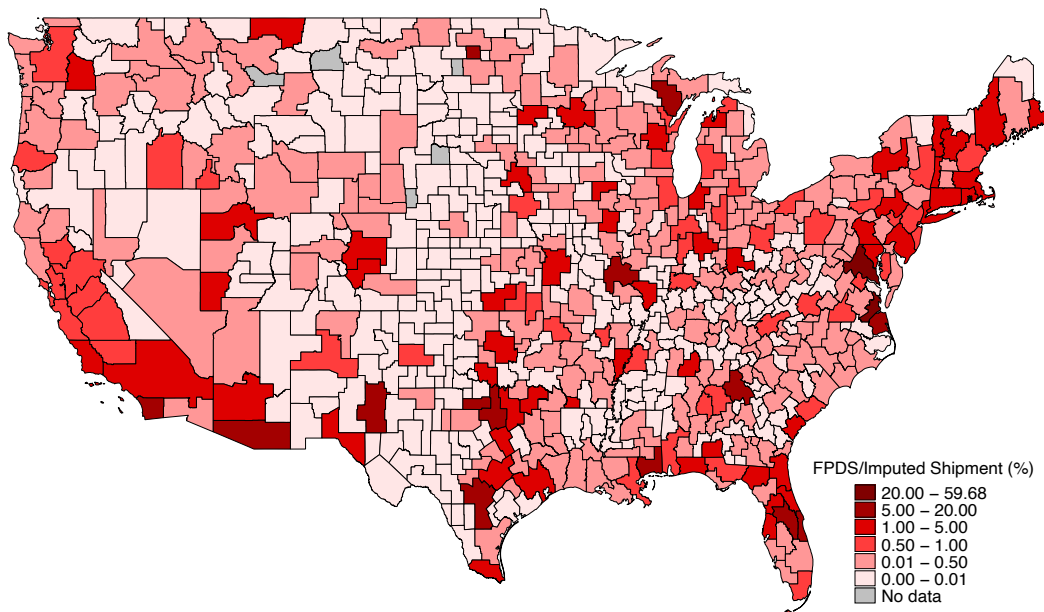
	A	B
Gov. Consumption	80	20
Priv. Consumption	20	80
Total Imports	10	20

In this example, a proportionality rule would assign to the government imports of A and B equal to, respectively, 8 and 4, resulting in an import penetration ratio of 12% for the government and 18% for the private sector (or 15% for the aggregate economy).

(2020) (calculated using import of both goods and services in 2014) and [Mulabdic and Rotunno \(2022\)](#) (calculated using only goods for the year 2015).

The geography of procurement spending. One of the advantages of employing contract-level data is that we can accurately describe the geographic distribution of government purchases. In our analysis of the employment effects of government spending, we will use commuting zones (CZs) as the local geographic areas. To this end, we construct a map based on CZs, as in [Tolbert and Sizer, 1996](#) and [Autor *et al.*, 2013](#).

Figure 3: Government Shares: Share of Revenues from Federal Procurement (Year 2001)



Notes: This figure reports the ratio between the amount of public procurement spending received by firms located in the commuting zone and the imputed total revenues (shipments) generated in the commuting zone calculated by multiplying the total shipments in a NAICS 6-digit industry by the CZ share of national employment in that NAICS industry. Darker colors indicate a higher share of shipments being purchased by the government.

To assess a CZ's dependency on government purchases, we require a measure of the total revenues generated in a CZ for each sector. Ideally, we would like to employ measures of revenues at the local level. However, such measures are not readily available for the US, so we apportion the total shipments (revenues) of NAICS 6-digit industry X_s to a CZ o according to the CZ's share of national employment in that sector. Specifically, we calculate $X_o = \sum_s \frac{L_{os}}{L_s} X_s$, where L_{os} represents employment in CZ o and industry s , and L_s is national employment in industry s . We then construct X_o^G / X_o , where X_o^G is the total FPDS awards granted to firms located in CZ o .²⁸

Figure 3 reports the government shares X_o^G / X_o for the first year of our dataset, 2001, across commuting zones. Notably, many CZs do not produce much for the government: for the majority

²⁸Total shipments X_o is from the NBER-CES dataset ([Becker *et al.*, 2013](#)).

of CZs, less than 1% of manufacturing revenues come from sales to the government. However, several CZs' government share is above 5%, indicating a substantial economic role of government purchases.

In the next section, we set up a model that captures government consumption and production as separate from the rest of the economy and allows us to reproduce the geographic and sector dimensions of the FPDS data and perform counterfactuals that reveal the benefits and costs of BAA.

4 Model

We employ a quantitative trade model à la [Eaton and Kortum \(2002\)](#) with the following features: i) two separate markets in terms of production and consumption: one for government goods and one for private goods; ii) multiple sectors and an input-output structure as in [Di Giovanni *et al.* \(2014\)](#) and [Caliendo and Parro \(2015\)](#); iii) a choice for workers between non-employment (home production) and employment across multiple sectors as in [Caliendo *et al.* \(2019\)](#) and [Galle *et al.* \(2022\)](#); iv) the presence of external economies of scale at the sector level, as in [Kucheryavyi *et al.* \(2023\)](#) and [Bartelme *et al.* \(2024\)](#). These modeling choices allow us to incorporate key features of the BAA, i.e., restrictions on the purchase of both final and intermediate goods when selling to the government, and they allow the policy to affect both total local employment and productivity.

The economy consists of S production sectors indexed by s and k , along with a home production sector represented by h . There are $N + 1$ regions in the world, including N regions in the US and the rest of the world (ROW), denoted by o (origin) or d (destination). For each region within the US and for each sector, there are two types of buyers and two types of producers, which we denote by $j \in \{G, M\}$ to indicate the government (G) and the private market (M). Regions outside of the US only have M producers and buyers. G buyers represent government agencies that enter into procurement contracts with G producers, while M buyers buy from M sellers and represent the rest of the market. In turn, G producers buy inputs from M producers, but face restrictions on the share of intermediate inputs they can source from foreign firms, as established by the BAA. Preferences of all buyers are CES with an elasticity of substitution σ_s across the continuum of goods within each sector $s \in S$ and are Cobb-Douglas across sectors s with expenditure shares β_{ds}^j .

4.1 Labor Supply

Labor supply is determined by workers' choices across sectors. Denote $\mathbf{z} = \{z_1, z_2, \dots, z_S\}$ the multi-dimensional skills, which are independently drawn from a Fréchet distribution with a scale parameter A_{os} and a shape parameter κ_o . Labor endowment in region o is given by L_o . In home production h , non-employed individuals obtain consumption z_h , where z_h is independently drawn from a Fréchet distribution with a scale parameter b_{oh} and a shape parameter κ_o . Denote the wage

rate per efficiency unit of labor by w_{os} . In home production, such wage is taken as exogenous, and normalized to be one. The set of workers that work in sector s is $\Omega_{os} = \{z \text{ s.t. } w_{os}z_s \geq w_{ok}z_k \text{ for all } k = 1, \dots, S \text{ and } (1 - \delta_o)w_{os}z_s \geq z_h\}$, where δ_o is the constant income tax rate.²⁹ The share of workers in region o that work in sector s is:

$$\pi_{os} = \frac{A_{os}(1 - \delta_o)^{\kappa_o} w_{os}^{\kappa_o}}{(\Phi_o/\xi_o)^{\kappa_o}} \quad \forall o \quad (1)$$

where $\Phi_o = \xi_o \left(\sum_{s'} A_{os'}(1 - \delta_o)^{\kappa_o} w_{os'}^{\kappa_o} + b_{oh} \right)^{1/\kappa_o}$ and $\xi_o = \Gamma(1 - 1/\kappa_o)$. The employment rate in region o is hence given by $e_o = \frac{(\Phi_o/\xi_o)^{\kappa_o} - b_{oh}}{(\Phi_o/\xi_o)^{\kappa_o}}$ while the labor supply in efficiency units in region o and sector s is given by $Z_{os} = L_o \int_{\Omega_{os}} z_s dF_o(z) = \frac{\Phi_o}{(1 - \delta_o)w_{os}} \pi_{os} L_o$.³⁰

4.2 Production

In each sector s and region o , each producer of individual variety ω combine labor $l_{os}(\omega)$ and a bundle of intermediate inputs $m_{o,s's}(\omega)$ through a Cobb-Douglas production function of the form:

$$q_{os}(\omega) = z_{os}(\omega) l_{os}(\omega)^{\alpha_{o,s}} \prod_{s'} [m_{o,s's}(\omega)]^{\alpha_{o,s's}}$$

where $\alpha_{o,s}$ is the labor share while $\alpha_{o,s's}$ denotes the share of input s' in the production of s . Productivity $z_{os}(\omega)$ is independently drawn from a Fréchet distribution (common to G and M producers) with a scale parameter $T_{os}L_{os}^{\nu_s}$ and a shape parameter θ_s . The parameter ν_s represents the scale elasticity, capturing the strength of external economies of scale, as in [Bartelme et al. \(2024\)](#), and L_{os} represents the employment of industry s in o . This is the source of externalities that could in principle make the protection of domestic industries welfare improving, if concentrated in industries with large external economies of scale. Even though employing the same technology, G producers may incur different unit costs of production from M producers, due to the domestic content requirement of the BAA in inputs. Producers of type $j \in \{G, M\}$ in region o and industry s face unit cost

$$c_{os}^j = \phi_{os} w_{os}^{1 - \alpha_{o,s}} \prod_{s'} (P_{o,s's}^{j,j})^{\alpha_{o,s's}} \quad \forall o \quad (2)$$

where $\phi_{os} = \prod_{s'} (\alpha_{o,s's})^{-\alpha_{o,s's}} (1 - \alpha_{o,s})^{-(1 - \alpha_{o,s})}$ and the price index of inputs from the upstream industry s' is:

$$P_{o,s's}^{j,j} = \Gamma_{s'} \left[\sum_{o'} T_{o's'} L_{o's'}^{\nu_{s'}} (\tau_{o's',os}^{j,j} c_{o's'}^M)^{-\theta_{s'}} \right]^{-\frac{1}{\theta_{s'}}} \quad \forall o \in US \text{ if } j = G; \quad \forall o \text{ if } j = M \quad (3)$$

²⁹We assume for simplicity that $\delta_o = \delta \in [0, 1) \forall o \in US$ and that $\delta_o = 0 \forall o \in ROW$.

³⁰Hence, the expected income per worker in o is then $\frac{(1 - \delta_o)w_{os}Z_{os}}{\pi_{os}L_o} = \Phi_o = \xi_o [\sum_{s'} A_{os'}(1 - \delta_o)^{\kappa_o} w_{os'}^{\kappa_o} + b_{oh}]^{1/\kappa_o}$.

and $\Gamma_{s'}$ is a constant.³¹ The parameter $\tau_{o's',os}^{i,j} \geq 1$ denotes the costs of shipping the upstream inputs s' from region o' to type j producers in downstream sector s and region o , with $\tau_{o's',os}^{i,j} = 1$ if $o' = o$. Due to BAA restrictions, G producers may face higher trade costs $\tau_{o's',os}^{i,G}$ of sourcing foreign inputs than the costs faced by M producers, $\tau_{o's',os}^{i,M}$. Notice how this intermediate input price index depends on $c_{o's'}^M$ irrespectively of the type of producer buying it: G producers only produce for final consumption by G buyers, while M producers produce for final consumption by M buyers as well as for intermediate good used by both G and M producers.

The price index for final goods faced by G consumers in a U.S. destination region d is as follows:

$$P_{ds}^{f,G} = \Gamma_s \left[\sum_{o \notin US} T_{os} L_{os}^{v_s} (\tau_{ods}^{f,G} c_{os}^M)^{-\theta_s} + \sum_{o \in US} T_{os} L_{os}^{v_s} (\tau_{ods}^{f,G} c_{os}^G)^{-\theta_s} \right]^{-\frac{1}{\theta_s}} \quad \forall d \in US \quad (4)$$

while M consumers of good s in destination d face the following price index:

$$P_{ds}^{f,M} = \Gamma_s \left[\sum_o T_{os} L_{os}^{v_s} (\tau_{ods}^{f,M} c_{os}^M)^{-\theta_s} \right]^{-\frac{1}{\theta_s}} \quad \forall d. \quad (5)$$

Here $\tau_{ods}^{f,j} \geq 1$ is the iceberg cost of shipping final goods s from region o to j consumers in region d , with $\tau_{ods}^{f,j} = 1$ if $o = d$. Notice how final good price indices (4) and (5) differ due to both sourcing restrictions (e.g., M buyers only buy from M producers) and the different trade costs resulting from BAA restrictions: (i) G buyers source from domestic G producers, who may incur higher production costs (c_{os}^G) relative to domestic M producers (c_{os}^M) due to the domestic content restriction of component inputs imposed on the former group; and (ii) G buyers face different (potentially higher) costs $\tau_{ods}^{f,G}$ of buying foreign final goods relative the costs $\tau_{ods}^{f,M}$ borne by M buyers.

4.3 Trade Shares

Even though the components of the model are standard, the novel aspect of incorporating asymmetry in buyer types and trade costs makes it particularly important to report trade shares for both intermediate and final goods. The share of intermediate good expenditures $\lambda_{os,dk}^{i,j}$ from producers in region o and industry s by type $j \in \{G, M\}$ producers in region d and industry k is:

$$\lambda_{os,dk}^{i,j} = \frac{T_{os} L_{os}^{v_s} (\tau_{os,dk}^{i,j} c_{os}^M)^{-\theta_s}}{\left(P_{d,sk}^{i,j} / \Gamma_s \right)^{-\theta_s}} \quad \forall o, d \in US \text{ if } j = G; \quad \forall o, d \text{ if } j = M. \quad (6)$$

³¹ $\Gamma_{s'} = \left[\Gamma \left(\frac{\theta_{s'} + 1 - \sigma_{s'}}{\theta_{s'}} \right) \right]^{\frac{1}{1 - \sigma_{s'}}$

The share of expenditure on final goods by G consumers in region $d \in US$ in industry s on exports from region o in the US, is given by:

$$\lambda_{ods}^{f,G} = \frac{T_{os} L_{os}^{v_s} (\tau_{ods}^{f,G} c_{os}^G)^{-\theta_s}}{\left(P_{ds}^{f,G} / \Gamma_s\right)^{-\theta_s}} \quad \forall o \in US, d \in US. \quad (7)$$

while the same import share from a region $o \notin US$ is:

$$\lambda_{ods}^{f,G} = \frac{T_{os} L_{os}^{v_s} (\tau_{ods}^{f,G} c_{os}^M)^{-\theta_s}}{\left(P_{ds}^{f,G} / \Gamma_s\right)^{-\theta_s}} \quad \forall o \in ROW, d \in US. \quad (8)$$

Finally, share of total expenditures on final goods by M consumers in region d in industry s on exports from o , or $\lambda_{ods}^{f,M}$, is given by:

$$\lambda_{ods}^{f,M} = \frac{T_{os} L_{os}^{v_s} (\tau_{ods}^{f,M} c_{os}^M)^{-\theta_s}}{\left(P_{ds}^{f,M} / \Gamma_s\right)^{-\theta_s}} \quad \forall o, d. \quad (9)$$

4.4 Market Clearing Conditions and Equilibrium

Goods and labor market clearing conditions. We allow for trade imbalances and denote by D_o the trade deficit of region o . We assume that $D_o = \iota_o \sum_{o'} \sum_s X_{o's}$, where $X_{o's}$ is the total output of industry s in region o' and ι_o is treated as an exogenous structural parameter that determines the magnitude of lump-sum transfers across regions. This implies that each region receives an exogenously determined share of world's total income.

Federal procurement is financed through tax revenues, which is given by $\sum_{o \in US} \delta_o \sum_s w_{os} Z_{os} = \sum_{o \in US} \delta_o \sum_s \alpha_{o,s} X_{os}$. The total procurement budget is allocated to each region $d \in US$ according to shares γ_d , where $\sum_{d \in US} \gamma_d = 1$. Hence, the amount of procurement consumed in region d can be expressed as $\gamma_d \sum_{o \in US} \delta_o \sum_s \alpha_{o,s} X_{os}$. This total spending is allocated across sectors according to expenditure shares β_{ds}^G . Then, goods market clearing implies that:

$$X_{os}^G = \begin{cases} \sum_{d \in US} \lambda_{ods}^{f,G} \beta_{ds}^G \gamma_d \sum_{d' \in US} \delta_{d'} \sum_k \alpha_{d',s} (X_{d'k}^G + X_{d'k}^M) & \forall o \in US \\ 0 & \forall o \notin US \end{cases} \quad (10)$$

$$X_{os}^M = \begin{cases} \sum_{d \in US} \sum_k \lambda_{os,dk}^{i,G} \alpha_{d,sk} X_{dk}^G + \sum_d \sum_k \lambda_{os,dk}^{i,M} \alpha_{d,sk} X_{dk}^M + \\ \quad + \sum_d \lambda_{ods}^{f,M} \beta_{ds}^M [(1 - \delta_d) \sum_k \alpha_{d,k} (X_{dk}^G + X_{dk}^M) + D_d] & \forall o \in US \\ \sum_{d \in US} \sum_k \lambda_{os,dk}^{i,G} \alpha_{d,sk} X_{dk}^G + \sum_d \sum_k \lambda_{os,dk}^{i,M} \alpha_{d,sk} X_{dk}^M \\ \quad + \sum_{d \in US} \lambda_{ods}^{f,G} \beta_{ds}^G \gamma_d \sum_{d' \in US} \delta_{d'} \sum_k \alpha_{d',s} (X_{d'k}^G + X_{d'k}^M) \\ \quad + \sum_d \lambda_{ods}^{f,M} \beta_{ds}^M [(1 - \delta_d) \sum_k \alpha_{d,k} (X_{dk}^G + X_{dk}^M) + D_d] & \forall o \notin US, \end{cases} \quad (11)$$

where X_{os}^G and X_{os}^M represent the output of industry s in region o by G and M respectively, and $X_{os} = X_{os}^G + X_{os}^M$. Note that for the ROW, since there are only M producers, $X_{os}^G = 0$. M producers in the U.S. face demand originating from three sources: (i) the demand for intermediate inputs by G producers in the US, (ii) the demand for intermediate inputs by M producers worldwide, and (iii) the demand of final consumer goods worldwide. M producers in the ROW face additional demand from G consumers in the US, who can purchase from them upon meeting one of the waiver conditions described in Section 2.2.

The labor market clearing condition is given by

$$\alpha_{o,s} (X_{os}^G + X_{os}^M) = \frac{\xi_o (\sum_{s'} A_{os'} (1 - \delta_o)^{\kappa_o} w_{os'}^{\kappa_o})^{\frac{1}{\kappa_o}} \pi_{os} L_o}{1 - \delta_o} \quad \forall o. \quad (12)$$

Equilibrium. Given $\{L_o, A_{os}, b_{oh}, \kappa_o, T_{os}, \theta_s, v_s, \alpha_{o,s}, \alpha_{o,sk}, \beta_{os}^G, \beta_{os}^M, \delta_o, \gamma_o, \iota_o\}$, and trade costs $\{\tau_{ods}^{f,G}, \tau_{ods}^{f,M}, \tau_{os,dk}^{i,G}, \tau_{os,dk}^{i,M}\}$, an equilibrium is characterized by a wage vector $\{w_{os}\}$ that satisfies equations (1)-(9), goods market clearing conditions (10)-(11), and labor market clearing condition (12).

4.5 Welfare

In this section, we formulate consumer welfare by incorporating the utility derived from public goods. Without loss of generality, we normalize the size of the US working-age population so that $\sum_{o \in US} L_o = 1$.

The expected welfare for consumers in $o \in US$, denoted as V_o , follows a Cobb-Douglas structure, where personal consumption (Q_o^M) and public goods (Q_o^G) are assigned utility weights of φ and $1 - \varphi$ respectively. More specifically, consumer welfare is given by $V_o = (Q_o^M)^\varphi (Q_o^G)^{1-\varphi}$. We consider two alternative formulations for welfare, depending on the assumptions regarding how public goods enter into consumers' utility function.

Case I: Nationwide public good. In the first case, we assume that consumers have access to the composite public goods compiled by procurement from all US states, $Q_o^G = \prod_{o'} (Q_{o'}^G)^{\gamma_o}$. The contribution from each state Q_o^G is, in turn, the combination of procurement from various industries, $Q_o^G = \prod_s (Q_{os}^G)^{\beta_{os}^G}$. This is an appropriate description of the utility from public goods like defense

where Army and Navy bases across the country provide a nationwide defense service to US residents. The component of personal consumption is determined by expected real income, $\xi_o [\sum_{s'} A_{os'} (1 - \delta_o)^{\kappa_o} w_{os'}^{\kappa_o} + b_{oh}]^{1/\kappa_o} / P_o^{f,M}$. Taken together,

$$V_o = \left(\frac{\left(\sum_s A_{os} (1 - \delta)^{\kappa_o} w_{os}^{\kappa_o} + b_{oh} \right)^{\frac{1}{\kappa_o}}}{P_o^{f,M}} \right)^\varphi \left(\prod_{o'} \left(\prod_s (Q_{o's}^G)^{\beta_{o's}^G} \right)^{\gamma_{o'}} \right)^{1-\varphi}. \quad (13)$$

Case II: Local public good. In the second scenario, we adopt an alternative assumption that consumers in $o \in US$ only have access to the composite public goods produced locally. This is more representative of public goods that are consumed more locally, such as national parks, where it is reasonable to assume that residents of Maine benefit less from Yosemite National Park than residents of California. As a result, the quantity of public goods available to consumers in o is $Q_o^G = \prod_s (Q_{os}^G)^{\beta_{os}^G} / L_o$, and the expected welfare is given by:

$$V_o^{alt} = \left(\frac{\left(\sum_s A_{os} (1 - \delta)^{\kappa_o} w_{os}^{\kappa_o} + b_{oh} \right)^{\frac{1}{\kappa_o}}}{P_o^{f,M}} \right)^\varphi \left(\frac{\prod_s (Q_{os}^G)^{\beta_{os}^G}}{L_o} \right)^{1-\varphi}. \quad (14)$$

The formulations of welfare presented in (13) and (14) represent two extreme cases. Throughout the quantitative analyses in Section 7, we report the welfare consequences of policy shocks using both (13) and (14), which capture a range of plausible welfare outcomes.

5 Taking the Model to the Data

The model described in the previous section allows us to answer the questions we posed at the beginning of this paper through a series of counterfactual exercises that remove or tighten current restrictions, through the exact hat algebra of [Dekle *et al.* \(2007\)](#). However, in order to do so and to link the model to the data, we need sectoral and regional information for various variables, including: bilateral trade shares $\lambda_{ods}^{f,G}, \lambda_{ods}^{f,M}, \lambda_{os,dk}^{i,G}$ and $\lambda_{os,dk}^{i,M}$, shares of value added in gross output $\alpha_{o,s}$, input-output coefficients $\alpha_{o,sk}$, consumption shares β_{os}^G and β_{os}^M , outputs X_{os}^G and X_{os}^M , labor allocations π_{os} , employment ratio e_o , income tax rate δ_o , procurement budget shares γ_o , global portfolio shares ι_o , and utility weight on public goods φ . Estimates are required for the following parameters: sectoral trade elasticities θ_s , sectoral scale elasticities ν_s , and labor supply elasticities κ_o . Furthermore, we need to quantify the BAA wedges imposed on imports of final goods, which reflects the differences between $\tau_{ods}^{f,G}$ and $\tau_{ods}^{f,M}$, as well as the wedges on component inputs, which captures the disparities between $\tau_{os,dk}^{i,G}$ and $\tau_{os,dk}^{i,M}$. We match the model to the data moments observed in the year 2014.

In this section, we briefly describe various data sources used to compute these variables. In addition, we outline the procedures for calibrating the BAA wedges imposed on imports of final goods and component inputs. Further details are provided in Appendix B.

5.1 Regions and Sectors

We calibrate the model to the 48 US mainland states, the rest of the world, and a total of 29 sectors classified according to the North American Industry Classification System (NAICS). These sectors comprise 16 manufacturing sectors, 5 tradable mining and service sectors, and 8 non-tradable service sectors, which are listed in Appendix B.2. The selection of the number of sectors was guided by the maximum level of disaggregation at which we could collect the production and trade data needed to use our model. The labor market is defined at the region-sector level, including the home production sector. As a result, there are a total of 1470 labor markets.

5.2 Trade and Production Data

The bilateral trade and production data for the year 2014 are from the World Input-Output Database (WIOD). The WIOD contains data on trade flows of goods for final consumption among countries, along with information on input-output linkages across countries and sectors. For our purpose, we consolidate countries other than the US into a single entity referred to as the Rest of the World (ROW). Furthermore, we make additional necessary adjustments and expansions to the WIOD to gather all the relevant information required for quantitative analyses. More details are described in Appendix B.3.

First, the WIOD makes use of a similar proportionality assumption to the one we discussed in Section 3: the ratios between imported use and total use are the same across industries for each input (Dietzenbacher *et al.*, 2013). Hence, in the WIOD, the heterogeneity of import intensity of intermediate inputs among industries may be understated. Since the import share of component inputs is crucial for evaluating how binding the domestic content requirement imposed by the BAA are, we adjust the data on imports for intermediate use and final use. We ensure that in the adjusted data: (i) the imports by each manufacturing industry in the US align with the actual imports reported in the Profile of US Importing and Exporting Companies from the U.S. Census Bureau³²; and (ii) the total imports by the US remain consistent with the original WIOD data.

Secondly, we expand the adjusted WIOD by incorporating spatial data for the U.S. economy as discussed in Section 3. The extended world input-output matrix includes additional blocks as follows: (i) bilateral trade flows of goods for final use between G (respectively, M) in each US state

³²https://www.census.gov/foreign-trade/Press-Release/edb/profile_hist.html. The importer and exporter profiles were created from import and export merchandise trade information and company characteristics contained in the Census Bureau's database of company information, the Business Register. We obtain the data on Imports by 3-Digit North American Industry Classification System for the year 2014.

and the ROW; (ii) bilateral trade flows of goods for intermediate use between G (respectively, M) in each US state and the ROW; (iii) inter-regional trade flows of goods for final use among the US states respectively for G and M ; and (iv) inter-regional trade flows of goods for intermediate use among the U.S. states respectively for G and M . While trade in final goods (i) and (iii) is observed for both M (using WIOD and Commodity Flow Survey - CFS) and G (using FPDS data), we do not have measures of trade in intermediate inputs specific to G , so we proceed by imputation for (ii) and (iv). The imputation, described in detail in section B.3.2, is done by combining the information derived from the FPDS, WIOD, Commodity Flow Survey (CFS), and the County Business Patterns (CBP). The imputation procedure ensures that: (a) the aggregation of the expanded I-O table to the country-sector level remains consistent with the original data, and (b) the data on bilateral trade flows of G goods at the disaggregated level aligns with the FPDS data.

Using the expanded world input-output table, we can directly compute the bilateral trade shares $\lambda_{ods}^{f,G}$, $\lambda_{ods}^{f,M}$, $\lambda_{os,dk}^{i,G}$ and $\lambda_{os,dk}^{i,M}$, the share of value added in gross output $\alpha_{o,s}$, the input-output coefficients $\alpha_{o,sk}$, the consumption shares β_{os}^G and β_{os}^M , and the outputs X_{os}^G and X_{os}^M . Given the structure of our model, we may also compute the employment shares according to $\pi_{os} = \frac{\alpha_{o,s}(X_{os}^G + X_{os}^M)}{\sum_{s'} \alpha_{o,s'}(X_{os'}^G + X_{os'}^M)} \cdot e_o$, where the data on e_o is derived based on wage and salary employment data obtained from the BEA and working-age (ages 18-64) population data from the National Vital Statistics System.³³ For the states in the US, we set a constant income tax rate δ so that the implied income tax revenue equals the government procurement at the national level. The allocations of procurement budget across the states γ_o are set to align with the shares of each state in total federal procurement expenditure, as observed in the data. The portfolio shares l_o are disciplined to match the observed trade imbalances. Lastly, we calibrate the utility weight on public goods $1 - \varphi$ so that $(1 - \varphi)/\varphi$ matches the ratio of FPDS procurement to the U.S. personal consumption expenditure. Specifically, we take $\varphi = 0.966$.³⁴

5.3 Elasticities

In all subsequent counterfactual simulations, we adopt the following estimated parameters from the existing literature. The trade elasticities, θ_s , are obtained from the estimates provided by [Giri et al. \(2021\)](#). The scale elasticities, ν_s , are collected from the estimates presented in [Bartelme et al. \(2024\)](#).³⁵ The values of these industry-specific parameters are reported in Table E.1. To investigate

³³For the ROW, we employ information from the World Development Indicators (WDI). Specifically, we calculate e_o by averaging the employment ratios across countries other than the U.S., using countries' working-age population as weights.

³⁴FPDS procurement is \$418 billion in 2014, while US personal consumption expenditure is \$11,874 billion in 2010. (<https://fred.stlouisfed.org/release/tables?eid=43861&od=2010-01-01&rid=53>). We consider the entire FPDS expenditure, and not just manufacturing, to make it comparable with aggregate personal consumption.

³⁵Note that [Bartelme et al. \(2024\)](#) employ the auxiliary estimates of θ_s from [Giri et al. \(2021\)](#) to estimate ν_s . Since our model embeds both θ_s and ν_s , for the sake of consistency, we also adopt the estimated value of θ_s from [Giri et al. \(2021\)](#) in our baseline analysis.

the role of scale economies, we further adopt an alternative specification by letting $\nu_s = 0$ for all s . Following [Galle et al. \(2022\)](#) we set the labor supply elasticity $\kappa = 1.5$. For robustness, we also consider an alternative value of $\kappa = 3$.

5.4 Calibrating the BAA Wedges

In this section, we calibrate the wedges faced by G producers and G consumers due to BAA restrictions in a model-consistent way. There are two dimensions: (i) the wedges affecting imported input prices resulting from the domestic content requirement on component inputs used by G producers; and (ii) the wedges on the price of imported final goods due to strict limitations on the purchase of foreign manufactured products by G consumers.

5.4.1 BAA Wedges on Imports of Component Inputs

As already discussed, BAA imposes restrictions on imports of intermediate inputs. So we posit that, when a destination is located in the U.S., i.e. $d \in US$, the iceberg costs on imported component inputs used by M and G producers have the following relationship:

$$\begin{cases} \tau_{os,dk}^{i,G} = \tau_{os,dk}^{i,M} \tau_k^{i,G} & \forall o \notin US; d \in US \\ \tau_{os,dk}^{i,G} = \tau_{os,dk}^{i,M} & \forall o \in US; d \in US \end{cases}$$

where $\tau_k^{i,G}$ denotes the additional iceberg cost born by G producers of downstream industry k in the manufacturing sector when importing inputs from the ROW. This cost reveals the extent to which the BAA domestic content restriction on component inputs imposes binding constraints. As the BAA stipulations do not vary across regions within the U.S., we calibrate these wedges using the data aggregated to the country-industry level. Hence, $o, d = US$ or ROW .

Denote C as the set of goods considered as component inputs for production.³⁶ We infer wedges $\tau_k^{i,G}$ by considering two cases depending on whether the equilibrium share of foreign components for G producers, $\sum_{s \in C} \frac{\alpha_{us,sk}}{\sum_{s' \in C} \alpha_{us,s'k}} \lambda_{row,s;us,k}^{i,G}$ exceeds 50% of all component inputs. Specifically,

- If the domestic content restriction is non-binding, i.e., $\sum_{s \in C} \frac{\alpha_{us,sk}}{\sum_{s' \in C} \alpha_{us,s'k}} \lambda_{row,s;us,k}^{i,G} < 0.5$, then we assume that G producers are not constrained and are using the same sourcing strategy as M producers. This implies that $\tau_k^{i,G} = 1$.
- If the domestic content restriction is binding, i.e., $\sum_{s \in C} \frac{\alpha_{us,sk}}{\sum_{s' \in C} \alpha_{us,s'k}} \lambda_{row,s;us,k}^{i,G} = 0.5$, then G produc-

³⁶According to BAA regulations, we include goods from Manufacturing industries (31-33), as well as Transportation and Warehousing (48-49), as component inputs.

ers are constrained and we can back out $\tau_k^{i,G}$ according to

$$\frac{\lambda_{row,s;us,k}^{i,G} / \left(1 - \lambda_{row,s;us,k}^{i,G}\right)}{\lambda_{row,s;us,k}^{i,M} / \left(1 - \lambda_{row,s;us,k}^{i,M}\right)} = \left(\frac{\tau_{row,s;us,k}^{i,G}}{\tau_{row,s;us,k}^{i,M}}\right)^{-\theta_s} = \left(\tau_k^{i,G}\right)^{-\theta_s} \quad (15)$$

Although we don't directly observe $\lambda_{row,s;us,k}^{i,G}$ and $\lambda_{row,s;us,k}^{i,M}$ in (15) from the original WIOD data, Appendix B.3.2 delineates an approach to back out $\lambda_{row,s;us,k}^{i,G}$, $\lambda_{row,s;us,k}^{i,M}$ and $\tau_k^{i,G}$ together. This method leverages available data on the output respectively by G and M producers in each downstream sector, the aggregate import share data for each input-output pair, the bindingness of the domestic content restriction on component inputs for each downstream sector, and the structural relation (15).

Figure 4 presents the effective wedges in logarithm, $\theta_s \ln(\tau_k^{i,G})$, encountered by G producers from different downstream industries across various upstream inputs. Computer and Electronic Product Manufacturing (334) is the sole industry that exhibits positive values for $\theta_s \ln(\tau_k^{i,G})$. This finding aligns with the data, as it is the only industry where the equilibrium foreign share of component inputs exceeds 50% (see Appendix B.3.1.) Therefore, the BAA domestic content restriction on foreign inputs is generally not binding for the majority of industries under current rules, although the picture is expected to change substantially under announced domestic content restrictions, as we will document in Section 7.3.

5.4.2 BAA Wedges on Imports of Final Goods

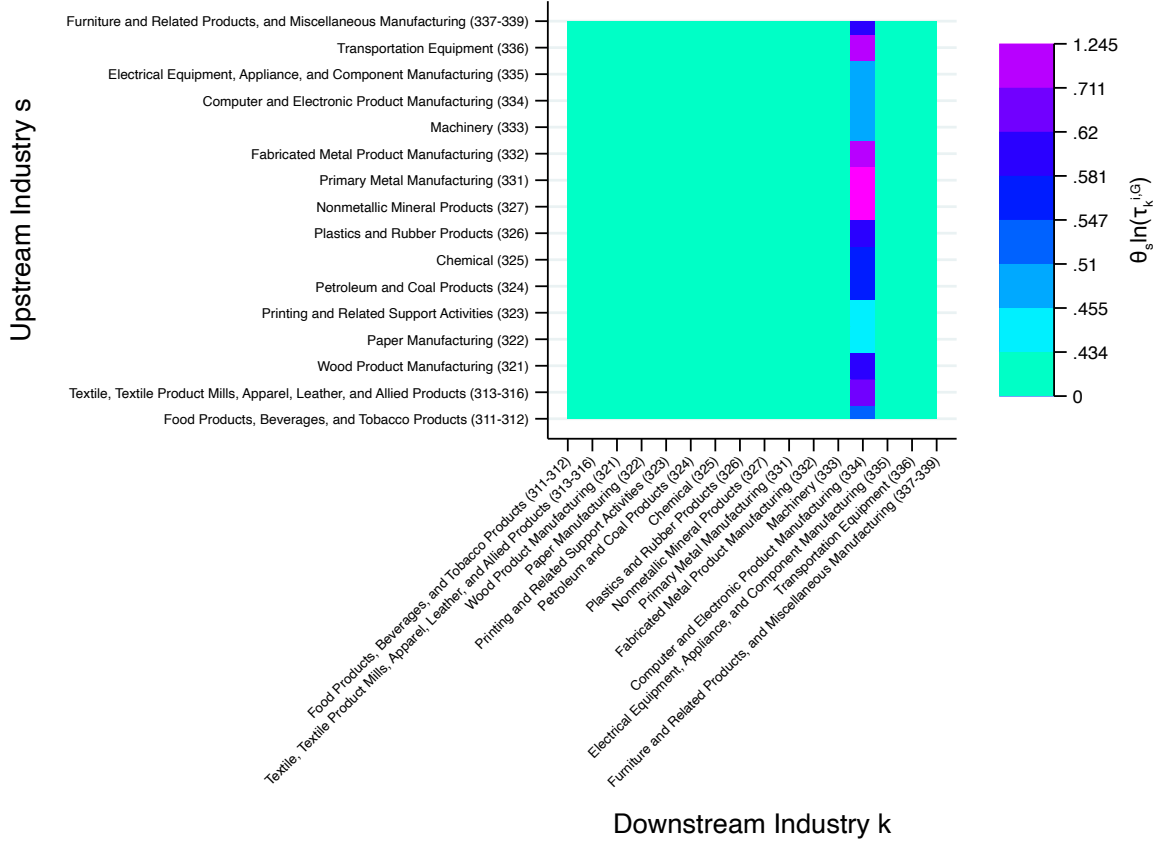
Broader Measure: As with intermediate inputs, we assume that for $d \in US$, the iceberg costs on final goods purchased by M and G consumers follow the relationship:

$$\begin{cases} \tau_{ods}^{f,G} = \tau_{ods}^{f,M} \tau_s^{f,G} & \forall o \notin US \\ \tau_{ods}^{f,G} = \tau_{ods}^{f,M} & \forall o \in US \end{cases}$$

where $\tau_s^{f,G}$ varies across industries. This captures the additional iceberg costs born by G producers on imported goods from industry s in the manufacturing sector as a result of the BAA limitations on purchases from foreign producers. With the data aggregated to the country-industry level, we back out $\tau_s^{f,G}$ based on the following relation:

$$\frac{\lambda_{row,us,s}^{f,G} / \left(1 - \lambda_{row,us,s}^{f,G}\right)}{\lambda_{row,us,s}^{f,M} / \left(1 - \lambda_{row,us,s}^{f,M}\right)} = \left(\tau_s^{f,G}\right)^{-\theta_s} \left(\frac{c_{us,s}^G}{c_{us,s}^M}\right)^{\theta_s} \quad (16)$$

Figure 4: Effective BAA Wedges on Imported Inputs Faced by G Producers: $\theta_s \ln(\tau_k^{i,G})$



Notes: This figure reports the estimates of effective trade barriers, expressed in logarithm, encountered by G producers due to BAA restrictions, $\theta_s \ln(\tau_k^{i,G})$. Here, $\tau_k^{i,G}$ is the estimate of the BAA wedges faced by the G producers in the downstream sector k , and θ_s represents the trade elasticity of the upstream sector s .

While the unit costs of production $c_{us,s}^G$ and $c_{us,s}^M$ in the above equation are not directly observable, they can be inferred based on the structure of our model:

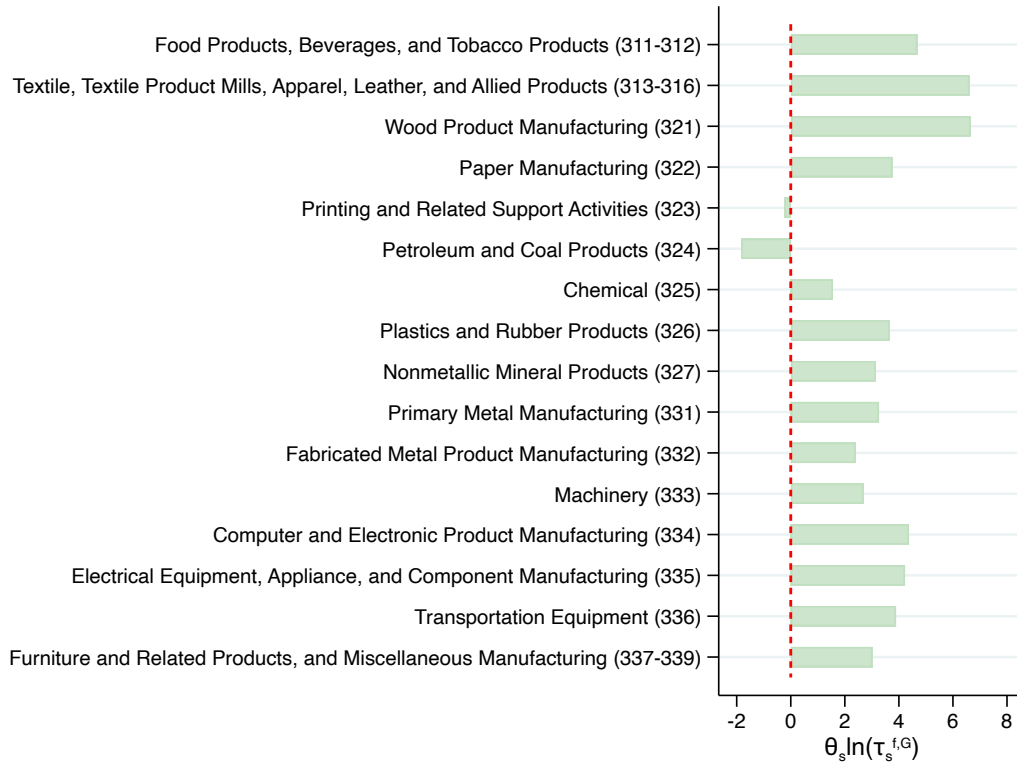
$$\begin{aligned} \frac{c_{us,s}^G}{c_{us,s}^M} &= \prod_{s'} \left(\frac{p_{us,s'}^{i,G}}{p_{us,s'}^{i,M}} \right)^{\alpha_{us,s's}} = \prod_{s'} \left(\frac{\left[T_{row,s'} L_{row,s'}^{v,s'} (\tau_{row,s';us,s}^{i,M} c_{row,s'})^{-\theta_{s'}} + T_{us,s'} L_{us,s'}^{v,s'} (c_{us,s'}^M)^{-\theta_{s'}} \right]^{\frac{1}{\theta_{s'}}}}{\left[T_{row,s'} L_{row,s'}^{v,s'} (\tau_{row,s';us,s}^{i,G} c_{row,s'})^{-\theta_{s'}} + T_{us,s'} L_{us,s'}^{v,s'} (c_{us,s'}^M)^{-\theta_{s'}} \right]^{\frac{1}{\theta_{s'}}}} \right)^{\alpha_{us,s's}} \\ &= \prod_{s'} \left((\tau_s^{i,G})^{\theta_{s'}} \lambda_{row,s';us,s}^{i,G} + \lambda_{us,s';us,s}^{i,G} \right)^{\frac{\alpha_{us,s's}}{\theta_{s'}}} \end{aligned}$$

where $\tau_s^{i,G}$, $\lambda_{row,s';us,s}^{i,G}$ and $\lambda_{us,s';us,s}^{i,G}$ have been calibrated in the previous step. This expression has the intuitive interpretation that the difference in unit cost of production between G and M producers is related to a weighted average of wedges imposed on G 's inputs sourced from different regions.

We report the estimates of effective wedges in logarithm, $\theta_s \ln(\tau_s^{f,G})$, in Figure 5. Most industries have $\theta_s \ln(\tau_s^{f,G})$ significantly greater than 0, except for two industries: Printing and Related Support Activities (323) and Petroleum and Coal Products (324). The mean of $\theta_s \ln \tau_s^{f,G}$ is 3.24, with

a standard deviation of 2.16.³⁷ This indicates that the BAA restrictions reduce imports by G consumers by 96.1%³⁸ for an average industry in the manufacturing sector. Furthermore, in comparison to the effective BAA wedges observed on components (Figure 4), the wedges on final goods are significantly larger.

Figure 5: Effective BAA Wedges on Imported Final Goods Faced by G Consumers: $\theta_s \ln(\tau_s^{f,G})$



Notes: This figure reports the estimates of effective trade barriers, expressed in logarithm, encountered by G consumers due to BAA restrictions, $\theta_s \ln(\tau_s^{f,G})$. Here, $\tau_s^{f,G}$ is the estimate of the broader measure of the BAA wedges faced by G consumers of good s , and θ_s represents the trade elasticity of sector s .

Narrower Measure: The wedges inferred from the trade shares not only reveal trade barriers resulting from BAA restrictions, but may also encompass other costs encountered by foreign firms that are unrelated to the BAA. For example, foreign firms may incur higher costs in understanding the U.S. government procurement auction process and engaging in contract bidding.³⁹ We therefore consider a narrower measure of BAA wedges that separates costs that may not be directly related to the BAA restrictions from the broader measure. Specifically, the narrower measure of

³⁷The mean of $\tau_s^{f,G}$ is 2.58, with a standard deviation of 1.29.

³⁸Calculated as $100 * (\exp(-3.24) - 1)$.

³⁹We describe in Appendix D.1 that there is no significant difference in the registration procedure to bid for government procurement contracts for domestic and foreign firms.

BAA wedge is linked to the broader measure according to $\tau_s^{f,G} = t_s^{f,G} t^e$, where $t_s^{f,G}$ denotes the trade barriers directly resulting from the BAA restrictions, and t^e is the additional cost (or home bias) faced by foreign producers in contract bidding which is invariant across industries.

In Appendix E.1, we outline the approach that yields an upper bound estimate of t^e (and hence, a lower bound estimate of $t_s^{f,G}$). Specifically, we take advantage of two institutional features: (i) federal procurement conducted in regions outside of the U.S. is not subjected to the same stringent limitations on the purchase of foreign manufacturing products, while (ii) the additional costs (or home bias) encountered by foreign producers should be present regardless of the procurement location. Therefore, when procurement takes place outside of the U.S., the effective wedge is $\tau_s^{f,G} = t^e$.⁴⁰

We back out t^e based on the ratio of: (i) the share for procurement conducted in the EU sourced from the EU relative to that sourced from the US, and (ii) the share of consumption by the EU market sourced from the EU compared to that sourced from the US. Specifically, $t^e = \left(\frac{\lambda_{eu,eu}^{f,G} / \lambda_{us,eu}^{f,G}}{\lambda_{eu,eu}^{f,M} / \lambda_{us,eu}^{f,M}} \right)^{-1/\theta}$, where $\lambda_{eu,eu}^{f,G}$ is the share of procurement used in the EU that is sourced from the EU; $\lambda_{us,eu}^{f,G}$ represents the share of procurement used in the EU that is sourced from the U.S.; $\lambda_{eu,eu}^{f,M}$ denotes the share of imports by the EU that is sourced from the EU itself; and $\lambda_{us,eu}^{f,M}$ is the share of imports by the EU that is sourced from the U.S.. The calibrated value of $t^e = 1.28$. This finding implies that, measured in terms of tariff-equivalent trade costs, the wedge due to home bias may account for up to 18% of the broader measure of BAA wedge.⁴¹

Together with the measure of $\tau_s^{f,G}$, we can infer $t_s^{f,G}$. The trade barriers attributed directly to the BAA restriction remain substantial, even after factoring in unrelated costs. Specifically, the mean of $\theta_s \ln t_s^{f,G}$ across manufacturing industries is 2.20, which indicates that the BAA restrictions reduce imports by G consumers by at least 88.9% on average.⁴²

5.4.3 Robustness: Compositional Bias

A potential issue is that our baseline estimates of BAA wedges on final goods are biased upward, if within an aggregated NAICS industry s , G (respectively, M) may have a larger consumption weight on goods with lower (respectively, higher) inherent import intensities. In such cases, the estimated wedges based on aggregated trade flow data may reflect the different compositions of consumption bundles of G and M , rather than the actual trade barriers imposed by the BAA restrictions. To assess the potential compositional biases, in Appendix E.1, we leverage the data at the 6-digit

⁴⁰ Although procurement conducted outside of the U.S. is not subject to the same stringent BAA restrictions as those conducted within the U.S., some restrictions still apply. Hence, the calibrated value of t^e still incorporates trade barriers resulting from the restrictions on the purchase of foreign products, resulting in an upward bias in the estimation of home bias.

⁴¹ Calculated as $100 * (1.28 - 1) / (2.58 - 1)$.

⁴² Calculated as $100 * (\exp(-2.20) - 1)$.

NAICS level. Three related findings suggest that our baseline estimated wedges, derived from the aggregated data, are unlikely to be biased upward due to different expenditure compositions between G and M . Firstly, the data shows no discernible correlation between expenditure shares of G (and M) and import intensities across 6-digit NAICS industries. Secondly, when aggregating the wedges calibrated at the 6-digit NAICS level to the aggregated industry level, we obtain estimates that are closely aligned with the baseline estimates. Thirdly, industries with products characterized by a high level of specificity, which are presumed to have inherent low import intensities for G due to national security considerations, do not exhibit larger BAA wedges.

6 Reduced Form Evidence

In this section, we undertake the intermediate step of providing empirical evidence for the effects of procurement demand shocks on local labor markets. This is not only an interesting exercise per se, but also constitutes a prerequisite for the rest of the analysis. In particular, if we did not find government procurement to affect employment, then whether it is biased towards domestic producers would seem irrelevant for the purpose of job creation. This key relationship will also be revisited to evaluate the predictive performance of the quantitative model later. In order to ensure sufficient statistical power for identification and because the data necessary for this exercise is more disaggregated, we employ commuting zones (CZs) as geographic units to define local labor markets as in [Autor et al. \(2013\)](#).

The regression specification is as follows:

$$\Delta y_{o,t} = \beta \Delta Proc_PW_{o,t} + W'_{o,00} \gamma_t + D_{d,t} + D_o + \varepsilon_{o,t}. \quad (17)$$

We define $\Delta y_{o,t} = \tilde{y}_{o,t} - \tilde{y}_{o,t-5}$ as the change in a labor market outcome in CZ o over a five-year period. Here, $\tilde{y}_{o,t} = (y_{o,t-1} + y_{o,t} + y_{o,t+1})/3$ represents the 3-year moving average of $y_{o,t}$. $\tilde{y}_{o,t-5}$ is constructed analogously. $\Delta Proc_PW_{o,t} = \sum_s \frac{\tilde{X}_{os,t} - \tilde{X}_{os,t-5}}{L_{o,t-5}}$ measures the per-worker exposure to the change in procurement from o over the 5-year period, where $\tilde{X}_{os,t}^G = (X_{os,t-1}^G + X_{os,t}^G + X_{os,t+1}^G)/3$ is the 3-year moving average of G output of sector s in o , and $\tilde{X}_{os,t-5}^G$ are defined accordingly. By construction, $Proc_PW_{o,t}$ can be interpreted as dollar value (in units of 1,000 USD) output growth in CZ o for G procurement on a per-worker basis. We employ the moving averages to construct both the dependent and outcome variables. This is to smooth out the large fluctuations due to lumpy contract values associated with Indefinite Delivery Vehicle (IDV) contracts, which involve multiple deliveries over several years.

The regression in equation (17) stacks the first differences of three periods, 2001-2006, 2006-2011, and 2011-2016. The first differencing removes any time-invariant determinants of labor market outcomes that are specific to each CZ. The vector $W_{o,00}$ contains controls for demographic

and socioeconomic characteristics of CZs in 2000.⁴³ We interact these CZ initial characteristics with time dummies to capture their potential time-varying effects on outcomes of interest. $D_{d,t}$ represents the census division-by-time dummies, which capture any census division-specific trends that extend across the CZs within the division. In addition, the CZ dummies, D_o , account for cross-CZ differences in $\Delta y_{o,t}$, or equivalently CZ-specific linear time trends in $y_{o,t}$. Hence, the coefficient β is identified off variation in procurement shocks across CZs within census divisions, as well as within CZs over time. We weight each observation by CZ's working-age population in 2000, and cluster standard errors at the state level.

We consider three labor market outcomes, including: (i) the ratio of manufacturing to the working-age population, (ii) the ratio of total wage and salary employment to the working-age population, and (iii) per capita personal income. To construct these outcome variables, we acquire the employment and wage data from the BEA Local Area Personal Income and Employment Database, along with population data from the National Vital Statistics System.⁴⁴

An immediate concern with ordinary least-squares estimates in specification (17) is that the realized output expansion of G , $\Delta Proc_PW_{o,t}$, is correlated with productivity or factor supply shocks that may affect labor market outcomes at the same time. To address the concern, we employ a shift-share or Bartik IV, to isolate exogenous demand shocks from $\Delta Proc_PW_{o,t}$. This IV is constructed by combining information on the initial employment composition within CZs together with industry-level shifts in federal procurement:

$$\Delta FPDS_PW_{o,t}^{IV} = \sum_s \frac{L_{os,00}}{L_{s,00}} \frac{\tilde{X}_{s,t} - \tilde{X}_{s,t-5}}{L_{o,00}}, \quad (18)$$

where $\tilde{X}_{s,t} = (X_{s,t-1} + X_{s,t} + X_{s,t+1})/3$ is the 3-year moving average of total procurement from a 6-digit NAICS industry s , and $\tilde{X}_{s,t-5}$ is defined analogously. For each industry s , we apportion the procurement growth at the national level to CZs according to their initial shares of the industry's total employment, $L_{os,00}/L_{s,00}$ in 2000. Again, we express the IV in units of 1,000 USD per worker by normalizing the measure with the CZ's total employment in the 2000, $L_{o,00}$.⁴⁵

Intuitively, according to the IV described in equation (18), CZs specialized in industries with greater procurement growth tend to experience a larger positive procurement demand shock. The validity of the IV strategy rests on the assumption that, conditional on time-varying effects of $W_{o,00}$

⁴³Following Autor *et al.* (2021), these control variables include CZ employment composition (shares of employment in manufacturing, routine-task-intensive occupations, and off-shorable occupations, as well as employment share among women), and initial period CZ demographic conditions (shares of the college-educated, the foreign-born, non-white individuals, and those age 18–24, 25–39, and 40–64 in the population). The data on these control variables are obtained from Autor *et al.* (2013).

⁴⁴Appendix B.4 contains further details on the BEA data, and provides summary statistics on outcome and explanatory variables employed in the reduced form analyses.

⁴⁵Data on $L_{os,00}/L_{s,00}$ and $L_{o,00}$ are obtained from the CBP. We employ the imputed dataset developed by Eckert *et al.* (2020) and aggregate the employment data to the CZ-industry level.

as well as the census division-time and CZ fixed effects, $\Delta FPDS_PW_{it}^{IV}$ is uncorrelated with other unobserved time-varying, CZ-specific shocks to the outcome variable that would be captured in the regression error, $\varepsilon_{o,t}$, in equation (17).

Table 1 presents the results of the IV regression, indicating that CZs witnessing more positive procurement demand shocks experience relatively faster growth in employment and income.⁴⁶ Specifically, the estimate in Column (1) finds that a one-standard-deviation rise in procurement shock (about \$2,947 per worker) leads to an increase in manufacturing employment-to-working-age population ratio by 0.47 percentage points. In Columns 2 and 3, the corresponding estimated effects on total wage and salary employment-to-working-age population ratio and personal income per capita are found to be 1.65 percentage points and 2.03 percent, respectively.

Table 1: Labor Market Outcomes and Procurement Shocks, 2SLS

Dependent Variable:	Δ Mfg empl/ working-age pop (1)	Δ Total wage and salary empl/ working-age pop (2)	Δ Log personal income per capita (3)
$\Delta FPDS_PW$	0.0016*** (0.0005)	0.0056*** (0.0015)	0.0071** (0.0031)
Initial CZ characteristics \times Year FEs	Y	Y	Y
Census Division \times Year FEs	Y	Y	Y
CZone FEs	Y	Y	Y
Observations	2,166	2,166	2,166
F-stat	28.429	28.429	28.429

Notes: All regressions are weighted by the working-age population in 2000. FPDS per worker is defined in equation 18 and is expressed in 1,000's of USD. Robust standard errors clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

7 Counterfactuals to evaluate past and future BAA restrictions

This section conducts four sets of counterfactual experiments, each serving different purposes: (i) evaluating the model's predictive performance regarding the effects of procurement demand shocks on various local labor market outcomes, (ii) quantifying the impacts of the BAA restrictions on welfare and employment, (iii) examining the implications on welfare and employment when the domestic content requirement for component inputs is raised from 50% to 75%, and (iv) assessing the extent to which the current distribution of the BAA wedges across industries leverages the external economies of scale (EES) and exploring potential policy refinement.

We perform the counterfactuals by applying the exact hat algebra method (Dekle *et al.*, 2007). The method solves for the proportional change $\hat{x} = x'/x$ in any endogenous variable between the initial equilibrium (x) and the counterfactual equilibrium (x') in response to exogenous changes

⁴⁶The reported Kleibergen-Paap F-statistics surpass the Stock-Yogo 10 percent threshold, confirming the relevance of the IV.

in fundamentals and policies. Across different counterfactual experiments, we consider counterfactual changes in federal procurement, $\hat{\delta}_o = \delta'_o/\delta_o$, and the BAA wedges, $\hat{\tau}_s^{f,G} = \tau_s'^{f,G}/\tau_s^{f,G}$ and $\hat{\tau}_k^{i,G} = \tau_k'^{i,G}/\tau_k^{i,G}$. The solution algorithm and additional details are described in Appendix F.

7.1 Reducing Federal Procurement

In the first counterfactual simulation, we lower the federal procurement by 50% by setting $\hat{\delta}_o = 0.5 \forall o \in US$. This is to mimic reducing the federal procurement from the level in 2014 to that in 2001. We conduct this experiment to evaluate the validity of our model. Specifically, we compare the effects of the simulated demand shocks from the government measured in \$1,000 per worker on various simulated labor market outcomes with those estimated using the actual data. Specifically, to run the simulated regression, we proceed as follows. Firstly, we compute the counterfactual output level for each state according to $X_o^G = \sum_s X_{os}^G$. With the measure, we construct the measure of exposure to the policy shock on the per-worker basis analogous to our reduced form analysis: $\Delta x_o^G = \frac{X_o^G - X_o^C}{L_o}$. Then we relate various labor market outcomes to this simulated exogenous shock, including: the change in the manufacturing employment-to-working age population ratio $\Delta(\sum_{s \in mfg} \pi_{os})$, the change in the employment-to-working age population ratio Δe_o , and the change in log personal income per capita $\Delta \ln w_o$. We perform counterfactual simulations for two cases: $\kappa = 1.5$ and $\kappa = 3$.

Figure 6 presents the estimated effects for the simulated regressions.⁴⁷ To assess the model's performance, we compare the estimates derived from the simulated data with those obtained from the actual data (Table 1) within the same figure. In the case of $\kappa = 1.5$, we observe a close alignment between the simulated effects of the procurement demand shock on manufacturing employment and personal income and those estimated using the actual data. The model's implied effect of the procurement shock on employment ratio is somewhat smaller compared to that obtained from the actual data. In addition, the specification with $\kappa = 1.5$ matches the data better than that with $\kappa = 3$. Overall, the causal responses of various labor market outcomes to procurement demand shocks predicted by the model are close to the observed ones, lending support to the empirical credibility of our model's predictions.

7.2 Evaluating Current Buy American Restrictions: the Removal of BAA

7.2.1 Removal of BAA Wedges on Imports of Final Goods (Broader Measure)

To quantify the impact of the domestic content restrictions imposed by the BAA on the imports of final goods, we conduct counterfactual experiments by setting $\hat{\tau}_s^{f,G} = 1/\tau_s^{f,G}$. The simulation results are reported in Table 2. To interpret the findings, we first focus on the results in Row (a)

⁴⁷The regression results are also reported in Table F.1. The simulated results in Figure 6 and Table F.1 are based on the model with EES. In Table F.2, we report the simulated regression results based on the model without EES.

Figure 6: Effects of Per Worker Exposure on Labor Market Outcomes: Simulated versus Real Data



Notes: This figure reports the estimates obtained from the simulated regressions when $\kappa = 1.5$ (red circle) and $\kappa = 3$ (green square). The dependent variables are the change in manufacturing employment-to-working age population ratio (Panel A), the change in the employment-to-working age population ratio (Panel B), and the change in log personal income per capita (Panel C), respectively. For the purpose of comparison, the figure also includes the IV estimates obtained from regressions using the actual data presented in Table 1 (orange triangle).

of Panel A. In this baseline specification, the model incorporates EES, a labor supply elasticity of $\kappa = 1.5$, and welfare changes are calculated based on equation (F.8) assuming that consumers have access to composite public goods from different states (Case I). Our findings indicate that removing the BAA wedges on final-use consumption by G leads to an increase in welfare in the US by 0.092 percent (Column 1), corresponding to a consumption equivalent variation per capita of \$66.92 (Column 5).

Column 6 indicates that the removal of the BAA wedges $\tau_s^{f,G}$ and the subsequent intensified import competition results in a loss of 99,901 manufacturing jobs. Due to the input-output linkages, the adverse demand shocks originating from the manufacturing sector propagate to other sectors, leading to a slightly larger decline in employment, totaling 105,615 (Column 8). The findings suggest that the BAA restrictions preserve employment. However, as is shown in Column 7 (respectively, Column 9), the welfare cost per manufacturing job (respectively, per job) preserved is substantial, amounting to \$132,142 (respectively, \$124,993).⁴⁸

⁴⁸We discuss the comparison with other policies in Section 7.5.

The uneven procurement intensity and G production activity across space, coupled with their differential sectoral exposure to BAA restrictions, implies that the welfare and employment impacts of the removal of BAA wedges vary across regions. While the average welfare change across states is 0.084 percent (Column 2), it masks a large spatial heterogeneity. Specifically, the minimum and maximum of state-level welfare changes are 0.008 and 0.148 percent, respectively (Columns 3 and 4). Figures 7 and 8 further visualize the significant heterogeneity across states in terms of changes in welfare measured by consumption equivalent variation and changes in manufacturing employment-to-working age population ratio. For example, North Dakota experiences welfare gains amounting to \$158, whereas Maine only sees an increase of \$6. Furthermore, states that derive smaller benefits from the removal of the BAA wedges tend to face larger employment losses.⁴⁹

Table 2: Removal of BAA Wedges on Imports of Final Goods (Broader Measure)

Welfare Measure	\hat{V}_{US}	Distribution of \hat{V}_o			EV _{US} (USD)	Δ Mfg. Jobs	Costs per Mfg. Job	Δ Jobs	Costs per Job
		Mean	Min	Max					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: With EES									
(a) Nationwide Public Goods ($\kappa = 1.5$)	0.0917	0.0839	0.0081	0.1479	66.92	-99,901	132,142	-105,615	124,993
(b) Local Public Goods Only ($\kappa = 1.5$)	0.0975	0.0746	-0.0844	0.7214	69.74	-99,901	137,714	-105,615	130,263
(c) Nationwide Public Goods ($\kappa = 3$)	0.0894	0.0827	0.0177	0.1362	65.32	-184,931	69,675	-196,672	65,515
(d) Local Public Goods Only ($\kappa = 3$)	0.0959	0.0740	-0.0763	0.7221	68.62	-184,931	73,199	-196,672	68,829
Panel B: Without EES									
(a) Nationwide Public Goods ($\kappa = 1.5$)	0.0945	0.0864	0.0107	0.1498	68.97	-96,336	141,230	-101,918	133,494
(b) Local Public Goods Only ($\kappa = 1.5$)	0.1003	0.0771	-0.0834	0.7224	71.78	-96,336	146,982	-101,918	138,931
(c) Nationwide Public Goods ($\kappa = 3$)	0.0942	0.0871	0.0283	0.1405	68.79	-174,787	77,645	-185,991	72,968
(d) Local Public Goods Only ($\kappa = 3$)	0.1006	0.0783	-0.0739	0.7245	72.04	-174,787	81,311	-185,991	76,413

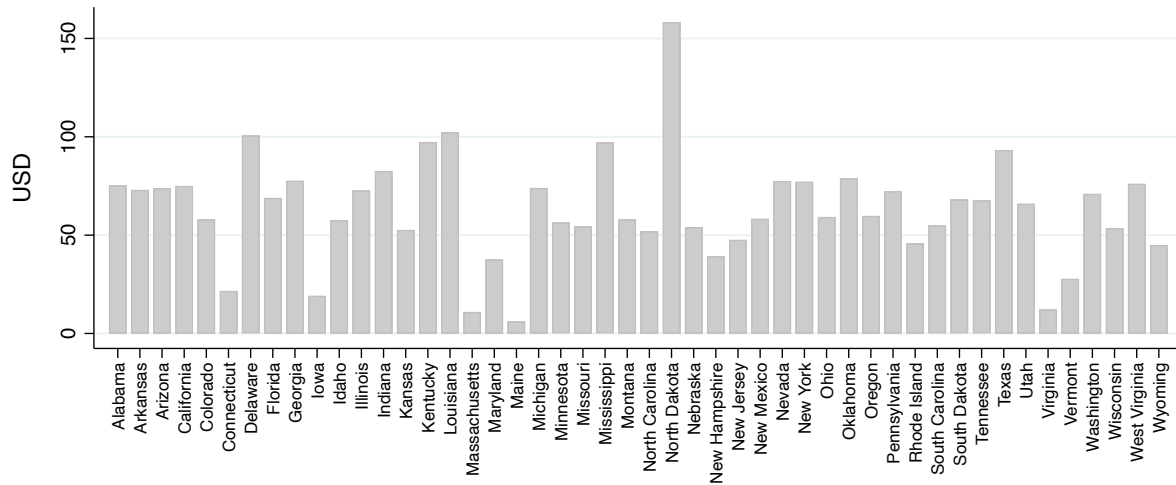
Notes: This table shows the effects of the policy experiment that removes the BAA wedges (broader measure) on final goods on welfare and employment. In Row (a), welfare changes are calculated according to (F.8), assuming consumers have access to the composite public goods from different states. In Row (b), welfare changes are calculated according to (F.9), assuming consumers only have access to the locally produced public goods. Rows (c) and (d) report the corresponding results with an alternative labor supply elasticity. Column (1) shows the aggregate welfare effect for the US, in percentage terms $100(\sum_o \frac{L_o}{L_{US}} \hat{V}_o - 1)$. Columns (2)-(4) present the summary statistics of the distribution of \hat{V}_o across states: Column (2) shows the mean welfare effect $100(\frac{1}{N_o} \sum_o \hat{V}_o - 1)$; and Columns (3) and (4) show the minimum and maximum of $100(\hat{V}_o - 1)$, respectively. Column (5) displays the consumption equivalent variation (EV) per worker measured by USD. Column (6) shows the counterfactual change in the number of manufacturing jobs for the US. Column (7) displays the cost per manufacturing job saved due to the BAA wedges on final goods $\tau_s^{f,G}$. Column (8) shows the counterfactual change in the number of jobs for the US. Column (9) displays the cost per job saved due to the BAA wedges on final goods $\tau_s^{f,G}$.

In Row (b), we reassess the welfare implications by employing an alternative specification that computes welfare consequences under the assumption that consumers only have access to locally produced public goods. Compared to the baseline specification, the aggregate welfare effect of removing $\hat{\tau}_s^{f,G}$ remains similar. However, there is a greater degree of heterogeneity in welfare gains across states, spanning from -0.084 to 0.721 percent.⁵⁰ Rows (c) and (d) repeat the exercises in Rows (a) and (b), but adopt a larger labor supply elasticity $\kappa = 3$. In these cases, the adverse demand shock leads to employment losses that are nearly twice as large compared to those in

⁴⁹In Figures F.2 and F.3, we show the impacts on changes in employment-to-working age population ratio and on percentage changes in wages across states, respectively.

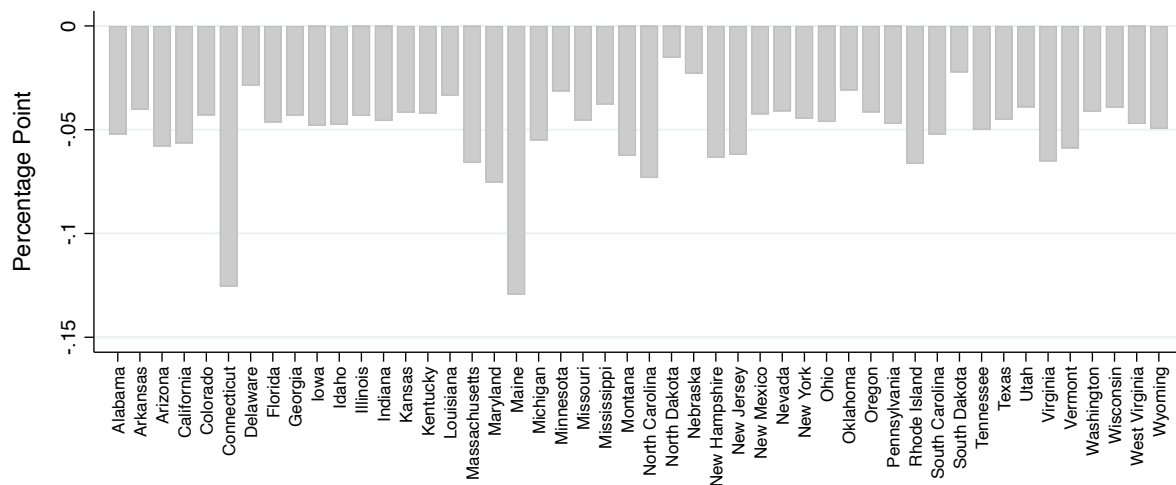
⁵⁰Figure F.4 illustrates the distribution of welfare changes across the states for this alternative welfare formulation.

Figure 7: Consumption Equivalent Variation: Remove the BAA Wedges on Imports of Final Goods (Broader Measure)



Notes: This figure presents the counterfactual changes in welfare across states resulting from the removal of the BAA wedges on imports of final goods $\tau_s^{f,G}$. The welfare changes are measured by consumption equivalent variation. The calculation assumes that consumers have access to the composite public goods from different states.

Figure 8: Changes in Manufacturing Employment to Working Age Population Ratio: Remove the BAA Wedges on Imports of Final Goods (Broader Measure)



Notes: This figure presents the counterfactual changes in manufacturing employment to working age population ratio resulting from the removal of the BAA wedges on imports of final goods $\tau_s^{f,G}$.

the baseline specification. Due to the larger employment responses, the welfare gains are slightly smaller than the baseline case. Altogether, the welfare costs per preserved job resulting from the BAA restrictions are reduced by almost half.

Finally, BAA may serve as a policy intervention that directs demand towards domestic producers, strategically leveraging positive external economies of scale that may be strong in certain manufacturing sectors (Harrison and Rodríguez-Clare, 2010). To investigate this channel, in Panel B, we shut down external economies of scale (EES) by setting the scale elasticities $\nu_s = 0$ for all sectors. In the absence of EES, the removal of the BAA restrictions leads to a contraction of production scale of the affected sectors, but it does not affect their productivity. Hence, the policy experiment results in a larger welfare gains while yields smaller employment losses. However, the difference in welfare changes between cases with and without EES is quantitatively small. For example, when comparing Rows (a) across Panels A and B, the aggregate welfare gains exhibit a minor change from 0.092 to 0.095 percent. The lack of quantitative significance of external economies of scale will be further examined in Section 7.4.

7.2.2 Removal of BAA Wedges on Imports of Final Goods (Narrower Measure)

The broader measure of wedges $\tau_s^{f,G}$ based on the approach outlined in Section 5.4 may embed costs faced by foreign producers that are unrelated to the BAA restrictions. Even after the removal of BAA limitations on the purchase of foreign products, these unrelated costs, including factors like inherent home bias, may continue to persist. To address the issue, we employ the narrower measure of BAA wedges, $t_s^{f,G}$, obtained from Section 5.4.2, and implement the counterfactual simulation by setting $\hat{\tau}_s^{f,G} = 1/t_s^{f,G}$.

The findings are reported in Table 3. Since $t_s^{f,G}$ may understate the trade barriers arising from BAA restrictions, we interpret the quantitative results as offering conservative estimates of the welfare and employment impacts of the BAA restrictions. Row (a) suggests that removing the BAA-induced trade barriers would lead to a welfare improvement of at least 0.039 percent and a reduction in manufacturing employment of at least 50,699. The effects' magnitude is about 50 percent of the results based on the broader measure of BAA wedges as reported in Table 2. The implied cost per manufacturing job saved due to the wedges is \$111,470, which aligns closely with the corresponding value in Table 2.

7.2.3 Robustness: Factor in National Security Considerations

It is arguable that a complete removal of all BAA wedges may not be advisable, as some products may be subject to national security (NS) concerns. To address this issue, we identify the 6-digit NAICS industries that are linked to NS concerns. Specifically, according to the Federal Acquisition Regulation, procurement contracts could be awarded without full and open competition if the products are associated with NS concerns. The FPDS data contains contract-level information that indicates such cases, which allows us to discern the relevant 6-digit NAICS industries.⁵¹ We then

⁵¹In Appendix C, we provide additional details for the implementation of this procedure.

Table 3: Removal of BAA Wedges on Imports of Final Goods (Narrower Measure)

Welfare Measure	\hat{V}_{US}	Distribution of \hat{V}_o			EV _{US} (USD)	Δ Mfg. Jobs	Costs per Mfg. Job	Δ Jobs	Costs per Job
		Mean	Min	Max					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: EES									
(a) Nationwide Public Goods ($\kappa = 1.5$)	0.0392	0.0353	-0.0050	0.0660	28.65	-50,699	111,470	-53,555	105,525
(b) Local Public Goods Only ($\kappa = 1.5$)	0.0478	0.0388	-0.0436	0.3762	34.00	-50,699	132,316	-53,555	125,259
(c) Nationwide Public Goods ($\kappa = 3$)	0.0382	0.0348	-0.0005	0.0601	27.91	-93,498	58,890	-99,385	55,402
(d) Local Public Goods Only ($\kappa = 3$)	0.0471	0.0386	-0.0393	0.3771	33.52	-93,498	70,718	-99,385	66,528
Panel B: Without EES									
(a) Nationwide Public Goods ($\kappa = 1.5$)	0.0408	0.0367	-0.0036	0.0670	29.77	-48,775	120,410	-51,561	113,902
(b) Local Public Goods Only ($\kappa = 1.5$)	0.0493	0.0402	-0.0429	0.3787	35.12	-48,775	142,055	-51,561	134,378
(c) Nationwide Public Goods ($\kappa = 3$)	0.0408	0.0372	0.0062	0.0623	29.76	-88,166	66,587	-93,775	62,604
(d) Local Public Goods Only ($\kappa = 3$)	0.0496	0.0409	-0.0380	0.3807	35.34	-88,166	79,070	-93,775	74,341

Notes: This table shows the effects of the policy experiment that removes the BAA wedges (narrower measure) on final goods on welfare and employment. In Row (a), welfare changes are calculated according to (F.8), assuming consumers have access to the composite public goods from different states. In Row (b), welfare changes are calculated according to (F.9), assuming consumers only have access to the locally produced public goods. Rows (c) and (d) report the corresponding results with an alternative labor supply elasticity. Column (1) shows the aggregate welfare effect for the US, in percentage terms $100(\sum_o \frac{L_o}{L_{US}} \hat{V}_o - 1)$. Columns (2)-(4) present the summary statistics of the distribution of \hat{V}_o across states: Column (2) shows the mean welfare effect $100(\frac{1}{N_o} \sum_o \hat{V}_o - 1)$; and Columns (3) and (4) show the minimum and maximum of $100(\hat{V}_o - 1)$, respectively. Column (5) displays the consumption equivalent variation (EV) per worker measured by USD. Column (6) shows the counterfactual change in the number of manufacturing jobs for the US. Column (7) displays the cost per manufacturing job saved due to the BAA wedges on final goods $t_s^{f,G}$. Column (8) shows the counterfactual change in the number of jobs for the US. Column (9) displays the cost per job saved due to the BAA wedges on final goods $t_s^{f,G}$.

aggregate the information and calculate the fraction of procurement spending subject to NS at the aggregated sector level, which is denoted as ρ_s .⁵²

We proceed with the counterfactual experiment, taking NS concerns into account when reducing BAA wedges on imports of final goods. This is done by setting $\hat{\tau}_s^{f,G} = \frac{1}{(1-\rho_s)\tau_s^{f,G}}$, where $(1-\rho_s)\tau_s^{f,G}$ represents the BAA wedges that are *not* related to NS. The simulation results are presented in Table F.3. Compared to the baseline analysis in Table 2, the welfare and employment impacts are slightly reduced in magnitude; nevertheless, they retain quantitative significance. For example, the findings based on the baseline specification indicate that relaxing the BAA restriction, while accounting for NS concerns, leads to a 0.078 percent increase in aggregate welfare, alongside a reduction of 91,590 manufacturing jobs.

7.2.4 Robustness: Remove the BAA Wedges on Imports of both Final Goods and Component Inputs

Table F.4 presents the simulation results of the counterfactual analysis, where we examine the effects of removing the BAA wedges on both imports of final goods and component inputs. To be specific, we introduce simultaneous shocks to the economy by setting $\hat{\tau}_s^{f,G} = 1/\tau_s^{f,G}$ and $\hat{\tau}_k^{i,G} = 1/\tau_k^{i,G}$. Compared to the baseline case, where solely the wedges on imports of final goods are removed, the effects on welfare and employment show only a modest increase. This is because, for most downstream industries, the BAA domestic content requirement on component inputs is

⁵²As is discussed in Appendix C, the sectors that are affected by NS concerns are “Chemical (325)” and “Transportation Equipment (336).” The fraction of procurement spending subject to NS in each of these two sectors is roughly 5%.

non-binding in the baseline economy.

7.3 The Increasing Cost of Creating Jobs: Required Domestic Share of Inputs Rising from 50% to 75%

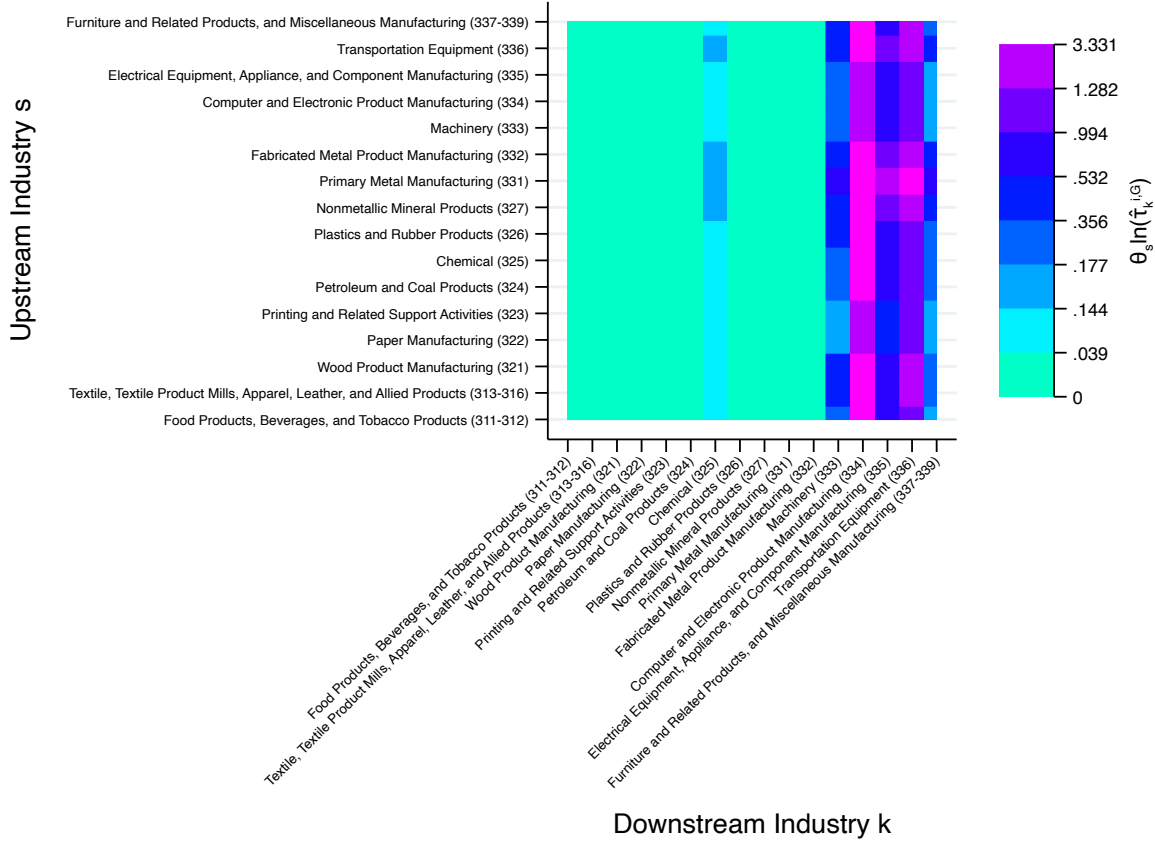
Based on the recent amendments to the BAA introduced by both the Trump and Biden administrations that we discussed in Section 2, the domestic content requirement for component inputs is scheduled to rise from 50% to 75% in 2029.⁵³ To understand the impacts on welfare and labor market outcomes, we first calibrate the implied changes in BAA wedges on component inputs, $\hat{\tau}_k^{i,G}$, so that the foreign share of component inputs for each industry in the manufacturing sector is 25% or below. A positive value of $\hat{\tau}_k^{i,G}$ indicates that the domestic content requirement becomes binding or more binding when the BAA restriction is tightened. Appendix E.2 provides further details for the calibration procedure.

Figure 9 displays the implied changes in effective wedges, measured in logarithmic form as $\theta_s \ln(\hat{\tau}_k^{i,G})$, faced by G producers from different downstream industries across various upstream inputs. In this counterfactual case, G producers from several industries face a more binding constraint, including Chemical (325), Machinery (333), Computer and Electronic Product Manufacturing (334), Electrical Equipment, Appliance, and Component Manufacturing (335), Transportation Equipment (336), and Furniture and Related Products, and Miscellaneous Manufacturing (337-339). Due to the increased wedges on component inputs, G producers from these industries have to choose sub-optimal input bundles, wherein the foreign share of component inputs is limited to 25%. This binding constraint leads to higher unit production costs, which are subsequently passed on to G consumers. At the same time, higher costs of foreign inputs have an impact on the demand for domestic inputs and domestic labor. To quantify these impacts, we consider the shocks $\hat{\tau}_k^{i,G}$ in the counterfactual experiment.

Row (a) of Panel A in Table 4 presents the baseline simulation results. We find that the increase in domestic content requirement for component inputs to 75% lowers the aggregate welfare in the US by 0.068 percent (Column 1), which amounts to \$49.78 in terms of per capita consumption equivalent variation (Column 5). This policy shock, which leads to an increased domestic content of G products, raises domestic manufacturing employment by 41,295 and total employment by 43,823 (Columns 6 and 8). However, compared to the restriction on imports of final goods (Table 2), it is even more costly to create employment generated by tightening domestic content requirements on component inputs. Specifically, Column 6 (respectively, Column 9) shows that the cost per manufacturing job (respectively, per job) created amounts to \$237,788 (respectively, \$224,072). The cost of preserving employment is lower when we consider a formulation of welfare such that public goods are consumed only locally (Row (b)): the cost amounts to \$153,967 (respectively,

⁵³See Appendix A.5 for the timeline detailing the recent amendments made to the BAA.

Figure 9: Counterfactual Changes in $\theta_s \ln(\hat{\tau}_k^{i,G})$: $\underline{\zeta} = 0.75$



Notes: This figure reports the changes in effective trade barriers encountered by G producers when the domestic content requirement on imported component inputs is raised from 50% to 75%, $\theta_s \ln(\hat{\tau}_k^{i,G})$. Here, $\hat{\tau}_k^{i,G}$ is the proportional change in the BAA wedges faced by the downstream sector k , and θ_s represents the trade elasticity of the upstream sector s .

\$145,086) per manufacturing job (respectively, per job).

Relative to Tables 2 and 3, the welfare cost per job created is higher in this case, in particular in the case of a nationwide public good (Row (a)). There are two effects at play here. First, when we increase restrictions on intermediate goods, it turns out that stronger protection is provided to industries with a lower labor share compared to the pattern of protection placed on final goods.⁵⁴ This means that the increase in the demand for labor in sectors producing intermediate inputs whose prices are rising is more muted. Second, the large increase in Row (a) is due to the nature of the public good as a nationwide object. As previously described, in this case, every region benefits from the public good procurement of other regions according to the procurement share γ_o . The tightening of domestic component requirements leads to rising procurement costs of different

⁵⁴The correlation between labor share, $\alpha_{us,s}$, and the heightened protection resulting from tightening domestic content requirements on component inputs, $\sum_k m_{sk} \ln(\hat{\tau}_k^{i,G})$, is -0.40, with m_{sk} representing downstream sector k 's share in the economy-wide use of intermediate inputs sourced from upstream sector s . In comparison, the correlation between labor share and BAA wedges on final goods $\ln(\hat{\tau}_s^{f,G})$ is 0.26.

goods, with sector-level exposure influenced by $\hat{\tau}_k^{i,G}$. Due to the differences in their procurement bundles, states encounter varying impacts from the increasing procurement costs. It happens that states witnessing a larger reduction in public good consumption tend to have higher values of γ_o . This leads to a more pronounced impact on welfare aggregated at the national level, thus resulting in a higher cost for generating the same number of jobs. We provide more details about this mechanism in Appendix F.4.

In terms of spatial heterogeneity, the average welfare change is -0.065 percent across states, with a range between -0.094 to -0.037 percent (Columns 2-4). Figures 10 and 11 further illustrate respectively the dispersed spatial impacts on welfare and manufacturing employment.⁵⁵

In Rows (b) to (d) of Panel A, we consider a different specification of welfare and an alternative value of labor supply elasticity. When consumers only have access to the locally produced public goods, the overall decline in welfare is less pronounced compared to the baseline case,⁵⁶ while the spatial variation of the welfare impact becomes more significant. With a larger labor supply elasticity $\kappa = 3$, employment reacts more strongly to the demand shock. In Panel B, we shut down the EES channel for all sectors. When compared to the baseline case, the impacts of the more stringent domestic content requirement on component inputs is slightly more negative for welfare and less positive for employment.⁵⁷

7.4 Rearrange Buy American Wedges to Target High EES Sector

As is shown in Kucheryavyy *et al.* (2023) and Bartelme *et al.* (2024), the strength of the EES channel through which a trade cost shock influences output is governed by the product of trade elasticity and scale elasticity, $\theta_s \nu_s$. Given this insight, we examine the relationship between the BAA wedges on imports of final goods ($\ln(\tau_s^{f,G})$) and the strength of EES ($\theta_s \nu_s$) in Figure 12. Panel A reveals a positive correlation. However, if we exclude the outlier sector Petroleum and Coal Products (324), the correlation becomes negative. Panel B finds an insignificant rank correlation between $\ln(\tau_s^{f,G})$ and $\theta_s \nu_s$. These findings indicate that the current policy, as inferred from the BAA wedges, does not effectively leverage the EES, which may partly explain the limited quantitative significance of the EES observed in Tables 2 and 4.

For the last set of counterfactuals, we maintain the distribution of $\tau_s^{f,G}$, but rearrange the

⁵⁵In Figures F.5 and F.6, we show the impacts on changes in employment-to-working age population ratio and on percentage changes in wages across states, respectively.

⁵⁶When consumers only have access to the locally produced public goods, the aggregated welfare change at the national level is determined by averaging welfare changes across states, with weights being each state's population share. It turns out that the reduction in state-level public good provisions shows a weaker correlation with population share compared to procurement share. For additional details, see Appendix F.4.

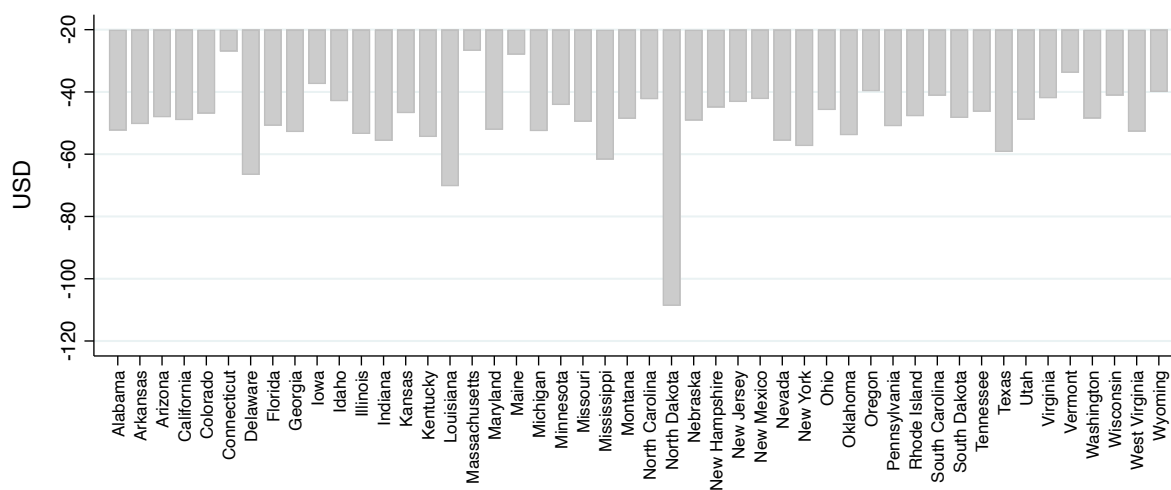
⁵⁷In the case with EES, tightening the domestic content requirement for component inputs leads to an increase in the production scale of upstream sectors, resulting in improved productivity. However, the higher production costs associated with this change cause the scale of downstream sectors to decrease, resulting in a deterioration in productivity. It is the former channel that dominates the latter one. As a result, we observe a smaller decline in welfare and a larger employment increase in the case with EES.

Table 4: Increasing the Required Domestic Share of Component Inputs for G from 50% to 75%

Welfare Measure	\hat{V}_{US}	Distribution of \hat{V}_o			EV _{US} (USD)	Δ Mfg. Jobs	Costs per Mfg. Job	Δ Jobs	Costs per Job
		Mean	Min	Max					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: With EES									
(a) Nationwide Public Goods ($\kappa = 1.5$)	-0.0683	-0.0654	-0.0940	-0.0369	-49.78	41,295	237,788	43,823	224,072
(b) Local Public Goods Only ($\kappa = 1.5$)	-0.0450	-0.0389	-0.1919	0.0305	-32.23	41,295	153,967	43,823	145,086
(c) Nationwide Public Goods ($\kappa = 3$)	-0.0683	-0.0657	-0.0891	-0.0389	-49.81	75,762	129,706	80,766	121,669
(d) Local Public Goods Only ($\kappa = 3$)	-0.0453	-0.0395	-0.1972	0.0269	-32.48	75,762	84,581	80,766	79,340
Panel B: Without EES									
(a) Nationwide Public Goods ($\kappa = 1.5$)	-0.0691	-0.0661	-0.0948	-0.0377	-50.35	40,238	246,848	42,724	232,486
(b) Local Public Goods Only ($\kappa = 1.5$)	-0.0458	-0.0395	-0.1926	0.0289	-32.79	40,238	160,742	42,724	151,390
(c) Nationwide Public Goods ($\kappa = 3$)	-0.0697	-0.0670	-0.0911	-0.0400	-50.86	72,755	137,900	77,600	129,291
(d) Local Public Goods Only ($\kappa = 3$)	-0.0467	-0.0407	-0.1990	0.0244	-33.49	72,755	90,795	77,600	85,126

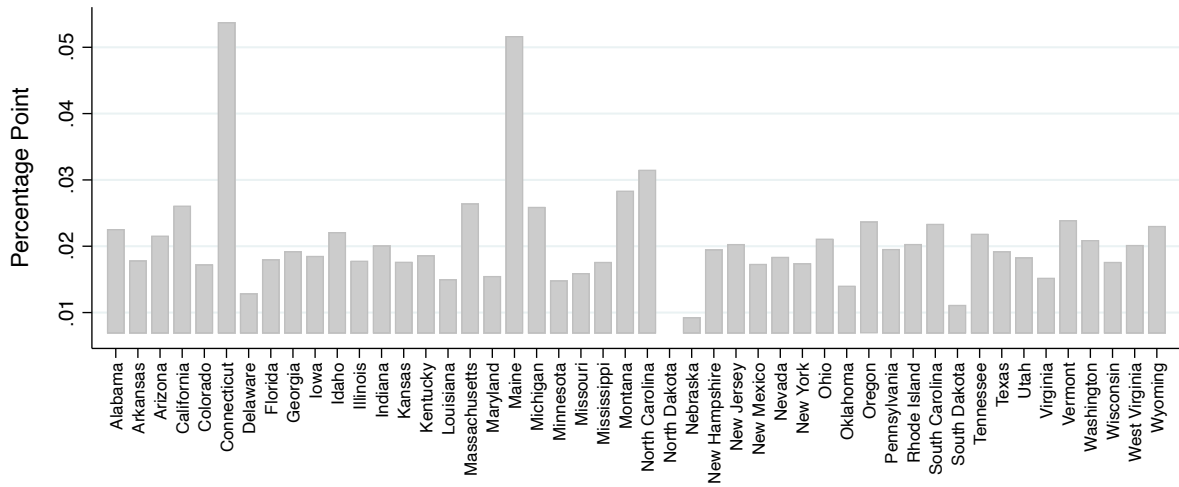
Notes: This table shows the effects of the policy experiment that increases the required domestic share of inputs to 75% for G production. In Row (a), welfare changes are calculated according to (F.8), assuming consumers have access to the composite public goods from different states. In Row (b), welfare changes are calculated according to (F.9), assuming consumers only have access to the locally produced public goods. Rows (c) and (d) report the corresponding results with an alternative labor supply elasticity. Column (1) shows the aggregate welfare effect for the US, in percentage terms $100(\sum_o \frac{1}{N_o} \hat{V}_o - 1)$. Columns (2)-(4) present the summary statistics of the distribution of \hat{V}_o across states: Column (2) shows the mean welfare effect $100(\frac{1}{N_o} \sum_o \hat{V}_o - 1)$; and Columns (3) and (4) show the minimum and maximum of $100(\hat{V}_o - 1)$, respectively. Column (5) displays the consumption equivalent variation (EV) per worker measured by USD. Column (6) shows the counterfactual change in the number of manufacturing jobs for the US. Column (7) displays the cost per manufacturing job saved due to the policy experiments that raise the required domestic share of inputs to 75% for G production. Column (8) shows the counterfactual change in the number of jobs for the US. Column (9) displays the cost per job saved due to the policy experiments that raise the required domestic share of inputs to 75% for G production.

Figure 10: Consumption Equivalent Variation: Increase the Required Domestic Share of Component Inputs for G to 75%



Notes: This figure presents the counterfactual changes in welfare across states resulting from an increase in the required domestic share of component inputs for G production to 75%. The welfare changes are measured by consumption equivalent variation. The calculation assumes that consumers have access to the composite public goods from different states.

Figure 11: Changes in Manufacturing Employment to Working Age Population Ratio: Increase the Required Domestic Share of Component Inputs for G to 75%

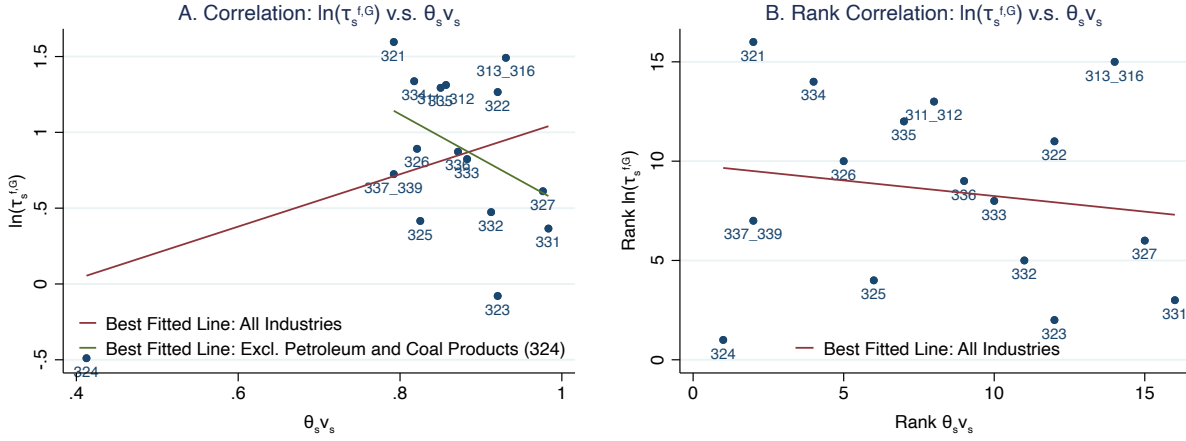


Notes: This figure presents the counterfactual changes in manufacturing employment to working age population ratio across states resulting from an increase in the required domestic share of component inputs for G production to 75%.

wedges so that they perfectly align with the strength of EES across manufacturing industries. The simulation results for the baseline specification are presented in Row (a) of Table 5. Two intriguing findings emerge. Firstly, if the policy had fully leveraged the EES, welfare would have improved by 0.005 percent or \$3.69 measured by consumption equivalent variation (Columns 1 and 5). The modest impact on welfare can be attributed, in part, to the relatively small share of G consumption in the overall output in the U.S.⁵⁸ Hence, its influence on the production scale is limited. Secondly, in the counterfactual scenario, manufacturing employment and total employment would have experienced a decline of 13,738 and 14,347, respectively (Columns 6 and 9). This result indicates that the current arrangement of the BAA wedges promotes employment. Specifically, the correlation between BAA wedges $\ln(\tau_s^{f,G})$ and labor intensity $\alpha_{us,s}$ across manufacturing industries stands at 0.26 in the data. In the counterfactual experiment aligning the BAA wedges with the strength of EES, the correlation between the counterfactual BAA wedges $\ln(\tau_s^{f,G'})$ and $\alpha_{us,s}$ diminishes to 0.07. As reported in Rows (b) to (d), we obtain qualitatively similar results for the alternative specifications. Taken together, these findings are consistent with the historical narrative and current political discourse that the BAA serves as an employment measure. (For further details on the BAA, see Appendix A.)

⁵⁸Recall that the utility weight on public goods is $1 - \varphi = 0.034$.

Figure 12: Correlation between BAA Wedges and Strength of EES



Notes: Panel A of the figure shows the relation between the BAA wedges (broader measure) in logarithm, $\ln(\tau_s^{f,G})$, and the strength of EES, $\theta_s v_s$. The red line corresponds to the best-fitted line across all sectors, while the green line represents the best-fitted line for the sample that excludes Petroleum and Coal Products (324). Panel B illustrates the rank correlation between $\ln(\tau_s^{f,G})$ and $\theta_s v_s$.

Table 5: Rearrange $\tau_s^{f,G}$ to be Positively Aligned with $\theta_s v_s$

Welfare Measure	\hat{V}_{US}	Distribution of \hat{V}_o			EV _{US} (USD)	Δ Mfg. Jobs	Costs per Mfg. Job	Δ Jobs	Costs per Job
		Mean	Min	Max					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(a) Nationwide Public Goods ($\kappa = 1.5$)	0.0050	0.0044	-0.0156	0.0104	3.69	-13,738	52,922	-14,347	50,677
(b) Local Public Goods Only ($\kappa = 1.5$)	0.0146	0.0190	-0.0178	0.3361	9.99	-13,738	143,510	-14,347	137,422
(c) Nationwide Public Goods ($\kappa = 3$)	0.0055	0.0051	-0.0139	0.0106	4.07	-24,983	32,162	-26,370	30,470
(d) Local Public Goods Only ($\kappa = 3$)	0.0150	0.0196	-0.0162	0.3354	10.33	-24,983	81,566	-26,370	77,275

Notes: This table shows the effects of the policy experiment that removes the “Buy American” wedges on final goods on welfare and employment. In Row (a), welfare changes are calculated according to (F.8), assuming consumers have access to the composite public goods from different states. In Row (b), welfare changes are calculated according to (F.9), assuming consumers only have access to the locally produced public goods. Rows (c) and (d) report the corresponding results with an alternative labor supply elasticity. Column (1) shows the aggregate welfare effect for the US, in percentage terms $100(\sum_o \frac{L_o}{L_{US}} \hat{V}_o - 1)$. Columns (3)-(4) present the summary statistics of the distribution of \hat{V}_o across states: Column (2) shows the mean welfare effect $100(\frac{1}{N_o} \sum_o \hat{V}_o - 1)$; and Columns (3) and (4) show the minimum and maximum of $100(\hat{V}_o - 1)$, respectively. Column (4) displays the consumption equivalent variation (EV) per worker measured by USD. Column (5) shows the counterfactual change in the number of manufacturing jobs for the US. Column (6) displays the cost per manufacturing job saved due to the misalignment between the BAA wedges on final goods $\tau_s^{f,G}$ and the strength EES across sectors. Column (7) shows the counterfactual change in the number of jobs for the US. Column (8) displays the cost per job saved due to the misalignment between the BAA wedge on final goods $\tau_s^{f,G}$ and the EES across sectors.

7.5 The Cost of Creating Jobs: Discussion and Comparison with Other Policies

The main contribution of this paper is to offer a rigorous evaluation of the cost of creating jobs using Buy American provisions. This is only one of the many policy levers governments have to promote the creation of jobs. In this section, we compare the numbers we obtain to others in the literature. Before we do so, it is essential to note that these papers generally differ from ours in the measure of “cost” they employ. It may sometimes be the cost in terms of government expenditures, while in other cases, it is the welfare cost calculated as the welfare change or just consumer surplus change computed in the model divided by the number of jobs created coming from external sources. Our methodology has the advantage of taking both welfare and job changes from the

same model counterfactual. These caveats are important when evaluating the vast heterogeneity in the numbers one can find across various studies.

On the higher range of the cost per job are papers like [Flaen *et al.* \(2020\)](#), which estimates that the cost to consumers per job created due to the 2018 Section 201 tariffs on washing machines was over \$815,000. Policy briefs by [Haufbauer and Jung \(2018\)](#) and [Hufbauer and Lowry \(2020\)](#) estimate a consumer surplus loss of \$650,000 and \$900,000 per job created in the steel and tire industries by tariffs or anti-dumping duties. Our estimates are substantially lower than these figures.

Other studies estimate the effect of government spending associated with employment using different shocks. This is akin to our reduced-form exercise and does not involve any welfare calculations. These studies find figures that range from \$30,000 per year ([Serrato and Wingender, 2016](#)) to \$125,000 ([Wilson, 2012](#))-\$150,000 ([Garin, 2019](#)) per job. For place-based policies, the estimated cost per job varies across programs, ranging from \$12,000 for firm-specific subsidies in the U.S. ([Slattery and Zidar, 2020](#)), to \$18,000 for Empowerment Zones ([Busso *et al.*, 2013](#); [Bartik, 2019](#)), with [Bartik \(2020\)](#) finding that the typical incentive package generates a job at a discounted cost of \$180,000. In other countries, these estimates are once again different. For instance, in the United Kingdom, the European investment subsidies have a cost per job between \$3,541 and \$26,572 ([Crisuolo *et al.*, 2019](#)). These numbers are more readily comparable to our reduced form estimates in Section 6. When we manipulate our coefficient to make it analogous to these studies the figure we obtain is roughly \$125,000 per job.⁵⁹

8 Conclusion

This paper employs a combination of micro-data and a quantitative model to provide a rigorous estimate of the restrictiveness and costs of current and future Buy American provisions on Federal government procurement. The model we employ adds separate consumption by and production for the government, non-employment, and external economies of scale to a workhorse quantitative trade model. Returning to the initial motivation of the paper and the more general policy discourse, there are three main takeaways.

The first is that the micro-data reveals that government imports are much smaller than aggregate data reveals, indicating both that we ought to employ the correct data to detect the stringency of this policy and also that the purported violations of Buy American provisions are not as frequent as recent U.S. Presidents have claimed.

The second takeaway is that, despite these very low import shares, we find that the welfare

⁵⁹Because our coefficient in Column 2 of Table 1 reports the increase in $\frac{Emp}{Pop}$ due to a \$1,000 increase in $\frac{GovSpending}{Emp}$ where Emp is total employment and Pop is working age population we need to perform this simple back of the envelope calculation: $\frac{\Delta GovSpending \times 1000}{\Delta Emp} = \frac{Emp \times 1,000}{0.0056 \times Pop} = \frac{0.7}{0.0056} \times 1,000$, using an employment-to-population ratio of 70% in our sample.

cost of *current* Buy American provisions is not necessarily exorbitant when calculated consistently within the model. The program has created a modest amount of jobs, at most 100,000, at a cost of roughly \$130,000 per job.

The third main takeaway is that the *future* version of Buy American restrictions, centered on tightening domestic content restrictions in component inputs, will likely increase the welfare cost of creating additional jobs, both because they will protect industries that do not use labor as intensively and because they will hit more heavily regions that play a prominent role in public procurement.

We consider the carefully estimated costs of creating additional jobs through public policies as the first of two essential inputs in the discussion around their desirability. The second necessary input in this discussion is the societal value attached to jobs, especially during the two decades we examine, when labor force participation in certain socio-economic groups has seen strong declines (Abraham and Kearney, 2020). The causes of this decline are still debated (Aguiar *et al.*, 2021; Binder and Bound, 2019), but the potential consequences are broad-ranging, including increasing morbidity, mortality and political polarization (Pierce and Schott, 2020; Autor *et al.*, 2019, 2020). Whether policies that favor job creation and support workers' income can counteract such trends is still an open question,⁶⁰ We view the results of this paper as contributing to this broader debate.

⁶⁰Dow *et al.* (2020) show that policies like minimum wages and the EITC have reduced some of the 'deaths of despair' (Case and Deaton, 2015, 2017).

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A Buy American Act

A.1 Origin of the Policy

The first years of 1930s were characterized by high economic distress, with one quarter of the workforce being jobless. Several members of Congress started to support protectionist measures to revitalize the American economy during the Great Depression, partly also in response to other Governments becoming increasingly protectionist.

The Smoot Hawley Tariff Act of 1930 was the first protectionist measure implemented, establishing the second-highest tariff levels in U.S. history. This act was a response to the problems of American agriculture, which had failed to recover from the recession of 1920–21. It was magnified by the imposition of import duties on wheat by Germany, Italy, and France (Eichengreen, 2002). While the Smoot Hawley Act was originally conceived as agricultural relief, it then evolved into a bill extending protection to portions of both industry and agriculture, increasing tariffs on more than 20,000 items.

The BAA can be seen as instead a way to counteract the 'buy-British' clauses in all public purchase and construction contracts in the United Kingdom (Nagle, 2012). Initially discussed only in the context of the Army's procurement budget in 1932, Congress expanded 'buy-American' restrictions to cover all Federal agency purchases partly due to the Hoover Dam controversy (Nagle, 2012). Purchases of heavy electrical equipment for large-scale projects like the Hoover Dam spanned several years, and domestic bidders raised objections against foreign competition in various contracts.⁶¹ Specifically, manufacturers of heavy electrical equipment in California and Pennsylvania expressed apprehension about potential competition from German manufacturers for contracts related to the Hoover Dam.⁶²

To respond to their protests and address domestic unemployment concerns, Senator Johnson introduced his bill on February 2, 1933. Senator Vandenberg described the legislation as " primarily an employment measure. American tax money should maintain American labor in a moment of American crisis and exigency. [...] Why have American make-work programs which make work in Europe or Asia?". Despite the bid opening for hydraulic apparatus for the Hoover power plant being initially set for February 3, 1933, it was delayed until March 10, 1933, due to the introduction of the bill. President Hoover signed the bill into law on his last day in office, March 3, 1933, with immediate effect. Just seven days later, on March 10, 1933, the impact of the legislation became apparent during the bid opening for the hydraulic apparatus. The act resulted in the

⁶¹An example is the contract for turbines used in the Madden Dam for the Panama Canal. Although a German firm appeared to offer the lowest bid for the project, additional factors beyond price, which would ultimately affect the total cost to the United States, prompted the decision to award the contract to the second lowest bidder.

⁶²The Act was also supported by the Common Brick Manufacturers Association of America, among others. Testimony revealed that the cement used in the Hoover Dam project was sourced from Belgium.

disqualification of six foreign bidders for the contract, all of whom were the lowest bidders.

A.2 Debates on BAA

Starting in 1953, the mass media began advocating for the repeal of the Act, arguing against what they perceived as unjust and stringent measures. This push gained momentum when a British company, despite offering the lowest bid for electrical generators needed for the Chief Joseph Dam, was disqualified due to the Act's provisions. As a result, the contract was awarded to a domestic manufacturer at a significantly higher expense. Newspapers on both sides of the Atlantic joined in calling for the Act's abolition, raising concerns among foreign nations about its effect on global commerce and its conflict with broader principles of US international trade policies.

Critics of the BAA saw it as damaging to the United States' position as a leader in post-war endeavors to lessen trade barriers and foster international trade. Another notable critique centered on the elevated expense of domestic goods compared to similar foreign options. To address the growing discord between protectionist and trade liberal factions in the US, President Eisenhower tasked numerous committees with examining the matter. The Gray report determined that the Buy American principle directly contradicted core US foreign economic policies. Likewise, the Bell report emphasized that Buy American limitations inflated government expenditures and essentially imposed a "super tariff" on goods procured by the government.

A.3 Waivers

A.3.1 Non-Agency Specific Waivers

A waiver of the BAA can be authorized if the head of the procuring agency determines that adhering to the BAA is contrary to the public interest. This provision is invoked when an agency possesses an agreement with a foreign government that provides a broad exemption from the BAA's requirements.

Besides, a waiver can also be obtained if domestic end products are "are unavailable in sufficient and reasonably available commercial quantities and of a satisfactory quality". Class determinations for articles are listed in FAR 25.104 and are published for comment at least once every 5 years. Individual determinations are made by the Head of Contracting Activity but can be delegated.

Furthermore, a waiver can be granted if the cost of acquiring the domestic product is deemed "unreasonable". Specifically, when a domestic offer (i.e., an offer for a domestic end product) is not the lowest offer, the procuring agency must add a certain percentage of the low offer's price (inclusive of duty) to that offer before determining which offer is the lowest priced for the government. During the period of our study, this percentage ranges from 6% for cases where the lowest domestic offer is from a large business, to 12% when the lowest domestic offer is from a small business, to 50% for Department of Defense procurement. For example, suppose that two firms

bid in a call for tenders: the domestic end product offer is \$50,000, while the foreign end product offer is \$40,000. The federal agency will compare the domestic offer to a foreign offer of \$42,400 (if the domestic offer is from a big firm) or to \$44,800 (if the domestic offer is from a small firm), while the Department of Defense will consider the foreign offer as bidding \$60,000 (regardless of the size). Then the Department of Defense will award the contract to the firm manufacturing the domestic product, while other agencies will award it to the firm manufacturing the foreign product.

Other waivers can be granted if goods are acquired specifically for commissary resale, or if the agency procures information technology that is a commercial item.

A.3.2 TAA

The Trade Agreements Act (TAA) of 1979 was established with the aim of promoting open international trade. The TAA essentially provides that the Government may acquire only “U.S.-made or designated country” products or services, thus ensuring that items from “designated countries” are considered equally with domestic ones. These eligible countries include those with which the U.S. has signed multilateral or bilateral agreements such as Free Trade Agreements or the World Trade Organization Government Procurement Agreement (WTO GPA), or those designated as TAA eligible, such as Least Developed Countries and Caribbean Basin Countries.

The TAA waiver is applicable when certain conditions are met: the procurement value falls above a specified threshold in the relevant trade agreement, involves goods or materials listed in the agreement, and does not qualify for other exceptions.⁶³ Thresholds for TAA applicability differ based on the trade agreement, and the President has delegated TAA’s waiver authority to the U.S. Trade Representative (USTR), who establishes TAA thresholds depending on the agreement and type of contract covered. For instance, currently thresholds for the WTO GPA are \$180,000 for supply and service contracts and \$6,932,000 for construction contracts, while Free Trade Agreement (FTA) thresholds vary from \$25,000 to \$180,000 for supplies and services and \$6,932,000 to \$10,441,216 for construction.

BAA and TAA apply different rules to define an end product as being domestic. Indeed, the TAA applies a rule-of-origin that requires products to be “wholly the growth, product or manufacture” or “substantially transformed .. into a new and different article of commerce with a name, character, or use distinct from that of the article or articles from which it was transformed” in the U.S. or a designated country.⁶⁴ Contrary to the BAA, the assessment of substantial transformation for TAA purposes does not primarily hinge on the value or percentage of U.S. (or designated

⁶³For instance, BAA applies to specific types of acquisitions, irrespective of whether they surpass the TAA threshold, in the following cases: (1) acquisition for small business set-asides; (2) acquisition of end products for resale; (3) procurements of arms, ammunition, or war materials crucial for national security or defense purposes; (4) sole-source awards.

⁶⁴See FAR 25.003.

country) content. Instead, it revolves around whether the item in question has undergone a significant change in character or function as a result of the transformation process. The determination of “substantial transformation” can involve complex interpretations and applications that require case-specific consideration, with determinations typically made by the Bureau of Customs and Border Protection.

A.3.3 Department of Defense’s BAA Waivers

The Berry Amendment prohibits the Department of Defense (DOD)⁶⁵ from using its funds to buy certain covered items, including food, clothing, tents, specific textile fabrics and fibers, and hand or measuring tools. This measure, designed to protect national security interests and ensure the defense industry can supply necessary products during crises, demands a higher level of domestic content in DOD-purchased goods compared to BAA. Specifically, DOD funds can only be used to procure items “entirely grown, reprocessed, reused, or manufactured within the United States”. Several statutory exceptions exist, such as procurements for combat or contingency operations and those below a certain threshold.

The Specialty Metal domestic sourcing requirement, originally part of the Berry Amendment and now separately codified at 10 U.S.C.A. § 2533b, pertains to DOD acquisitions of certain items and components containing specialty metal, as well as the specialty metal itself, if not melted or produced in the United States. Specialty metals primarily include specific types of steel, nickel and iron-nickel alloys, cobalt alloys, titanium and its alloys, and zirconium and its alloys. This restriction bars DOD from purchasing aircraft, missile and space systems, ships, tank and automotive items, weapon systems, ammunition, or related components containing specialty metal not produced in the U.S. There are exceptions to this restriction, similar to those in the Berry Amendment, such as purchases deemed necessary for U.S. national security interests. Similar to the Berry Amendment, the BAA does not apply if the specialty metals restriction applies.

The Balance of Payments Program, governed by DFARS Subpart 225.75, is a DOD initiative that extends BAA, typically applicable to products used within the U.S., to apply to contracts for supplies to be used, and construction to be performed, outside the U.S.. The program only affects DOD procurements above a certain threshold,⁶⁶ with exemptions for specific items like petroleum products, industrial gases, and certain brand drugs. Similar to the BAA, the program includes exemptions such as the unavailability of domestic products or products intended for commissary resale. If the lowest offer contains nonqualifying end products or material, a price preference must be applied, with DOD’s preference being a 50% increase. However, TAA requirements may override mandates of the Balance of Payments Program.

⁶⁵10 U.S.C. § 2533a.

⁶⁶The simplified acquisition threshold, currently set at \$250,000 but subject to change.

A.4 Cost of Components

The definition of cost of components is important because it affects how stringent the requirement that at least 50% of it be U.S. made. When the contractor purchases components, the cost encompasses the expenses associated with acquisition (including transportation costs to the point where they are integrated into the final product or construction material), as well as any relevant duties; similarly, for components manufactured by the contractor, the cost includes all expenses related to the manufacturing process of the components (including transportation), as well as allocable overhead costs. However, profits and any expenses associated with manufacturing the end product are excluded from this calculation. Notice that labor applied by a contractor during the assembly of components is not factored into the cost analysis for components. The assessment centers on the actual costs of the components alone, excluding expenses incurred in their manufacturing processes such as cutting or drilling.

A.5 Recent Amendments to BAA

Both former President Trump and President Biden have issued Executive Orders addressing Buy American requirements and preferences.

Executive Order 13881, issued by President Trump on July 15, 2019 (Maximizing Use of American-Made Goods, Products, and Materials), bolstered the BAA in several ways. Firstly, it increased the domestic content threshold from 50% to 55%. Secondly, it established a stand-alone domestic content requirement for products made wholly or predominantly of iron and steel, allowing less than 5% of the component cost to be foreign. Thirdly, it heightened the price evaluation preference for domestic items in civilian agencies from 12% to 30% for small businesses and from 6% to 20% for large businesses.

One week into his presidency, President Biden signed Executive Order 14005, titled “Ensuring the Future Is Made in All of America by All of America’s Workers” on January 25, 2021, increasing further the domestic content threshold from 55 to 60%, then to 65% in 2024 and to 75% in 2029.⁶⁷

A.6 The BAA and Other Protectionist Measures

One prominent example is the “Buy America” restrictions, which are linked to specific grant funds managed by the Department of Transportation (DOT) and certain other federal agencies. The Buy America provisions typically mandate that steel, iron, and manufactured products primarily composed of steel or iron, used in infrastructure projects, must be produced or manufactured in the United States. The BAA does not automatically apply to these funds because, although the

⁶⁷In the remarks on “Delivering On Made In America Commitments”, President Biden announced “when I say Buy American, I mean buy all — all American. I want to increase the share of federal spending on goods and services that goes to small businesses in America — the backbone of our country” March 4, 2022)

funding originates from the federal government, purchases are not made directly by the federal government.

The American Recovery and Reinvestment Act of 2009 (ARRA) also contains Buy American provisions, mandating 100% domestic components in all ARRA-funded public buildings and works projects. More recently, the 2022 Inflation Reduction Act incorporates Buy American provisions.

B Data Appendix

B.1 FPDS

The Federal Procurement Data System (FPDS) tracks the universe of federal awards that exceed the micro-purchase threshold (\$3,500).⁶⁸ The Federal Acquisition Regulation (FAR) requires Contracting Officers (COs) to submit complete reports on all contract actions.⁶⁹ Thus, every observation corresponds to a contract action, representing either an initial award or a follow-on action, e.g., modification, termination, renewal, or exercise of options. For each observation, we observe detailed information, such as the dollar value of the funds obligated by the transaction; a four-digit product category code (PSC); six-digit Industry (NAICS) code; identification codes for the agency, sub-agency, and contracting office making the purchase; the location where the contracts is required, the identity (DUNS) and location (zip-code or country of origin if it's located abroad) of the vendor. Also, each observation indicates the type of contract type⁷⁰ and pricing (typically, fixed-price or cost-plus); the extent of competition for the award; characteristics of the solicitation procedure; the number of offers received; and the applicability of a variety of laws and statutes. We collapse all actions by unique contract ID variables (IDV-PIID and PIID). Moreover, the procurement officer is required report contract's *Place of Manufacture* in accordance with the FAR 25.1 (Buy American Act), and any exceptions or reasons for waivers employed compliance and applicability of the Buy American Act.

B.1.1 Procurement Offices

The federal government is organized into different layers: agencies, subagencies, and offices. Each layer is identified by a unique code. For example,

- Agency: DEPARTMENT OF JUSTICE (15):

⁶⁸The FAR 4.606 describes specific contract actions exempted from being reported to FPDS. In particular, it exempts contracts between public entities or contracts that involve fund transactions. The micro-purchase threshold was increased from \$3,500 to \$10,000 in 2018.

⁶⁹On an annual basis, the General Services Administration (GSA) requires federal agencies to state the completeness and accuracy percentages of their data contained in the FPDS.

⁷⁰There are two types of contract designs: Definitive contracts (DC) or Indefinite delivery vehicle (IDV), the latter correspond to long-term agreements with suppliers.

- Sub-agency: FEDERAL PRISON SYSTEM / BUREAU OF PRISONS (1540)
 - * Office #1: FPC ALDERSON (15B101), ALDERSON, WV, 24910
 - * Office #2: FCI ASHLAND (15B102), ASHLAND, KY, 41105
 - * Office #3: FCI BECKLEY (15B103), BEAVER, WV, 25813
 - * Office #4: FMC BUTNER (15B106), BUTNER, NC, 27509
 - * ...

The lowest level corresponds to procurement offices. Most federal procurement is decentralized; procurement offices use their budget to procure according to their needs. Each office’s location (zip code) is not provided in FPDS directly but can be obtained from the official list of active procurement offices.

B.1.2 Location Variables

The FPDS dataset includes variables to identify relevant locations:

- *Place of Manufacture*: This field must be populated for all reported manufactured end products, including those valued under the micro-purchase threshold. Procurement officers will choose “Not a Manufactured End Product” when the procurement is for services or for unmanufactured end products (e.g., ores, food, animals). Instead, they will choose “Manufactured Outside the U.S. – Use Outside the U.S.” when the procurement is for supplies acquired for use outside the United States (BAA does not apply). If the procurement is for supplies to be used inside the United States, it must be either manufactured in the U.S. (when the supplies are considered domestic end products) or “Manufactured Outside the U.S.” (and subject to Trade Agreements or to one of the exceptions).

Although BAA requirements do not apply to contract awards valued below the micro-purchase threshold (generally \$3,500 in fiscal year 2017), the FPDS-NG “Place of Manufacture” field does not have an option to indicate whether a contract is under the threshold. Instead, contracting officers entering information for awards under the micro-purchase amount must still state whether the product is domestic or foreign. If the product is foreign, the officials must select a Buy American Act exception authorizing the purchase, even though no exception is needed at these dollar levels. As a result, when agencies report in FPDS-NG that a BBAA exception or waiver applied for a procurement valued at less than \$3,500, that information would not be accurate. Based on our review, this may have involved about \$16 million in fiscal year 2017 obligations.

- *Place of performance*: This variable is reported by the procurement officer and indicates the location of the principal plant or place of business where the items will be produced, supplied

from stock, or where the service will be performed. For construction contracts, enter the site of construction. If more than one location is involved in performance, enter the principal place of performance.

- *Firm location*: This information is automatically populated based on the firm's DUNS number. The *Dun's and Bradstreet* registry is updated annually.⁷¹
- *Office location*: FPDS identifies procurement offices using unique office codes. The office codes can be combined with the registry of contracting office information available on the FPDS website to add characteristics and locations of procurement offices. The process required additional work as offices changed their code format between 2003 and 2016.⁷² The registry of contracting offices is only available from 2010 onwards, so if an office changed office code format before 2010, it would require some extra work to retrieve the corresponding new office code to merge with the registry.⁷³ The resulting dataset includes office zip codes if the office is located in the U.S. and the name of the country if located abroad.⁷⁴

B.1.3 FPDS Coverage

The Federal Acquisition Regulation (FAR 4.606) describes contract actions exempted from being reported to FPDS over the micro-purchase threshold. Notably, the FAR exempts the reporting of contract actions in which the required data would constitute classified information, contracts between public entities that involve fund transactions, or interagency agreements.

To evaluate the comprehensiveness of FPDS, we compare its aggregate spending data with the budget execution reports provided by the U.S. Government Budget Office. Table B.1 presents the spending figures by fiscal year.⁷⁵ Column 2 shows the aggregate amounts from FPDS, while column 3 provides the spending data for Budget's Object Class 20: "Contractual Services and

⁷¹Since the variable Place of Manufacture is sparsely populated in the early years of our study, we use firm location data (specifically, the firm's country) to infer U.S. government imports. However, firms based abroad may have U.S. branches, which could lead us to incorrectly classify some contracts as imports, even though the government is purchasing from firms with U.S. establishments. To address this, we manually check a sample of U.S. contracts awarded in 2015, where the place of performance is the U.S. but the winning firm is located in another country. We look for any evidence that these firms have a manufacturing establishment in the U.S., by browsing through their websites, looking at their LinkedIn profiles and vacancy announcements (to check where they hire). We find that in the vast majority of cases, these firms do not have any U.S. manufacturing establishment.

⁷²The new office code format was a 6-digit called "AAC" and was adopted by the DOD a few years before the rest of the federal government.

⁷³The process involved tracing multi-year contracts (PIID) that experienced changes in procurement office code; this way, we were able to identify office code transitions. This process was accompanied by a manual check of the most relevant procurement offices. As a result, only 1.5% of observations miss the office location (zip code, if located in the U.S.).

⁷⁴Most procurement offices located in foreign countries correspond to the Dept. of Defense or the Dept. of the State, which manages embassies and other government units.

⁷⁵The federal fiscal year begins on October 1st and ends on September 30th of the following year.

Supplies.” Column 4 adjusts these figures by excluding sub-categories unlikely to be reported in FPDS as per FAR 4.606.⁷⁶

We find that the spending amount reported in the FPDS falls within the range defined by the total Object Class 20 amount and the amount adjusted to exclude sub-categories that are unlikely to qualify under FAR 4.606. This result underscores the comprehensiveness of FPDS in capturing federal procurement expenditures.

B.1.4 Top NAICS in FPDS

Table B.2 lists the top 20 manufacturing industries at the 6-digit NAICS level with the highest procurement amounts.

B.2 List of Sectors

The sample of sectors used in the quantitative analysis includes: Mining and Oil and Gas Extraction (21); Construction (23)*; Manufacture of Food products, Beverages and Tobacco products (311-312); Textile, Textile Product Mills, Apparel, Leather, and Allied Products (313-316); Wood Product Manufacturing (321); Paper Manufacturing (322); Printing and Related Support Activities (323); Petroleum and Coal Products (324); Chemical (325); Plastics and Rubber Products (326); Nonmetallic Mineral Products (327); Primary Metal Manufacturing (331); Fabricated Metal Product Manufacturing (332); Machinery (333); Computer and Electronic Product Manufacturing (334); Electrical Equipment, Appliance, and Component Manufacturing (335); Transportation Equipment (336); Furniture and Related Products, and Miscellaneous Manufacturing (337-339); Wholesale and Retail Trade (42-45); Transportation and Warehousing (48-49); Information and Cultural Industries (51); Finance and Insurance (52)*; Real Estate and Rental and Leasing (53)*; Professional, Scientific and Technical Services, Management of Companies and Enterprises (54-55); Administrative and Support, Waste Management and Remediation Services (56)*; Educational Services (61)*; Health Care and Social Assistance (62)*; Accommodation and Food Services (72)*; Other Services (except Public Administration) (71,81)*. The corresponding 2-digit/3-digit NAICS codes for different industries are in parentheses. Nontradable industries are indicated by *. We exclude Agriculture, Forestry, Fishing and Hunting (11), Utilities (22), and Public Administration (91) sectors due to the lack of data on domestic trade flows from the CBP data.

⁷⁶While some of these sub-categories are generic, our interpretation of FAR 4.606 suggests that the following sub-categories may not qualify for FPDS reporting: “23.1 Rental payments to GSA,” “23.2 Rental payments to others,” and “25.3 Other goods and services from Federal sources.”

B.3 Construction of the Trade Matrix

B.3.1 Adjusting the World I-O Table

The common assumption found in most national I-O tables is import proportionality, which assumes that an industry's imports of each input relative to its total demand is the same as the economy-wide imports relative to total demand (Feenstra and Jensen, 2012). The World IO Table (WIOT) in the WIOD database relaxes this assumption by allowing the import ratios to be different across 'intermediate use', 'gross fixed capital formation' and 'final consumption' categories. Yet, for intermediate use by industries, the WIOD still operates under the proportionality assumption that the ratios between imported use and total use are the same across industries for each input (Dietzenbacher *et al.*, 2013). Hence, the WIOT may understate the heterogeneity of import intensity of intermediate inputs among industries. Since the import share of component inputs serves as the key data moment for assessing the extent of bindingness of the domestic content restriction imposed by the BAA, we address the measurement issue based on the following procedure. Firstly, we acquire data on total imports by different manufacturing industries in the U.S., sourced from the Profile of US Importing and Exporting Companies from the U.S. Census Bureau (Profile). Secondly, for each manufacturing industry in the U.S., we rescale the WIOT data on imported intermediate inputs. This adjustment ensures that the data on imports for intermediate use aligns with the corresponding information from the Profile. Lastly, we proportionally rescale the WIOT data on the remaining US imports so that the total imports by the US remain consistent with the original WIOT dataset.

Figure B.1 presents a comparison between the import intensities of component inputs obtained from the adjusted WIOT data and those from the original data. Manufacturing industries in the U.S. generally exhibit low levels of foreign shares for their component inputs, with an average of 0.237 (resp., 0.215) for the adjusted data (resp., original data). Notably, the adjusted WIOT data unveils a more substantial variation in foreign import shares among industries. However, even with the adjusted data, only one industry, namely Electronic Product Manufacturing (334), has a foreign share above 50%. This suggests that the BAA restriction on the domestic content of component inputs is in general non-binding. If the domestic content requirement had been raised to 75% (or the foreign share is limited to 25%), a larger number of industries would have been subject to binding constraints. They include: Chemical (325), Machinery (333), Computer and Electronic Product Manufacturing (334), Electrical Equipment, Appliance, and Component Manufacturing (335), Transportation Equipment (336), and Furniture and Related Products, and Miscellaneous Manufacturing (337-339).

With the adjusted WIOT data, we obtain data on material input shares across industries in the U.S. $\alpha_{us,sk}$, import shares of each input across industries $\lambda_{row,s;us,k}^{i,G+M}$, and total output of each industry $X_{us,k}$ in the US, which are the data required for the imputation of trade shares $\lambda_{row,us,k'}^{f,G}$ $\lambda_{row,us,k'}^{f,M}$

$\lambda_{row,s;us,k}^{i,G}$ and $\lambda_{row,s;us,k}^{i,M}$

B.3.2 Imputation of $\lambda_{row,us,k'}^{f,G}$, $\lambda_{row,us,k'}^{f,M}$, $\lambda_{row,s;us,k}^{i,G}$ and $\lambda_{row,s;us,k}^{i,M}$

Using the FDPS data, we can break down the US final-use consumption of goods from each origin and industry into two components: the portion consumed by G and the portion consumed by M . Thereby, we can obtain the data on $\lambda_{row,us,k}^{f,G}$ and $\lambda_{row,us,k}^{f,M}$.

Now, we turn to the imputation of trade shares related to intermediate use. With the adjusted WIOT, we can read the import share of input s for an entire downstream industry k , $\lambda_{row,s;us,k}^{i,G+M}$ directly from the data. Specifically,

$$\begin{aligned}\lambda_{row,s;us,k}^{i,G+M} &= \frac{\lambda_{row,s;us,k}^{i,G} \alpha_{us,sk} X_{us,k}^G + \lambda_{row,s;us,k}^{i,M} \alpha_{us,sk} X_{us,k}^M}{\alpha_{us,sk} (X_{us,k}^G + X_{us,k}^M)} \\ &= \frac{X_{us,k}^G}{X_{us,k}^G + X_{us,k}^M} \lambda_{row,s;us,k}^{i,G} + \frac{X_{us,k}^M}{X_{us,k}^G + X_{us,k}^M} \lambda_{row,s;us,k}^{i,M}.\end{aligned}\quad (\text{B.1})$$

Here, $X_{us,k}^G$ is the output of k by G which we obtain from the FPDS data, and $X_{us,k}^M = X_{us,k} - X_{us,k}^G$ is the output of k by M . Through the lenses of our model, $\lambda_{row,s;us,k}^{i,G} \leq \lambda_{row,s;us,k'}^{i,M}$ where the strict inequality holds when the domestic content restriction is binding. To impute $\lambda_{row,s;us,k}^{i,G}$ and $\lambda_{row,s;us,k'}^{i,M}$ we adopt the following procedure:

1. If the domestic content restriction is non-binding for k , $\tau_k^{i,G} = 1$ and $\lambda_{row,s;us,k}^{i,G+M} = \lambda_{row,s;us,k}^{i,G} = \lambda_{row,s;us,k}^{i,M} \forall s$. Since $\lambda_{row,s;us,k}^{i,G} \leq \lambda_{row,s;us,k'}^{i,M}$ the observed relation $\sum_{s \in C} \frac{\alpha_{us,sk}}{\sum_{s' \in C} \alpha_{us,s'k}} \lambda_{row,s;us,k}^{i,G+M} < 0.5$ indicates the non-binding cases.
2. If the domestic content restriction is binding for k , the foreign content in the component inputs used by producers G satisfies:

$$\sum_{s \in C} \frac{\alpha_{us,sk}}{\sum_{s' \in C} \alpha_{us,s'k}} \lambda_{row,s;us,k}^{i,G} = 0.5 \quad (\text{B.2})$$

Since $\lambda_{row,s;us,k}^{i,G} \leq \lambda_{row,s;us,k'}^{i,M}$ the observed relation $\sum_{s \in C} \frac{\alpha_{us,sk}}{\sum_{s' \in C} \alpha_{us,s'k}} \lambda_{row,s;us,k}^{i,G+M} > 0.5$ indicates the binding cases. To impute $\lambda_{row,s;us,k}^{i,G}$ and $\lambda_{row,s;us,k'}^{i,M}$, there are two sub-cases to consider, depending on whether s belongs to the set C .

- (a) Case I: $s \in C$. For each downstream k that faces a binding constraint, equations (B.1) and (B.2) provide $S_C + 1$ restrictions. In order to solve for $2 \times S_C$ unknown variables (i.e., $\lambda_{row,s;us,k}^{i,G}$ and $\lambda_{row,s;us,k}^{i,M}$), we introduce an additional S_C number of model-consistent restrictions as follows:

$$\frac{\lambda_{row,s;us,k}^{i,G} / \lambda_{us,s;us,k}^{i,G}}{\lambda_{row,s;us,k}^{i,M} / \lambda_{us,s;us,k}^{i,M}} = \frac{\lambda_{row,s;us,k}^{i,G} / (1 - \lambda_{row,s;us,k}^{i,G})}{\lambda_{row,s;us,k}^{i,M} / (1 - \lambda_{row,s;us,k}^{i,M})} = (\tau_k^{i,G})^{-\theta_s}. \quad (\text{B.3})$$

In sum, for each downstream k that faces a binding constraint, we may solve for $2 \times S_C + 1$ unknowns $\{\lambda_{row,s;us,k}^{i,G}, \lambda_{row,s;us,k}^{i,M}, \tau_k^{i,G}\}$ with $2 \times S_C + 1$ equations (B.1), (B.2) and (B.3).

(b) Case II: $s \notin C$. $\lambda_{row,s;us,k}^{i,G+M} = \lambda_{row,s;us,k}^{i,G} = \lambda_{row,s;us,k}^{i,M}$.

B.3.3 Expanding the Adjusted World I-O Table

We now expand the adjusted WIOT so that it contains the eight blocks in the trade matrix in Figure B.2, including: (i) imports of intermediate inputs respectively by G and M in each US state from the ROW; (ii) imports of intermediate inputs by the ROW respectively from G and M in each U.S. state; (iii) interregional trade flows of goods for intermediate use among the U.S. states respectively for G and M ; (iv) trade flows of goods for intermediate use within the ROW; (v) imports of goods for final-use consumption respectively by G and M in each U.S. state from the ROW; (vi) imports of goods for final-use consumption by the ROW respectively from G and M in each U.S. state; (vii) interregional trade flows of goods for final-use consumption among the US states respectively for G and M ; and (viii) trade flows of goods for final-use consumption within the ROW.

The imputation is implemented by combining the information derived from various datasets, including the FPDS, WIOD, Commodity Flow Survey (CFS), and the County Business Patterns (CBP). Specifically, we use information from the CFS for the year 2012, which is the closest available year to 2014. The CFS survey tracks pairwise trade flows between different industries across US states. We map the CFS industries, which are defined by various 3- to 5-digit NAICS codes, to the corresponding NAICS industries described in subsection B.2. Having constructed the bilateral trade flows for these NAICS industries, we compute: (i) how much of the sectoral expenditure of each state is spent on goods from each of the U.S. states, and (ii) how much of the sectoral revenue of each state is generated from sales to each of the U.S. states. We employ the CBP data for the year 2014, which tracks employment by county and industry. To protect confidentiality, employment for county-industry cells is sometimes reported as an interval instead of exact count. We employ the imputed dataset developed by Eckert *et al.* (2020) and aggregate the employment data to the state-industry level. With the data, we calculate the employment share of each state within each industry and the population share of each state.

Equipped with these data, we adopt the following approach to construct the matrix for each block:

(i) Imports of intermediate inputs respectively by G and M in each US states from the ROW

The imports of intermediate inputs by G in each US state from the ROW is computed as follows:

$$X_{row,s;d,k}^{i,G} = \lambda_{row,s;us,k}^{i,G} \alpha_{us,sk} X_{d,k}^G \quad \forall d \in US,$$

where $X_{d,k}^G$ is the G output of good k in state d , which is derived from the FPDS data. A portion $\lambda_{row,s;us,k}^{i,G}$ of the corresponding expenditure on input s (i.e., $\alpha_{us,sk} X_{d,k}^G$) is sourced from the ROW.

Analogously, the imports of intermediate inputs by M in each state from the ROW is computed according to:

$$X_{row,s;d,k}^{i,M} = \lambda_{row,s;us,k}^{i,M} \alpha_{us,sk} \left(\frac{L_{dk}}{L_k} X_{us,k}^M \right) \quad \forall d \in US,$$

where we apportion the total M output of good k in the U.S. to each state according to its employment share L_{dk}/L_k to calculate the state-level M output.

(ii) *Imports of intermediate inputs by the ROW respectively from G and M in each US state*

Given the setup of our model, G producers only serve demand from G final-use consumption in the US. Therefore, the imports of intermediate inputs by the ROW from G producers in each state is zero. The imports of intermediate inputs by the ROW from M producers in each US state is calculated as follows:

$$X_{o,s;row,k}^{i,M} = \frac{L_{os}}{L_s} X_{us,s;row,k}^{i,M} \quad \forall o \in US,$$

where we apportion the imports of inputs s by industry k in the ROW (i.e., $X_{us,s;row,k}^{i,M}$) to each US state according to its employment share in industry s (i.e., L_{os}/L_s).

(iii) *Inter-regional trade flows of goods for intermediate use among the US states respectively for G and M*

Since G producers only serve demand from G final-use consumption in the U.S., there are no trade flows of inputs from G producers to M or G producers among the states. Now, we consider the trade flows of inputs from M to G :

$$X_{o,s;d,k}^{i,G} = \frac{F_{ods}}{F_{ds}} (1 - \lambda_{row,s;us,k}^{i,G}) \alpha_{us,sk} X_{d,k}^G \quad \forall o, d \in US,$$

where $(1 - \lambda_{row,s;us,k}^{i,G}) \alpha_{us,sk} X_{d,k}^G$ represents the expenditure on goods s that originates from the US. We then compute how much of the sectoral expenditure of each state is spent on goods from each of US states. We do so by applying the expenditure share F_{ods}/F_{ds} calculated with the 2014 CFS data. Similarly, the trade flows of inputs from M to M is computed according to:

$$X_{o,s;d,k}^{i,M} = \frac{F_{ods}}{F_{ds}} (1 - \lambda_{row,s;us,k}^{i,M}) \alpha_{us,sk} \left(\frac{L_{dk}}{L_k} X_{us,k}^M \right) \quad \forall o, d \in US.$$

(iv) *Trade flows of goods for intermediate use within the ROW*

The data on $X_{row,s;row,k}^i$ is obtained from the original WIOT.

(v) *Imports of goods for final-use consumption respectively by G and M in each US state from the ROW*

For G final-use consumption, imports of good s from the ROW, $X_{row,d,s}^{f,G}$, is the data taken from the FPDS. For M final-use consumption, imports of good s from the ROW is calculated as follows:

$$X_{row,d,s}^{f,M} = \frac{L_d}{L} X_{row,us,s}^{f,M} \quad \forall d \in US,$$

$$\text{where } X_{row,us,s}^{f,M} = X_{row,s}^M - \sum_{d \in US} \sum_k X_{row,s;d,k}^{i,G} - \sum_{d \in US} \sum_k X_{row,s;d,k}^{i,M} - \sum_k X_{row,s;row,k}^{i,M} - \sum_{d \in US} X_{row,d,s}^{f,G} - X_{row,row,s}^{f,M}.$$

We allocate the nationwide imports of final-use goods by M (i.e., $X_{row,us,s}^{f,M}$) to each state according to their respective population shares L_d/L . $X_{row,us,s}^{f,M}$, in turns, is determined as the difference of total sectoral output in the ROW and the combined demands arising from intermediate use in both the U.S. and the ROW, and final consumption by G in the US and the ROW.

(vi) Imports of goods for final-use consumption by the ROW respectively from G and M in each US state

As G producers only serve demand from G final-use consumption in the US, there are no trade flows of final goods from G producers to the ROW. To calculate the state-level trade flows from M to the ROW, we distribute the US sectoral exports to each state based on its respective employment share:

$$X_{o,row,s}^{f,M} = \frac{L_{os}}{L_s} X_{us,row,s}^{f,M} \quad \forall o \in US.$$

(vii) Interregional trade flows of goods for final-use consumption among the US states respectively for G and M

As G final-use consumption is sourced only from G producers, the data on trade flows $X_{ods}^{f,G} \quad \forall o, d \in US$ is obtained from the FPDS. In addition, since G producers only serve demand from G final-use consumption in the US, there are no trade flows of final goods from G producers to M final-use consumers. In principle, the trade flows from M producers to M consumers can be computed as follows:

$$X_{ods}^{f,M} = \frac{F_{ods}}{F_{ds}} \left(\frac{L_{os}}{L_s} X_{us,us,s}^{f,M} \right) \quad \forall o, d \in US,$$

$$\text{where } X_{us,us,s}^{f,M} = X_{us,s}^M - \sum_{d \in US} \sum_k X_{us,s;d,k}^{i,G} - \sum_{d \in US} \sum_k X_{us,s;d,k}^{i,M} - \sum_k X_{us,s;row,k}^{i,M} - X_{us,row,s}^{f,M}.$$

The domestic final-use expenditure by M (i.e., $X_{us,us,s}^{f,M}$) is allocated to producers in each state according to their respective employment shares L_{os}/L_s . We then distribute the state-level output to consumers across different states by applying the revenue share F_{ods}/F_{ds} calculated with the 2014 CFS data. $X_{us,us,s}^{f,M}$, in turns, is determined as the difference of total sectoral output by M in the US and the combined demands arising from intermediate use in both the US and the ROW, and final consumption by the ROW.

The above imputation procedure yields several problematic cases where the total imputed

expense on inputs exceeds the total output for some os :⁷⁷

$$\sum_{o'} \sum_{s'} X_{o's',os}^{i,M} > \sum_{d \in US} \sum_k X_{os,dk}^{i,G} + \sum_{d \in US} \sum_k X_{os,dk}^{i,M} + \sum_k X_{os,row,k}^{i,M} + \sum_{d \in US} X_{ods}^{f,M} + X_{o,row,s}^{f,M}.$$

To address the problem, we adjust the imputed $X_{ods}^{f,M}$. We begin by identifying os where $\sum_{o'} \sum_{s'} X_{o's',os}^{i,M} > \sum_{d \in US} \sum_k X_{os,dk}^{i,G} + \sum_{d \in US} \sum_k X_{os,dk}^{i,M} + \sum_k X_{os,row,k}^{i,M} + X_{o,row,s}^{f,M}$. In such instances, we proceed to allocate a portion of total domestic final-use expenditure by M , $X_{us,us,s'}^{f,M}$ to o . The portion is denoted by $\tilde{X}_{os}^{f,M}$, and it is chosen so that $\sum_{o'} \sum_{s'} X_{o's',os}^{i,M} = \sum_{d \in US} \sum_k X_{os,dk}^{i,G} + \sum_{d \in US} \sum_k X_{os,dk}^{i,M} + \sum_k X_{os,row,k}^{i,M} + X_{o,row,s}^{f,M} + \tilde{X}_{os}^{f,M}$. (For other cases, $\tilde{X}_{os}^{f,M} = 0$.) The remaining domestic expenditure by M , denoted by $\tilde{X}_{us,us,s'}^{f,M}$ is then apportioned to producers in each state according to their respective employment shares. The revised interregional trade flows are then given by:

$$\tilde{X}_{ods}^{f,M} = \frac{F_{ods}}{F_{ds}} \left(\tilde{X}_{os}^{f,M} + \frac{L_{os}}{L_s} \tilde{X}_{us,us,s'}^{f,M} \right) \quad \forall o, d \in US.$$

(viii) *Trade flows of goods for final-use consumption within the ROW*

The data on $X_{row,row,s}^{f,M}$ is obtained from the original WIOT.

The final product of the imputation is an expanded bilateral trade flows matrix as is shown in Table E.1. The above approach ensures that: (a) the aggregation of the expanded I-O table to the country-sector level remains consistent with the original data, and (b) the data on bilateral trade flows of G goods aligns with the FPDS data. For each state-sector, the value added is calculated as the difference between the sectoral output and the sectoral expense on intermediate inputs.

B.4 Data Employed for the Reduced Form Analysis

B.4.1 BEA Local Area Personal Income and Employment Database

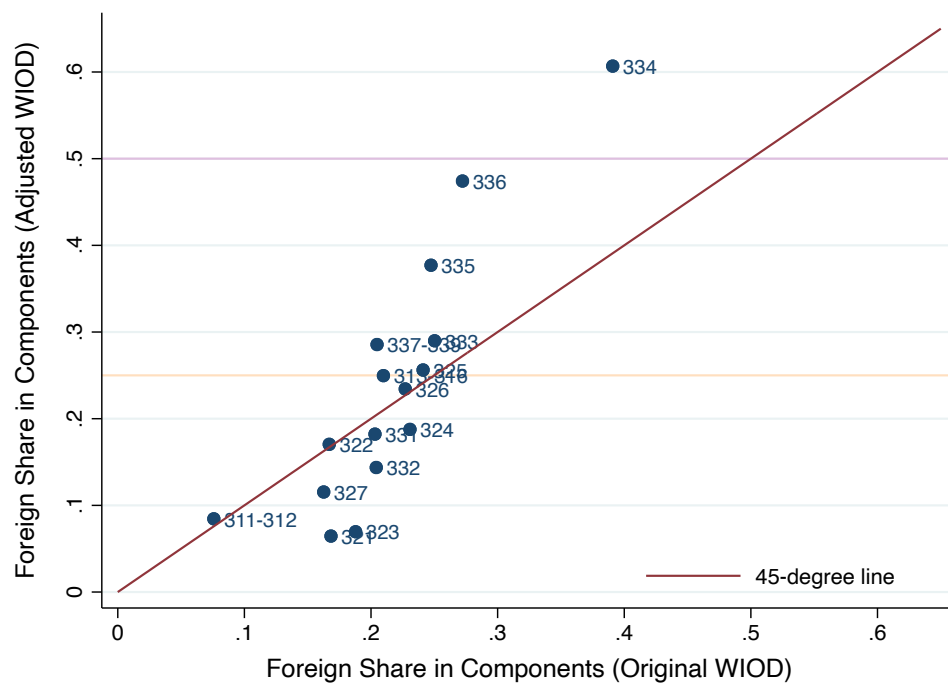
To construct measures of labor market outcomes in the reduced form analysis in Section 6, we employ data from BEA Local Area Personal Income and Employment Database, which provides disaggregated information on employment and personal income by county and sector. The BEA data primarily relies on comprehensive quarterly tabulations of unemployment insurance contribution reports, which are used by the Bureau of Labor Statistics to construct the Quarterly Census of Employment and Wages (QCEW). Additionally, the BEA incorporates supplementary data sources to account for employment in industries that may not be fully covered by unemployment insurance, resulting in slightly broader coverage of employment compared to the QCEW (Autor *et al.*, 2021). We aggregate the data from the county to the CZ level.

⁷⁷In the data, 7.8% of the os observations for which the total imputed expense on inputs exceeds the total output.

B.4.2 Summary Statistics

Table B.3 provides the summary statistics for the key variables employed in the reduced form analysis. We focus on the procurement shock $\Delta FPDS_PW$ and its IV $\Delta FPDS_PW^{IV}$, along with three outcome variables of interest: the manufacturing-to-working-age population ratio, the total wage and salary employment-to-working-age population ratio, and the logarithm of personal income per capita. The average 5-year output expansion for G procurement, $\Delta FPDS_PW$, across CZs and periods is 0.159. Moreover, the standard deviation is 2.947, highlighting the substantial spatial and temporal variation of the procurement shocks. The distribution of $\Delta FPDS_PW^{IV}$ exhibits a higher average but less dispersion in comparison to that of $\Delta FPDS_PW$. Manufacturing employment demonstrates a secular decline, with the 5-year growth in the manufacturing-to-working-age population ratio having an average of -0.6 percentage point. Still, CZs in the right-tail of the distribution experienced an expansion of manufacturing employment. For instance, CZs at the 90th percentile witnessed an increase of 1 percentage point in the ratio. For the total wage and salary employment-to-working-age population ratio, the median of 5-year growth stands at 0, indicating a stable trend. However, there is a notable standard deviation of 4.2 percentage points, revealing the variability across space and time. Lastly, for the 5-year growth of per capita personal income, our sample reveals an average of 13.2% and a standard deviation of 9.9%.

Figure B.1: Import Share in Total Component Inputs Used



Notes: This figure reports the foreign shares in component inputs used by different downstream industries in the manufacturing sector. The horizontal axis variable represents the foreign shares calculated from the original WIOD data, while the vertical axis variable is the adjusted foreign shares derived from the procedure detailed in Appendix B.3.1.

Figure B.2: The Structure of Extended World Input-Output Table

				Input use & value added															Final use					Total use			
				US										ROW					US			ROW					
				$d_{1, M}$			$d_{1, G}$...	$d_{N, M}$			$d_{N, G}$			$d_{1, M}$			$d_{1, G}$...	$d_{N, M}$	$d_{N, G}$				
				s_1	...	s_K	s_1	...	s_K	...	s_1	...	s_K	s_1	...	s_K	s_1	...	s_K	$d_{1, M}$	$d_{1, G}$...	$d_{N, M}$	$d_{N, G}$	ROW		
Output Supplied	US	$o_{1, M}$	s_1							...																	
																			
			s_K								...																
		$o_{1, G}$	s_1																								
			...																								
			s_K																								
	ROW	$o_{N, M}$	s_1							...																	
																			
			s_K								...																
		$o_{N, G}$	s_1																								
			...																								
			s_K																								
	Value added		s_1							...																	
	Gross output																		

Notes: As G producers only cater for the demand from G final-use consumption within the US, there are no trade flows of goods for intermediate use from G producers to G and M producers in either the U.S. or the ROW. Similarly, there are no trade flows of goods for final-use consumption from G producers to M consumers nor trade flows from M producers to G consumers in either the U.S. and the ROW. The relevant cells in the table are shaded in gray.

Table B.1: Comparison of FPDS and US Gov. Budget

Fiscal Year	FPDS (\$ Amount BN)	Budget US Gov. Obj. Class 20	
		All (\$ Amount BN)	Minus 23.1, 23.2, 25.3 (\$ Amount BN)
2001	235.0	256.6	201.9
2002	303.7	328.7	270.5
2003	352.3	387.8	310.9
2004	321.1	401.6	325.5
2005	388.0	405.7	319.3
2006	391.9	437.0	350.8
2007	414.6	465.4	367.4
2008	452.0	494.4	389.9
2009	415.0	531.8	429.9
2010	420.4	553.8	444.5
2011	448.6	527.8	424.7
2012	418.2	583.1	409.2
2013	359.1	485.5	367.3
2014	376.0	503.6	369.1
2015	369.1	507.0	404.5
2016	394.3	509.7	409.3
2017	451.8	544.1	444.3
2018	398.9	544.1	444.3
2019	357.2	639.7	530.1

Notes: This table compares FPDS's amounts relative to U.S. Gov Budget's Object Class 20: "Contractual Services and Supplies," reported by the Office of Management and Budget (OMB). Column 4 excludes the following three sub-categories that are unlikely to be reported in FPDS: "23.1 Rental payments to GSA", "23.2 Rental payments to others", and "25.3 Other goods and services from Federal sources." The federal government's fiscal year begins on October 1st and ends on September 30th the following year.

Table B.2: Federal Procurement: Top 20 Manufacturing NAICS

Rank	NAICS	Name	Contracts/year (thousand)	Amount/year (billion)
1	336411	Aircraft Manuf.	3.41	30.92
2	336611	Ship Building and Repairing	4.60	13.99
3	336414	Guided Missile and Space Vehicle Manuf.	0.14	9.55
4	336413	Other Aircraft Parts and Auxiliary Equip. Manuf.	22.36	9.17
5	334511	Search, Detection, Navigation, Guidance, Aeronautical, and Nautical Syst. and Instr. Manuf.	4.46	7.96
6	336412	Aircraft Engine and Engine Parts Manuf.	4.57	4.55
7	324110	Petroleum Refineries	16.19	3.99
8	334220	Radio and Television Broadcasting and Wireless Communications Equip. Manuf.	6.70	2.78
9	336992	Military Armored Vehicle, Tank, and Tank Component Manuf.	2.16	2.53
10	334111	Electronic Computer Manuf.	18.61	2.48
11	332993	Ammunition (except Small Arms) Manuf.	0.35	1.98
12	336419	Other Guided Missile and Space Vehicle Parts and Auxiliary Equip. Manuf.	0.39	1.83
13	334290	Other Communications Equip. Manuf.	5.13	1.63
14	325412	Pharmaceutical Preparation Manuf.	2.18	1.55
15	336112	Light Truck and Utility Vehicle Manuf.	7.57	1.28
16	325414	Biological Product (except Diagnostic) Manuf.	0.62	1.18
17	332410	Power Boiler and Heat Exchanger Manuf.	0.38	1.08
18	334419	Other Electronic Component Manuf.	7.62	1.03
19	336212	Truck Trailer Manuf.	0.51	0.75
20	336111	Automobile Manuf.	13.02	0.67

Notes: This table describes the top 20 six-digit NAICS codes in terms of annual spending. Column 4 and 5 show the average number of contracts and amount per year in FPDS. These averages are calculated between 2001 and 2019.

Table B.3: Summary Statistics

	mean	std	10 th	25 th	50 th	75 th	90 th
Mfg empl/working-age pop (2001)	0.098	0.063	0.023	0.048	0.089	0.136	0.182
Mfg empl/working-age pop (2016)	0.077	0.053	0.021	0.038	0.067	0.102	0.144
$\Delta FPDS.PW$	0.159	2.947	-0.588	-0.104	0.011	0.293	1.086
$\Delta FPDS.PW^{IV}$	0.214	0.903	-0.498	-0.270	0.069	0.564	1.077
Δ Mfg empl/working-age pop	-0.006	0.016	-0.025	-0.013	-0.004	0.002	0.010
Δ Total wage and salary empl/working-age pop	0.003	0.042	-0.043	-0.017	0.000	0.029	0.051
Δ Log personal income per capita	0.132	0.099	0.017	0.046	0.138	0.194	0.236

Notes: This table reports the summary statistics of the independent and dependent variables employed in the reduced-form analysis in Section 6.

C National Security

We define a six-digit industry NAICS as subject to national security (NS) concerns based on contract-level information in FPDS. The Federal Acquisition Regulation (FAR Part 6.3) lays out a number of conditions for contracting without providing for full and open competition.⁷⁸ One of the exemptions, called “National Security” (FAR 6.302-6), considers that a procurement officer is allowed to restrict competition “when the disclosure of the agency’s needs would compromise the national security [...] contracts awarded using this authority shall be supported by the written justifications and approvals.” Between 2000 and 2019, we observe 32 thousand contracts that use the exemption to restrict competition. Even though the fraction of contracts that use this exemption is low, it is concentrated on specific industries, as 68% of all NAICS in FPDS never use this exception.⁷⁹

Using these data, we define that a six-digit NAICS as subject to NS concerns (for BAA removal counterfactual) if the NAICS has at least 1% of contracts using the National Security Exemption. Table C.1 lists all the six-digit NAICS that meet these criteria.⁸⁰ The main Manufacturing industries (in terms of spending) subject to NS are “Other Guided Missile and Space Vehicle Parts,” “Light Truck and Utility Vehicle Manufacturing,” “Automobile Manufacturing” and “Explosives Manufacturing”. Once we define the list of six-digit industries subject to NS, we can aggregate at the three-digit sector level. The two sectors affected by NS concerns are “Chemical (325)” and “Transportation Equipment (336).” The fraction of procurement spending subject to NS in each of these two sectors is roughly 5%.

Table C.1: NAICS Subject to National Security Concerns

NAICS	Name	(1) Fraction (%)	(2) Total Amount (M \$)
928110	National Security	10.78%	2,910
483114	Coastal and Great Lakes Passenger Transportation	2.89%	167
336111	Automobile Manufacturing	2.00%	13,800
336112	Light Truck and Utility Vehicle Manufacturing	1.58%	27,100
423140	Motor Vehicle Parts Merchant Wholesalers	1.49%	21
921190	Other General Government Support	1.42%	12,600
325920	Explosives Manufacturing	1.32%	4,310
336419	Other Guided Missile and Space Vehicle Parts and Auxiliary Equip. Manuf.	1.12%	33,500

Notes: This table presents the six-digit NAICS codes whose share of contracts with NS exception exceed 1%, i.e., meet the 1% NS rule. Column (1) shows the percentage of contracts that use the exemption. Column (2) shows the aggregate amount (in millions of dollars) of spending in each NAICS. Both measures are calculated using the complete FPDS sample (2001-2019). We exclude from the table a few small NAICS that applied the exemption less than ten times in the twenty-year window.

⁷⁸The most commonly used exceptions under FAR 6.3 are “Only One Source-Other (FAR 6.302-1 other),” “Authorized by Statute (FAR 6.302-5(a)(2)(i)),” “Simplified Acquisition Procedure Non-Competition (FAR 13),” “Urgency (FAR 6.302-2),” and “Follow-On Contract (FAR 6.302-1(a)(2)(ii/iii))”

⁷⁹The fraction of contracts using this exemption is in part low because the procurement office can avoid (full and open) competition under any of the other statutes granted in FAR 6.3.

⁸⁰The list excludes a few small NAICS that rarely appear in FPDS and have fewer than ten contracts with the National Security exemption.

D Bidding in the US Federal Procurement

D.1 Registration

To bid on contracts within the U.S. federal procurement system, companies must fulfill the requirement outlined in FAR 4.1102, which mandates that prospective contractors must be enrolled in the SAM database when submitting an offer or quotation. Enrollment can be done online through SAM.gov, with no associated fees, although companies are required to provide detailed information during the registration process. For example, both domestic and international entities need to verify their legal physical address or business name by submitting original documentation, like utility bills or bank statements, along with a self-certified translation if the original documents are not in English⁸¹. Moreover, they need to provide “points of contact,” which include the names of individuals within the organization who are knowledgeable about the registration process on SAM.gov and the reasons behind the entity’s interest in conducting business with the U.S. Federal government. Furthermore, to commence the registration process, entities must be linked to a DUNS number, a distinctive nine-digit identification code issued by Dun & Bradstreet (D&B). If an entity lacks a DUNS number, they can obtain one at no cost by visiting D&B, and the process typically takes 1-2 business days.⁸²

Nevertheless, certain details are exclusively mandated for domestic entities. For example, they must disclose the entity’s Tax ID Number (TIN), which is an employer identification number issued by the Internal Revenue Service. Acquiring a new EIN from the IRS typically takes 2-5 weeks. However, foreign entities that do not have U.S. employees are exempt from providing this information. Additionally, domestic companies must furnish their Electronic Funds Transfer details.

Before 2023, the primary distinction in the registration process for entities located outside the United States was the requirement to obtain an NCAGE (NATO Commercial and Government Entity) code first. This code serves as a unique identifier for suppliers to various government or defense agencies and is administered by NATO and the Ministry of Defense of the respective countries where the entities are based. Obtaining an NCAGE code could take varying amounts of time, with a minimum of 3 days. In contrast, U.S.-based entities were not required to apply for an NCAGE code. Once they submitted their registration on SAM for processing, SAM would forward their entity information to the Department of Defense’s Defense Logistics Agency (DLA)

⁸¹The self-certification is accompanied with the following text: “I [insert typed name], certify that I am fluent (conversant) in the English and [insert foreign language] languages, and that the above/attached document is an accurate translation of the document attached entitled [insert translated document name]. [Signature] [Typed Name] [Address] [Certification Date]”

⁸²In 2022, the Unique Entity ID, or UEI (SAM), replaced the DUNS number as the official government-wide identifier used for federal awards. The DUNS number is no longer used in the registration process for entities seeking to do business with the federal government.

for CAGE Code assignment. The DLA would assign the CAGE Code, which SAM would then receive and apply to the Entity Registration. Typically, no further action by the registrant was necessary unless the DLA requested additional information.⁸³

There are no registration fees for obtaining DUNS, NCAGE, CAGE, or SAM. Once all the required information is provided, it typically takes up to 10 business days to have an active profile in SAM. Once active, the entity can then pursue bidding opportunities with the U.S. government. SAM.gov mandates organizations to maintain their registration by verifying and updating information annually. An active registration is crucial for organizations to receive payments on existing awards and to be eligible for new awards or amendments.

D.2 Evaluation of Bids

For the evaluation of supply contracts, currently FAR Subpart 25.5 requires the contracting officer to perform the following steps in the order presented (unless otherwise specified in agency regulations):

1. Eliminate all offers or offerors that are unacceptable for reasons other than price; e.g., nonresponsive, debarred or suspended, or a prohibited source.
2. Rank the remaining offers by price.
3. If the solicitation specifies award on the basis of factors in addition to cost or price, apply the evaluation factors as specified and use the evaluated cost or price in determining the offer that represents the best value to the Government.

For acquisitions covered by the WTO GPA, the Contracting Officer must follow the following steps:

1. Consider only offers of U.S.-made or designated country end products, unless no offers of such end products were received;
2. If the agency gives the same consideration given eligible offers to offers of U.S.-made end products that are not domestic end products, award on the low offer. Otherwise, evaluate in accordance with agency procedures; and
3. If there were no offers of U.S.-made or designated country end products, make a nonavailability determination and award on the low offer.

For acquisitions not covered by the WTO GPA, but subject to the Buy American statute (an FTA or the Israeli Trade Act also may apply), the following applies:

- If the low offer is a domestic offer or an eligible offer under an FTA or the Israeli Trade Act, award on that offer.

⁸³Since February 2023, foreign-based entities no longer have to procure an NCAGE code.

- If the low offer is a noneligible offer and there were no domestic offers, award on the low offer. If the low offer is a noneligible offer and there is an eligible offer that is lower than the lowest domestic offer, award on the low offer.
- Otherwise, apply the appropriate evaluation factor provided in 25.106 to the low offer. If the evaluated price of the low offer remains less than the lowest domestic offer, award on the low offer. If the price of the lowest domestic offer is less than the evaluated price of the low offer, award on the lowest domestic offer.

When submitting a bid for construction contracts, a contractor can request a waiver based on unreasonable cost by presenting a reasonable survey of the market and a completed price comparison table as specified in FAR 52.225-9 and reported in Figure D.1. The contractor requesting a waiver must include several information in the survey of suppliers: a description of the foreign and domestic construction materials; unit of measure; quantity; and price, which must include all delivery costs to the construction site and any applicable duty. Moreover, the contractor must list name, address, telephone number, and contact for suppliers surveyed.

Figure D.1

Foreign and Domestic Construction Materials Price Comparison			
<u>Construction Material Description</u>	<u>Unit of Measure</u>	<u>Quantity</u>	<u>Price (dollars)*</u>
Item1:			
Foreign construction material	_____	_____	_____
Domestic construction material	_____	_____	_____
Item2:			
Foreign construction material	_____	_____	_____
Domestic construction material	_____	_____	_____

E Calibration: Additional Details

E.1 Robustness: Measuring the BAA Wedges

E.1.1 Compositional Bias

To assess the potential compositional biases, we turn to the more disaggregated data, specifically obtained from the U.S. Census Bureau for trade flow information, and from the NBER-CES Manufacturing Industry Database for output data. Together with the granular data from the FPDS, we may calculate the import shares $\lambda_{row,us,\zeta}^G$ and $\lambda_{row,us,\zeta}^M$ for G and M , respectively, for 6-digit NAICS codes (ζ) that belong to different aggregated industries (s) in the manufacturing sector. Note that due to the lack of world I-O table at the disaggregated level, we are unable to distinguish imports between final consumption and intermediate use. Hence, the following analyses should be interpreted through the lenses of a simplified model that assumes away the input-output linkages.⁸⁴

We first explore whether, within an aggregate industry s , G allocates more expenditure to the sub-industries with lower inherent import intensities which is reflected by $\lambda_{row,us,\zeta}^M$. Specifically, in column (1) (resp., column (2)) of Table E.2, we relate $\beta_{\zeta,s}^G$ (resp., $\beta_{\zeta,s}^M$) to $\lambda_{row,us,\zeta}^M$ where $\beta_{\zeta,s}^G$ (resp., $\beta_{\zeta,s}^M$) represents G 's (resp., M 's) expenditure share on goods from ζ within the aggregated industry s , as is measured from the FDPS data. The estimated correlations with $\lambda_{row,us,\zeta}^M$ are insignificant and statistically the same for G and M . The results are consistent when we include aggregated industry fixed effects in columns (3) and (4).

Using the disaggregated data, we can estimate the BAA wedges according to $\tau_{\zeta}^G = \left(\frac{\lambda_{row,us,\zeta}^G / \lambda_{us,us,\zeta}^G}{\lambda_{row,us,\zeta}^M / \lambda_{us,us,\zeta}^M} \right)^{-1/\theta_s}$. The underlying Eaton-Kortum structure of our baseline model implies that all of the trade shares are strictly positive. However, approximately 30% of the 6-digit NAICS industries (in the manufacturing sector) exhibit zero import values for G . To address this, we take a pragmatic approach of replacing each zero with a small positive constant ($1e^{-4}$) that is less than the smallest positive import value seen in the FPDS data. We then adopt alternative approaches to estimate the BAA wedges by employing data at different aggregation levels. The baseline approach uses the data at the level of aggregated industries (s) and estimate the wedges according to $\tau_s^G = \left(\frac{\lambda_{row,us,s}^G / \lambda_{us,us,s}^G}{\lambda_{row,us,s}^M / \lambda_{us,us,s}^M} \right)^{-1/\theta_s}$. The alternative approach first estimates the wedges at the 6-digit NAICS level, τ_{ζ}^G , and then aggregates the wedges to the corresponding aggregated industry based on $\tau_s^G = \prod_{\zeta \in s} (\tau_{\zeta}^G)^{\beta_{\zeta,s}^G}$.

Figure E.1 compares the estimates of $\theta_s \ln(\tau_s^G)$ from these two approaches. They align closely with the 45-degree line across most industries, except 311-312 (Food Products, Beverages, and Tobacco Products). This outlier observation is driven by the fact that we observe zero import values

⁸⁴The bias of calibrated BAA wedges, due to the omission of input-output linkages, is attributed to the potential differences of unit costs of production between G and M producers, $c_{us,s}^G / c_{us,s}^M$. The bias is zero for most industries, where the domestic content restriction on component inputs is non-binding implying that $c_{us,s}^G / c_{us,s}^M = 1$.

for G in over 75% of the 6-digit NAICS codes within this aggregated industry. An imputation of a small positive value may artificially generate a large estimate of τ_s^G .

The findings presented in Table E.2 and Figure E.1 suggest that there is no systematic correlation between expenditure shares of G (respectively, M) and inherent import intensities across 6-digit NAICS industries. The remaining issue is the potential presence of compositional biases within 6-digit NAICS industries. For instance, in the case where G procures a greater proportion of aircraft varieties characterized by higher level of specificity which perhaps have lower import intensities due to national security considerations, the calibrated wedge $(\tau_c^G)^{\theta_s}$ for the 6-digit industry "Aircraft Manufacturing" would be upwardly biased. To alleviate this concern, we compare the distributions of $\theta_s \ln(\tau_c^G)$ by groups of industries with different degree of product differentiation.⁸⁵ The idea is that if the aforementioned issue is valid, we should expect the distribution of the group with a high degree of differentiation to exhibit first-order stochastic dominance over that of the group with a low degree of differentiation. However, Figure E.2 reveals the opposite pattern.⁸⁶

Taken together, our baseline estimated wedges based on the aggregated data are unlikely to be biased upward due to different expenditure compositions between G and M . If anything, the baseline approach may understate trade barriers due to the "Buy American" restrictions for the outlier industry 311-312 (Food Products, Beverages, and Tobacco Products).

E.1.2 Separating Costs Not Directly Related to BAA Restrictions from the Broader Measure of BAA Wedges

To separate the costs that are not directly associated with the BAA restrictions from the broader measure of BAA wedges $\tau_s^{f,G}$, we take advantage of two institutional features: (i) federal procurement conducted in regions outside of the US is not subject to the same stringent limitations on the purchase of foreign manufacturing products, while (ii) the additional costs (or home bias) faced by foreign producers, such as those arising from extra efforts to understand the US government procurement auction process, should be present regardless the procurement location.

Specifically, when the procurement is conducted within the U.S., we assume that the broader measure of BAA wedges on imported final goods can be expressed in a multiplicative form as

⁸⁵Specifically, we employ the data from Rauch (1999), which classifies industries into one of the following three categories: homogeneous, reference priced, and differentiated products, according to the 4-digit SITC Rev.2 system. We map the data to the 6-digit NAICS codes, using the crosswalks that match between the 4-digit SITC and 6-digit HS codes and between the 6-digit HS and 6-digit NAICS codes. Our constructed measure of differentiation reflects the share of 6-digit HS goods that are classified as differentiated products within a 6-digit NAICS industry. The industries are then classified as Differentiated or Non-differentiated depending on whether the corresponding differentiation measure is above or below the median.

⁸⁶The finding may be consistent with the provisions embedded in the BAA that grant exemptions to procurement involving products not available in the US.

follows:

$$\tau_s^{f,G} = t_s^{f,G} t^e \quad (\text{E.1})$$

where $t_s^{f,G}$ denotes the trade barriers directly resulting from the BAA restriction, and t^e is the additional cost (or home bias) faced by foreign producers in contract bidding which is invariant across industries. When the procurement is conducted outside of the U.S., the ‘‘Buy American’’ restrictions no longer apply, and hence the wedges becomes $\tau_s^{f,G} = t^e$. Our goal is to separately identify $t_s^{f,G}$ given the calibrated $\tau_s^{f,G}$ obtained from the procedure outlined in Section 5.4. To accomplish this, we first calibrate t^e in equation (E.1) using the approach as follows.

Take a region j outside of the US, and consider the following data moment implied by the model:

$$\frac{\lambda_{j,j}^{f,G} / \lambda_{us,j}^{f,G}}{\lambda_{j,j}^{f,M} / \lambda_{us,j}^{f,M}} = (t^e)^{-\theta} \quad (\text{E.2})$$

where $\lambda_{j,j}^{f,G}$ is the share of procurement used in j that is sourced from j ; $\lambda_{us,j}^{f,G}$ represents the share of procurement used in j that is sourced from the US; $\lambda_{j,j}^{f,M}$ denotes the share of imports by j that is sourced from j itself; and $\lambda_{us,j}^{f,M}$ is the share of imports by j that is sourced from the US. The equality follows given the assumption that $\tau_{j,j}^{f,G} = \tau_{j,j}^{f,M} t^e$. That is, producers from j encounter an additional bidding cost t^e when selling to the US agencies in j , as opposed to selling to the market in j .

There are some notes to make about this approach. Firstly, the data is aggregated at the country level since t^e does not vary across industries. Secondly, although procurement conducted outside of the US is not subjected to the same stringent BAA restrictions as those conducted within the US, some restrictions still apply.⁸⁷ Hence, the calibrated value of t_e based on equation (E.2) still incorporates trade barriers linked to some domestic content restrictions, resulting in an upward bias. Therefore, we consider the calibrated t_e to be an upper bound of the true value of home bias.

In our calibration, region j consists of 15 early EU members, namely: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and the United Kingdom. The data on $\lambda_{j,j}^{f,G}$ and $\lambda_{us,j}^{f,G}$ are computed using the FPDS data, and the information on $\lambda_{j,j}^{f,M}$ and $\lambda_{us,j}^{f,M}$ are inferred from the WIOD data. We set $\theta = 4.21$, which is the average of θ_s across the manufacturing industries. The calibrated value of t^e is 1.28. We then back out $t_s^{f,G}$ according to equation (E.1), which could be lower bound for the true value. The mean of $\theta_s \ln(t_s^{f,G})$ across manufacturing industries is 2.20, which implies that the BAA restrictions reduce imports by G consumers by 88.9%⁸⁸ on average.

⁸⁷For instance, one notable restriction that still applies is the Berry Amendment, which effectively raises the BAA domestic content requirement to 100%. The restriction covers food, clothing, fabrics, fibers, yarns, other made-up textiles.

⁸⁸Calculated as $100 * (\exp(-2.20) - 1)$.

E.2 Changes in $\tau_k^{i,G}$ When the Domestic Content Restriction on Component Inputs is Tightened

When the domestic content share on components for G production is raised from 0.5 to $\underline{\zeta}$, the restriction could start being binding for some industries. For example, industries with $\sum_{s \in C} \frac{\alpha_{us,sk}}{\sum_{s' \in C} \alpha_{us,s'k}} \lambda_{row,s;us,k}^{i,G+M} > 1 - \underline{\zeta}$ would have faced a binding constraint for G production had the domestic content restriction been $\underline{\zeta}$. In a counterfactual experiment where $\underline{\zeta} > 0.5$, $\tau_k^{i,G}$ is calibrated for two separate cases as follows:

1. For k with $\sum_{s \in C} \frac{\alpha_{us,sk}}{\sum_{s' \in C} \alpha_{us,s'k}} \lambda_{row,s;us,k}^{i,G+M} > 1 - \underline{\zeta}$, we solve for $\tau_k^{i,G}$ so that

$$\sum_{s \in C} \frac{\alpha_{us,sk}}{\sum_{s' \in C} \alpha_{us,s'k}} \lambda_{row,s;us,k}^{i,G} = 1 - \underline{\zeta},$$

where according to equation (15), the counterfactual trade shares for G (i.e., $\lambda_{row,s;us,k}^{i,G}$) are given by:

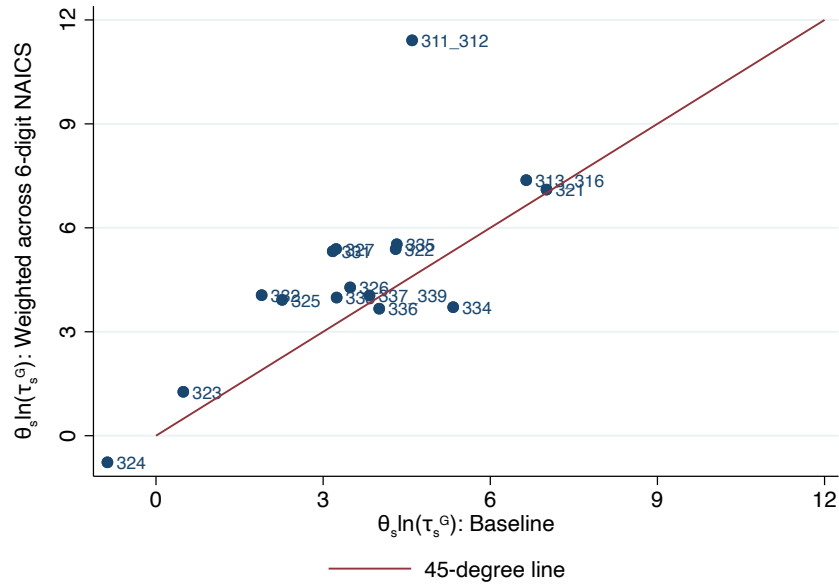
$$\lambda_{row,s;us,k}^{i,G} = \frac{(\tau_k^{i,G})^{-\theta_s} \lambda_{row,s;us,k}^{i,M} / (1 - \lambda_{row,s;us,k}^{i,M})}{1 + (\tau_k^{i,G})^{-\theta_s} \lambda_{row,s;us,k}^{i,M} / (1 - \lambda_{row,s;us,k}^{i,M})}.$$

Note that $\lambda_{row,s;us,k}^{i,M} = \lambda_{row,s;us,k}^{i,M}$ since the domestic content restriction is imposed only on G production.

2. For k where the constraint is non-binding, i.e., $\sum_{s \in C} \frac{\alpha_{us,sk}}{\sum_{s' \in C} \alpha_{us,s'k}} \lambda_{row,s;us,k}^{i,G+M} \leq 1 - \underline{\zeta}$, we have $\tau_k^{i,G} = \tau_k^{i,G} = 1$.

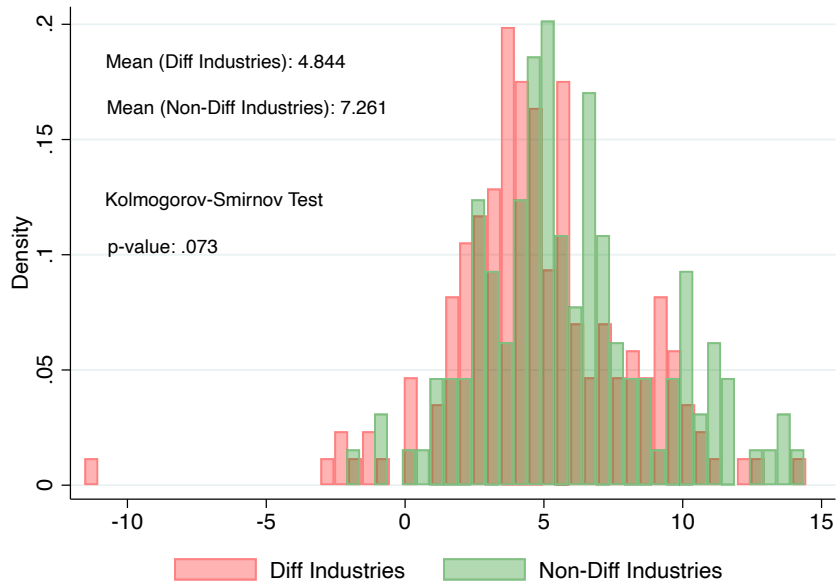
Figure 9 shows $\hat{\tau}_k^{i,G} = \tau_k^{i,G} / \tau_k^{i,G}$, when the domestic content restriction is raised to $\underline{\zeta} = 0.75$. More industries face a binding constraint in this counterfactual case, including: Chemical (325), Machinery (333), Computer and Electronic Product Manufacturing (334), Electrical Equipment, Appliance, and Component Manufacturing (335), Transportation Equipment (336), and Furniture and Related Products, and Miscellaneous Manufacturing (337-339).

Figure E.1: BAA Wedges Calibrated Using Data at Different Aggregation Levels



Notes: This figure reports the effective trade barriers faced by G consumers due to BAA restrictions, $\theta_s \ln(\tau_s^G)$ calibrated using data with different levels of aggregation, as described in Appendix E.1.1. The horizontal axis variable represents our baseline measure calibrated based on the data from the aggregated sectors listed in Table E.1. The vertical axis variable is the measure obtained from aggregating the trade barriers calibrated using the disaggregated data at the 6-digit NAICS level.

Figure E.2: Distribution of $\theta_s \ln(\tau_s^G)$: Differentiated v.s. Non-Differentiated Goods



Notes: This figure shows the distributions of effective trade barriers due to BAA restrictions at the 6-digit NAICS level, $\theta_s \ln(\tau_s^G)$, categorized by two groups of industries with different degree of differentiation. The p-value of the Kolmogorov-Smirnov test of the equality of the two distribution is 0.073.

Table E.1: Sector-Level Trade Elasticities (θ_s) and Scale Elasticities (ν_s)

Sectors	θ_s	ν_s
Mining and Oil and Gas Extraction (21)	4	0
Construction (23)	4	0
Manufacture of Food products, Beverages and Tobacco products (311-312)	3.57	0.24
Textile, Textile Product Mills, Apparel, Leather, and Allied Products (313-316)	4.43	0.21
Wood Product Manufacturing (321)	4.17	0.19
Paper Manufacturing (322)	2.97	0.31
Printing and Related Support Activities (323)	2.97	0.31
Petroleum and Coal Products (324)	3.75	0.11
Chemical (325)	3.75	0.22
Plastics and Rubber Products (326)	4.11	0.20
Nonmetallic Mineral Products (327)	5.14	0.19
Primary Metal Manufacturing (331)	8.94	0.11
Fabricated Metal Product Manufacturing (332)	5.07	0.18
Machinery (333)	3.27	0.27
Computer and Electronic Product Manufacturing (334)	3.27	0.25
Electrical Equipment, Appliance, and Component Manufacturing (335)	3.27	0.26
Transportation Equipment (336)	4.47	0.20
Furniture and Related Products, and Miscellaneous Manufacturing (337-339)	4.17	0.19
Wholesale and Retail Trade (42-45)	4	0
Transportation and Warehousing (48-49)	4	0
Information and Cultural Industries (51)	4	0
Finance and Insurance (52)	4	0
Real Estate and Rental and Leasing (53)	4	0
Professional, Scientific and Technical Services, Management of Companies and Enterprises (54-55)	4	0
Administrative and Support, Waste Management and Remediation Services (56)	4	0
Educational Services (61)	4	0
Health Care and Social Assistance (62)	4	0
Accommodation and Food Services (72)	4	0
Other Services (except Public Administration) (71,81)	4	0

Notes: This table lists the 29 sectors included in the quantitative analysis, and reports the trade elasticities (θ_s) obtained from [Giri et al. \(2021\)](#) and the scale elasticities (ν_s) obtained from [Bartelme et al. \(2024\)](#).

Table E.2: Government Expenditure Shares and Inherent Import Intensities

Dependent Variable:	$\beta_{\zeta,S}^G$ (1)	$\beta_{\zeta,S}^M$ (2)	$\beta_{\zeta,S}^G$ (3)	$\beta_{\zeta,S}^M$ (4)
$\lambda_{row,us,\zeta}^M$	-0.0065 (0.0145)	-0.0090 (0.0193)	0.0114 (0.0138)	0.0076 (0.0219)
p-value	0.8982		0.8711	
Aggregated Industry FEs	N	N	Y	Y
Observations	335	335	335	335
R-squared	0.0005	0.0006	0.1938	0.1184

Notes: The p-values reported are for the tests of whether the coefficients of $\lambda_{row,us,\zeta}^M$ are equal across models in columns (1) and (2) (respectively, columns (3) and (4)), based on the seemingly unrelated estimation. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

F Counterfactuals: Additional Details and Results

F.1 Exact Hat Algebra

We use x' to denote the counterfactual value of x , and \hat{x} to denote x'/x . We consider shocks to $\hat{\tau}_{ods}^{f,G}$, $\hat{\tau}_{os,dk'}^{i,G}$ and $\hat{\delta}_o$ in various counterfactual simulations. For instance, in the counterfactual experiment where the BAA restrictions are removed, we have $\hat{\tau}_{ods}^{f,G} = \frac{1}{\tau_s^{f,G}}$ and $\hat{\tau}_{os,dk'}^{i,G} = \frac{1}{\tau_k^{i,G}}$.

Define

$$\left\{ \begin{array}{l} \mu_{os,dk}^{i,G} = \frac{\lambda_{os,dk}^{i,G} \alpha_{d,sk} X_{dk}^G}{X_{os}} \quad \forall o, d \in US \\ \mu_{os,dk}^{i,M} = \frac{\lambda_{os,dk}^{i,M} \alpha_{d,sk} X_{dk}^M}{X_{os}} \quad \forall o, d \\ \mu_{ods}^{f,G} = \frac{\lambda_{ods}^{f,G} \beta_{ds}^G \gamma_d \sum_{d' \in US} \delta_{d'} \sum_k (\alpha_{d',k} X_{d'k}^G + \alpha_{d',k} X_{d'k}^M)}{X_{os}} \quad \forall o, d \in US \\ \mu_{ods}^{f,M} = \frac{\lambda_{ods}^{f,M} \beta_{ds}^M [(1-\delta_d) \sum_k (\alpha_{d',k} X_{d'k}^G + \alpha_{d',k} X_{d'k}^M) + D_d]}{X_{os}} \quad \forall o, d \end{array} \right.$$

$$\left\{ \begin{array}{l} \chi_{os}^G = \frac{(1-\delta_o) \alpha_{o,s} X_{os}^G}{(1-\delta_o) \sum_k (\alpha_{o,k} X_{ok}^G + \alpha_{o,k} X_{ok}^M) + D_o} \quad \forall o \\ \chi_{os}^M = \frac{(1-\delta_o) \alpha_{o,s} X_{os}^M}{(1-\delta_o) \sum_k (\alpha_{o,k} X_{ok}^G + \alpha_{o,k} X_{ok}^M) + D_o} \quad \forall o \end{array} \right.$$

$$\left\{ \begin{array}{l} \eta_{os}^G = \frac{\alpha_{o,s} X_{os}^G}{\sum_{o' \in US} \sum_k \alpha_{o',k} X_{o'k}^G + \sum_{o' \in US} \sum_k \alpha_{o',k} X_{o'k}^M} \quad \forall o \in US \\ \eta_{os}^M = \frac{\alpha_{o,s} X_{os}^M}{\sum_{o' \in US} \sum_k \alpha_{o',k} X_{o'k}^G + \sum_{o' \in US} \sum_k \alpha_{o',k} X_{o'k}^M} \quad \forall o \in US \end{array} \right.$$

$$s_{os} = \frac{X_{os}}{\sum_{o'} \sum_k X_{o'k}} \quad \forall o$$

where $\{\mu_{ods}^{f,G}, \mu_{ods}^{f,M}\}$ represent the share of revenue from the sales of final goods s by producers in region o that is generated from respectively buyers G and M in region d ; $\{\mu_{os,dk'}^{i,G}, \mu_{os,dk'}^{i,M}\}$ denote the share of revenue from the sales of intermediate goods s by producers in region o that is attributed to respectively producers G and M of downstream goods k in region d ; $\{\chi_{os}^G, \chi_{os}^M\}$ reflect the after-tax labor income of os as a share of total labor income in o adjusted for trade imbalance for G and M , respectively; $\{\eta_{os}^G, \eta_{os}^M\}$ are the labor income of os for respectively G and M as a share of total labor income in the US; and $\{s_{os}\}$ is the share of output by os in the world total output.

Expressed as the exact hat algebra, the equilibrium conditions consist of:

$$\hat{L}_{os} = \hat{\pi}_{os} = \left(\frac{1 - \delta_o \hat{\delta}_o}{1 - \delta_o} \right)^{\kappa_o} \hat{w}_{os}^{\kappa_o} \left(\left(\frac{1 - \delta_o \hat{\delta}_o}{1 - \delta_o} \right)^{\kappa_o} \sum_{s'} \pi_{os'} \hat{w}_{os'}^{\kappa_o} + (1 - e_o) \right)^{-1} \quad \forall o \quad (\text{F.1})$$

$$\left\{ \begin{array}{l} \hat{c}_{os}^G = \hat{w}_{os}^{1-\alpha_{o,s}} \Pi_{s'} (\hat{P}_{o,s's}^{i,G})^{\alpha_{o,s's}} \quad \forall o \in US \\ \hat{c}_{os}^M = \hat{w}_{os}^{1-\alpha_{o,s}} \Pi_{s'} (\hat{P}_{o,s's}^{i,M})^{\alpha_{o,s's}} \quad \forall o \end{array} \right. \quad (\text{F.2})$$

$$\begin{cases} \hat{p}_{o,s's'}^{i,G} = \left[\sum_{o'} \lambda_{o's',os}^{i,G} \hat{L}_{o's'}^{v_{s'}} (\hat{\tau}_{o's',os}^{i,G} \hat{c}_{o's'}^M)^{-\theta_{s'}} \right]^{-\frac{1}{\theta_{s'}}} & \forall o \in US \\ \hat{p}_{o,s's'}^{i,M} = \left[\sum_{o'} \lambda_{o's',os}^{i,M} \hat{L}_{o's'}^{v_{s'}} (\hat{\tau}_{o's',os}^{i,M} \hat{c}_{o's'}^M)^{-\theta_{s'}} \right]^{-\frac{1}{\theta_{s'}}} & \forall o \end{cases} \quad (F.3)$$

$$\begin{cases} \hat{P}_{os}^{f,G} = \left[\sum_{o' \notin US} \lambda_{o'os}^{f,G} \hat{L}_{o's}^{v_s} (\hat{\tau}_{o'os}^{f,G} \hat{c}_{o's}^M)^{-\theta_s} + \sum_{o' \in US} \lambda_{o'os}^{f,G} \hat{L}_{o's}^{v_s} (\hat{\tau}_{o'os}^{f,G} \hat{c}_{o's}^G)^{-\theta_s} \right]^{-\frac{1}{\theta_s}} & \forall o \in US \\ \hat{P}_{os}^{f,M} = \left[\sum_{o'} \lambda_{o'os}^{f,M} \hat{L}_{o's}^{v_s} (\hat{\tau}_{o'os}^{f,M} \hat{c}_{o's}^M)^{-\theta_s} \right]^{-\frac{1}{\theta_s}} & \forall o \end{cases} \quad (F.4)$$

$$\begin{cases} \hat{\lambda}_{ods}^{f,G} = \frac{\hat{L}_{ods}^{v_s} (\hat{\tau}_{ods}^{f,G} \hat{c}_{os}^G)^{-\theta_s}}{(\hat{p}_{ds}^{f,G})^{-\theta_s}} & \left\{ \begin{array}{l} \hat{\lambda}_{os,dk}^{i,G} = \frac{\hat{L}_{os}^{v_s} (\hat{\tau}_{os,dk}^{i,G} \hat{c}_{os}^M)^{-\theta_s}}{(\hat{p}_{d,sk}^{i,G})^{-\theta_s}} \quad \forall o \in US, d \in US \\ \hat{\lambda}_{os,dk}^{i,G} = \frac{\hat{L}_{os}^{v_s} (\hat{\tau}_{os,dk}^{i,G} \hat{c}_{os}^M)^{-\theta_s}}{(\hat{p}_{d,sk}^{i,G})^{-\theta_s}} \quad \forall o \notin US, d \in US \\ \hat{\lambda}_{os,dk}^{i,M} = \frac{\hat{L}_{os}^{v_s} (\hat{\tau}_{os,dk}^{i,M} \hat{c}_{os}^M)^{-\theta_s}}{(\hat{p}_{d,sk}^{i,M})^{-\theta_s}} \quad \forall o, d \end{array} \right. \\ \hat{\lambda}_{ods}^{f,G} = \frac{\hat{L}_{ods}^{v_s} (\hat{\tau}_{ods}^{f,G} \hat{c}_{os}^M)^{-\theta_s}}{(\hat{p}_{ds}^{f,G})^{-\theta_s}} \\ \hat{\lambda}_{ods}^{f,M} = \frac{\hat{L}_{ods}^{v_s} (\hat{\tau}_{ods}^{f,M} \hat{c}_{os}^M)^{-\theta_s}}{(\hat{p}_{ds}^{f,M})^{-\theta_s}} \end{cases} \quad (F.5)$$

$$\begin{cases} \hat{X}_{os}^G = \frac{X_{os}^G + X_{os}^M}{X_{os}^G} \sum_{d \in US} \mu_{ods}^{f,G} \hat{\lambda}_{ods}^{f,G} \sum_{d' \in US} \hat{\delta}_{d'} \sum_k (\eta_{d'k}^G \hat{X}_{d'k}^G + \eta_{d'k}^M \hat{X}_{d'k}^M) & \forall o \in US \\ \hat{X}_{os}^G = 0 & \forall o \notin US \\ \hat{X}_{os}^M = \frac{X_{os}^G + X_{os}^M}{X_{os}^M} \left\{ \sum_{d \in US} \sum_k \mu_{os,dk}^{i,G} \hat{\lambda}_{os,dk}^{i,G} \hat{X}_{dk}^G + \sum_d \sum_k \mu_{os,dk}^{i,M} \hat{\lambda}_{os,dk}^{i,M} \hat{X}_{d'k}^M \right. \\ \quad \left. + \sum_d \mu_{ods}^{f,M} \hat{\lambda}_{ods}^{f,M} \left[\frac{1 - \delta_d \hat{\delta}_d}{1 - \delta_d} \sum_k (\chi_{dk}^G \hat{X}_{dk}^G + \chi_{dk}^M \hat{X}_{dk}^M) + (1 - \sum_k \chi_{dk}^G - \sum_k \chi_{dk}^M) \hat{D}_d \right] \right\} & \forall o \in US \\ \hat{X}_{os}^M = \frac{X_{os}^G + X_{os}^M}{X_{os}^M} \left\{ \sum_{d \in US} \sum_k \mu_{os,dk}^{i,G} \hat{\lambda}_{os,dk}^{i,G} \hat{X}_{dk}^G + \sum_d \sum_k \mu_{os,dk}^{i,M} \hat{\lambda}_{os,dk}^{i,M} \hat{X}_{d'k}^M \right. \\ \quad \left. + \sum_{d \in US} \mu_{ods}^{f,G} \hat{\lambda}_{ods}^{f,G} \sum_{d' \in US} \hat{\delta}_{d'} \sum_k (\eta_{d'k}^G \hat{X}_{d'k}^G + \eta_{d'k}^M \hat{X}_{d'k}^M) \right. \\ \quad \left. + \sum_d \mu_{ods}^{f,M} \hat{\lambda}_{ods}^{f,M} \left[\frac{1 - \delta_d \hat{\delta}_d}{1 - \delta_d} \sum_k (\chi_{dk}^G \hat{X}_{dk}^G + \chi_{dk}^M \hat{X}_{dk}^M) + (1 - \sum_k \chi_{dk}^G - \sum_k \chi_{dk}^M) \hat{D}_d \right] \right\} & \forall o \notin US \\ \hat{X}_{os} = \frac{X_{os}^G}{X_{os}^G + X_{os}^M} \hat{X}_{os}^G + \frac{X_{os}^M}{X_{os}^G + X_{os}^M} \hat{X}_{os}^M & \forall o \end{cases} \quad (F.6)$$

where $\hat{D}_d = \sum_o \sum_s s_{os} \left(\frac{X_{os}^G}{X_{os}^G + X_{os}^M} \hat{X}_{os}^G + \frac{X_{os}^M}{X_{os}^G + X_{os}^M} \hat{X}_{os}^M \right)$.

$$\hat{X}_{os} = \left(\frac{1 - \delta_o \hat{\delta}_o}{1 - \delta_o} \right)^{\kappa_o - 1} \hat{w}_{os}^{\kappa_o} \left(\left(\frac{1 - \delta_o \hat{\delta}_o}{1 - \delta_o} \right)^{\kappa_o} \sum_{s'} \pi_{os'} \hat{w}_{os'}^{\kappa_o} + (1 - e_o) \right)^{\frac{1}{\kappa_o} - 1} \quad \forall o \quad (F.7)$$

F.2 Solution Algorithm

Given the parameters $\{\theta_s, v_s, \kappa_o\}$, and data on:

$$\begin{aligned} & \{\lambda_{ods}^{f,G}, \lambda_{ods}^{f,M}, \lambda_{os,dk}^{i,G}, \lambda_{os,dk}^{i,M}, \mu_{ods}^{f,G}, \mu_{ods}^{f,M}, \mu_{os,dk}^{i,G}, \mu_{os,dk}^{i,M}, X_{os}^G, X_{os}^M, X_{os}, \\ & \alpha_{o,s}, \alpha_{o,sk}, \chi_{os}^G, \chi_{os}^M, \eta_{os}^G, \eta_{os}^M, s_{os}, \pi_{os}, e_o, \delta_o, \gamma_o, \beta_{os}^G, \beta_{os}^M, t_o\} \end{aligned}$$

and shocks to $\tau_{ods}^{f,G}$, $\tau_{ods,dk'}^{i,G}$ and δ_o , we can solve for the system using the following solution algorithm:

1. Guess $\{\hat{w}_{os}\}$
 - Compute $\{\hat{L}_{os}\}$ given equations (F.1).
 - Solve for $\{\hat{P}_{o,s's'}^{i,M}, \hat{c}_{os}^M\}$ given equations (F.2) and (F.3).
 - Compute $\{\hat{P}_{o,s's'}^{i,G}, \hat{c}_{os}^G, \hat{P}_{os}^{f,G}, \hat{P}_{os}^{f,M}\}$ according to equations (F.2), (F.3) and (F.4).
 - Compute $\{\hat{\lambda}_{ods}^{f,G}, \hat{\lambda}_{ods}^{f,M}, \hat{\lambda}_{os,dk'}^{i,G}, \hat{\lambda}_{os,dk'}^{i,M}\}$ according to equations (F.5).
 - With $\{\hat{\lambda}_{ods}^{f,G}, \hat{\lambda}_{ods}^{f,M}, \hat{\lambda}_{os,dk'}^{i,G}, \hat{\lambda}_{os,dk'}^{i,M}\}$, solve for $\{\hat{X}_{os}^G, \hat{X}_{os}^M, \hat{X}_{os}\}$ given equations (F.6).
2. Update for $\{\hat{w}'_{os}\}$ using equations (F.7).
3. Repeat the above procedures until $\{\hat{w}'_{os}\}$ equals $\{\hat{w}_{os}\}$

F.3 Welfare

Under the assumption that consumers across the US have access to the composite public goods from different states, the change in welfare is given by:

$$\begin{aligned} \hat{V}_o &= \left(\frac{\left(\frac{1-\delta_o\delta_o}{1-\delta_o} \right)^{\kappa_o} \sum_s \pi_{os} \hat{w}_{os}^{\kappa_o} + (1-e_o)}{\hat{p}_o^{f,M}} \right)^{\frac{1}{\kappa_o}} \left(\prod_{o'} \left(\prod_s (\hat{Q}_{o's}^G)^{\beta_{o's}^G} \right)^{\gamma_{o'}} \right)^{1-\varphi} \\ &= \left(\frac{\left(\frac{1-\delta_o\delta_o}{1-\delta_o} \right)^{\kappa_o} \sum_s \pi_{os} \hat{w}_{os}^{\kappa_o} + (1-e_o)}{\hat{p}_o^{f,M}} \right)^{\frac{1}{\kappa_o}} \left(\prod_{o'} \left(\prod_s \left(\frac{\sum_{o'' \in US} \delta_{o''} \sum_k (\eta_{o''k}^G \hat{X}_{o''k}^G + \eta_{o''k}^M \hat{X}_{o''k}^M)}{\hat{p}_{o's}^{f,G}} \right)^{\beta_{o's}^G} \right)^{\gamma_{o'}} \right)^{1-\varphi} \quad \forall o \in US. \end{aligned} \quad (F.8)$$

where $\hat{p}_o^{f,M} = \prod_s (\hat{P}_{os}^{f,M})^{\beta_{os}^M}$.

Under the alternative formulation that consumers in $o \in US$ only have access to the public goods produced locally, the change in welfare is expressed as follows:

$$\begin{aligned} \hat{V}_o &= \left(\frac{\left(\frac{1-\delta_o\delta_o}{1-\delta_o} \right)^{\kappa_o} \sum_s \pi_{os} \hat{w}_{os}^{\kappa_o} + (1-e_o)}{\hat{p}_o^{f,M}} \right)^{\frac{1}{\kappa_o}} \left(\prod_s (\hat{Q}_{os}^G)^{\beta_{os}^G} \right)^{1-\varphi} \\ &= \left(\frac{\left(\frac{1-\delta_o\delta_o}{1-\delta_o} \right)^{\kappa_o} \sum_s \pi_{os} \hat{w}_{os}^{\kappa_o} + (1-e_o)}{\hat{p}_o^{f,M}} \right)^{\frac{1}{\kappa_o}} \left(\prod_s \left(\frac{\sum_{o' \in US} \delta_{o'} \sum_k (\eta_{o'k}^G \hat{X}_{o'k}^G + \eta_{o'k}^M \hat{X}_{o'k}^M)}{\hat{p}_{os}^{f,G}} \right)^{\beta_{os}^G} \right)^{1-\varphi} \quad \forall o \in US. \end{aligned} \quad (F.9)$$

F.4 Consumption Equivalent Variation

Denote ψ be the adjustment ratio of personal consumption to make the welfare change in the US as a whole to be the same as in the counterfactual case. Then:

$$\psi = \left(\sum_o \frac{L_o}{\sum_{o'} L_{o'}} \hat{V}_o \right)^{\frac{1}{\varphi}}.$$

Total personal consumption in the US is $\sum_o \sum_{d \in US} \sum_s X_{ods}^{f,M}$. Therefore, the consumption equivalent variation per capita is given by $(\psi - 1) \sum_o \sum_{d \in US} \sum_s X_{ods}^{f,M} / L_o$. The cost per manufacturing job (respectively, per job) created by the BAA wedges is then calculated as $(\psi - 1) \sum_o \sum_{d \in US} \sum_s X_{ods}^{f,M} / \Delta(\sum_{s \in mfg} \pi_{os} L_o)$ (respectively, $(\psi - 1) \sum_o \sum_{d \in US} \sum_s X_{ods}^{f,M} / \Delta(\sum_s \pi_{os} L_o)$).

F.5 Alternative Measures of Changes in Aggregated Welfare at the National Level

In this subsection, we discuss the difference in welfare changes aggregated at the national level derived from the two measures, each grounded on different assumptions: (i) where consumers have access to the nationwide public goods, as in equation (F.8), and (ii) where consumers only have access to local public goods, as in equation (F.9). For illustrative purposes, we contrast the measures in column (1) between rows (a) and (b) of the tables presenting the counterfactual simulation results (e.g., Table 4). The difference is given by:

$$\sum_o \frac{L_o}{L_{us}} \hat{V}_o - \sum_o \frac{L_o}{L_{us}} \hat{V}_o^{alt} = \sum_o \frac{L_o}{L_{us}} A_o \left(\prod_{o'} B_{o'}^{\gamma_{o'}} - B_o \right), \quad (\text{F.10})$$

where L_o/L_{us} denotes the population share of state o , $A_o = \left(\frac{\left(\left(\frac{1-\delta_o \delta_o}{1-\delta_o} \right)^{\kappa_o} \sum_s \pi_{os} \hat{w}_{os}^{\kappa_o} + (1-e_o) \right)^{\frac{1}{\kappa_o}}}{\hat{p}_o^{f,M}} \right)^{\varphi}$ and $B_o =$

$\left(\prod_s \left(\frac{\sum_{o' \in US} \delta_{o'} \sum_k (\eta_{o'k}^G \hat{X}_{o'k}^G + \eta_{o'k}^M \hat{X}_{o'k}^M)}{\hat{p}_{os}^{f,G}} \right)^{\beta_{os}^G} \right)^{1-\varphi}$. In general, the size of $\sum_o \frac{L_o}{L_{us}} \hat{V}_o - \sum_o \frac{L_o}{L_{us}} \hat{V}_o^{alt}$ depends on the means of A_o and $\frac{L_o}{L_{us}} \left(\prod_{o'} B_{o'}^{\gamma_{o'}} - B_o \right)$, as well as their covariance.

Note that the general equilibrium effects of the policy shocks through the component A_o have a smaller variation compared to the direct impacts on the component B_o . In the special case that A_o is a constant, $\sum_o \frac{L_o}{L_{us}} \hat{V}_o - \sum_o \frac{L_o}{L_{us}} \hat{V}_o^{alt}$ is proportional to:

$$\prod_o B_o^{\gamma_o} - \sum_o \frac{L_o}{L_{us}} B_o. \quad (\text{F.11})$$

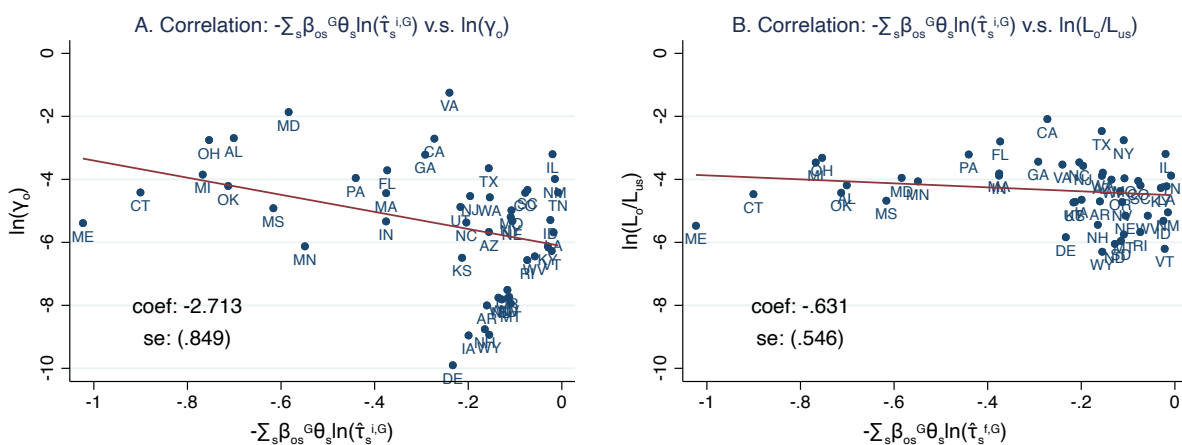
In the above expression, the first component is the geometric average of B_o with weights being the the procurement share (γ_o). The second component is the arithmetic average with weights being the population share (L_o/L_{us}). Hence, the difference in (F.10) is more negative when the correlation between B_o and γ_o is *smaller* compared to that between B_o and L_o/L_{us} .⁸⁹

⁸⁹The correlation between procurement share γ_o and L_o/L_{us} is 0.26.

As is discussed in Section 7.3, the magnitude of the welfare loss in Row (a) is significantly larger than that in Row (b) of Table 4. This is partly because, in this counterfactual experiment, the correlation between B_o and γ_o is -0.204, a value considerably lower than the correlation between B_o and L_o/L_{US} , which is -0.052.⁹⁰

To visualize the data, we proxy for $\ln B_o$ by $-\sum_s \beta_{os}^G \theta_s \ln(\hat{\tau}_s^{i,G})$ which reflects that the decline in public good provisions in state o is more significant if it procure more products with a larger increase in BAA wedges on imported inputs (i.e., $\theta_s \ln(\hat{\tau}_s^{i,G})$). Panels A and B in Figure F.1 reveal that the negative correlation between $-\sum_s \beta_{os}^G \theta_s \ln(\hat{\tau}_s^{i,G})$ and $\ln(\gamma_o)$ is more pronounced than the correlation with $\ln(L_o/L_{US})$. In other words, due to differential exposure to the policy shocks across sectors, states that experience a larger reduction in public good provisions tend to be the ones with a larger share in federal procurement, but not necessarily the ones with a larger population share. This lower the geometric average relative to the arithmetic average in expression (F.11).

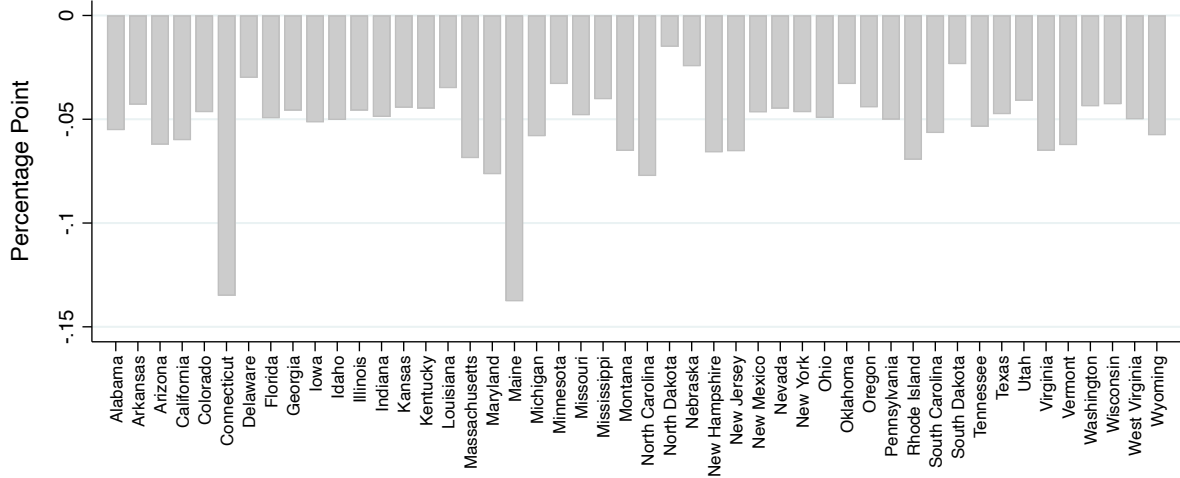
Figure F.1: Correlations: $-\sum_s \beta_{os}^G \theta_s \ln(\hat{\tau}_s^{i,G})$ v.s. $\ln(\gamma_o)$ and $\ln(L_o/L_{US})$



Notes: Panel A of the figure shows the relation between $-\sum_s \beta_{os}^G \theta_s \ln(\hat{\tau}_s^{i,G})$ and $\ln(\gamma_o)$, and Panel B presents the relation between $-\sum_s \beta_{os}^G \theta_s \ln(\hat{\tau}_s^{i,G})$ and $\ln(L_o/L_{US})$. The red line corresponds to the best fitted line across all states.

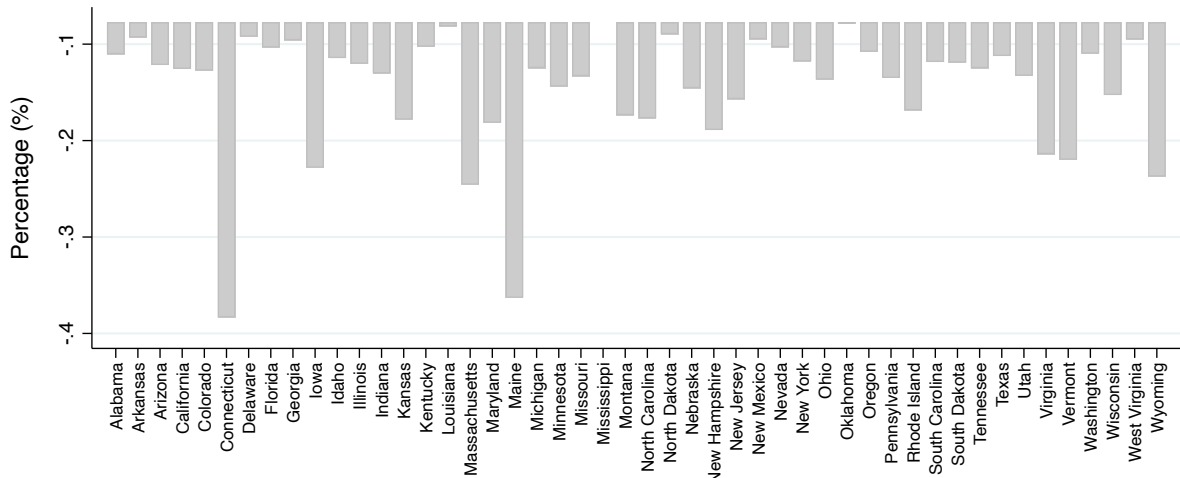
⁹⁰The welfare changes in rows (a) and (b) in Table 2 have more similar magnitudes. This is partly because, in this counterfactual experiment where we remove the BAA wedges on final goods, the correlation between B_o and γ_o is closer to that between B_o and L_o/L_{US} , which are respectively 0.029 and 0.096.

Figure F.2: Changes in Employment to Working Age Population Ratio: Remove the BAA Wedges on Imports of Final Goods (Broader Measure)



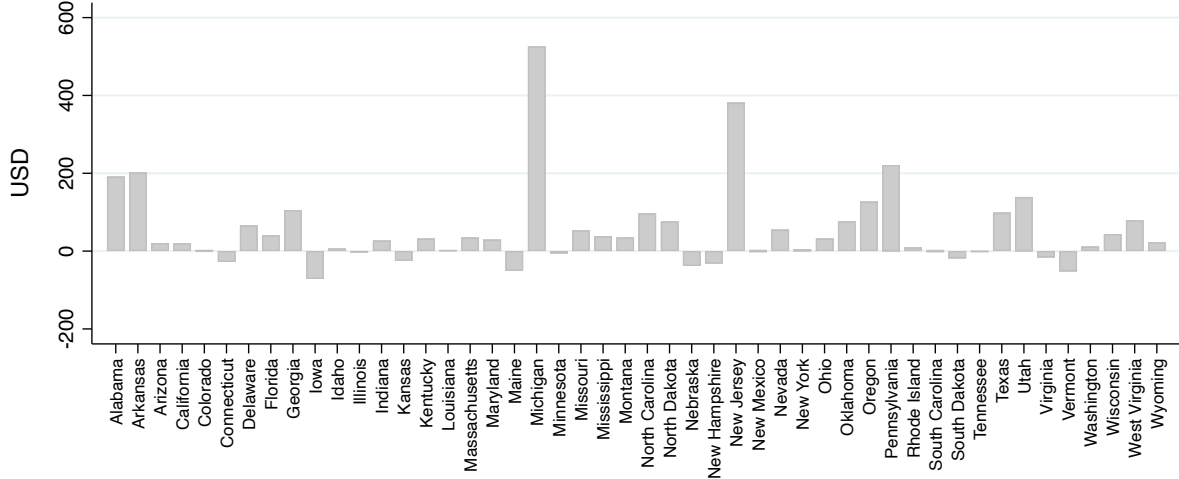
Notes: This figure presents the counterfactual changes in employment to working age population ratio resulting from the removal of the BAA wedges on imports of final goods $\tau_s^{f,G}$.

Figure F.3: Percentage Changes in Wages: Remove the BAA Wedges on Imports of Final Goods (Broader Measure)



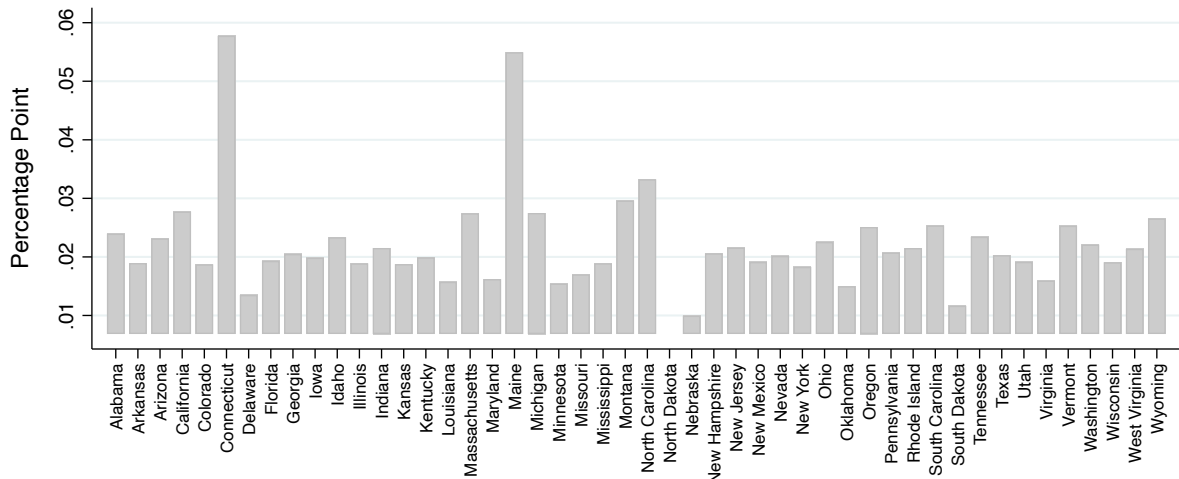
Notes: This figure presents the counterfactual percentage changes in wages across states resulting from the removal of the BAA wedges on imports of final goods $\tau_s^{f,G}$.

Figure F.4: Consumption Equivalent Variation (Alternative Formulation of Welfare): Remove the BAA Wedges on Imports of Final Goods (Broader Measure)



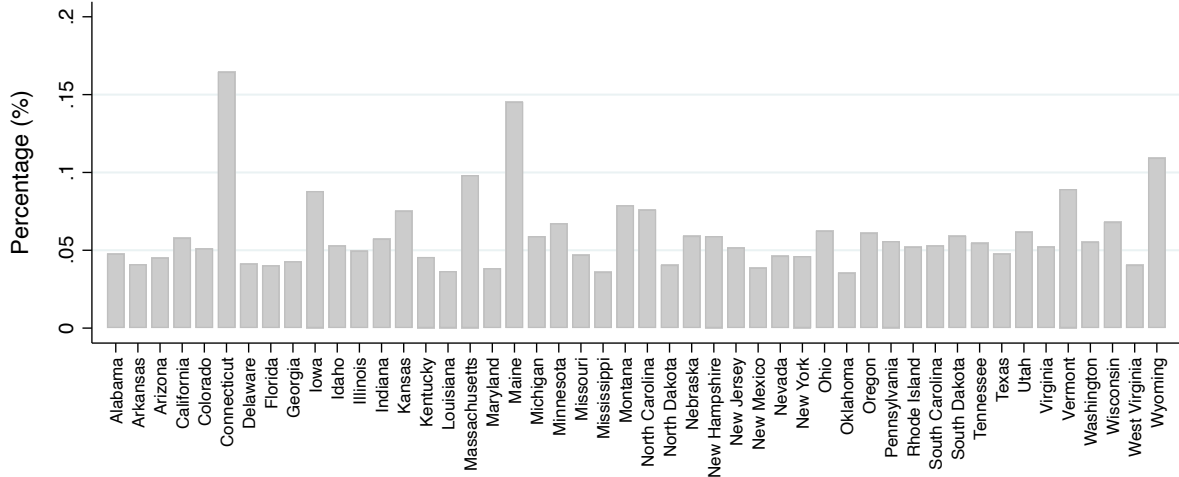
Notes: This figure presents the counterfactual changes in welfare across states resulting from the removal of the BAA wedges on imports of final goods $\tau_s^{f,G}$. The welfare changes are measured by consumption equivalent variation. The calculation assumes that consumers only have access to the locally produced public goods.

Figure F.5: Changes in Employment to Working Age Population Ratio: Increase the Required Domestic Share of Component Inputs for G to 75%



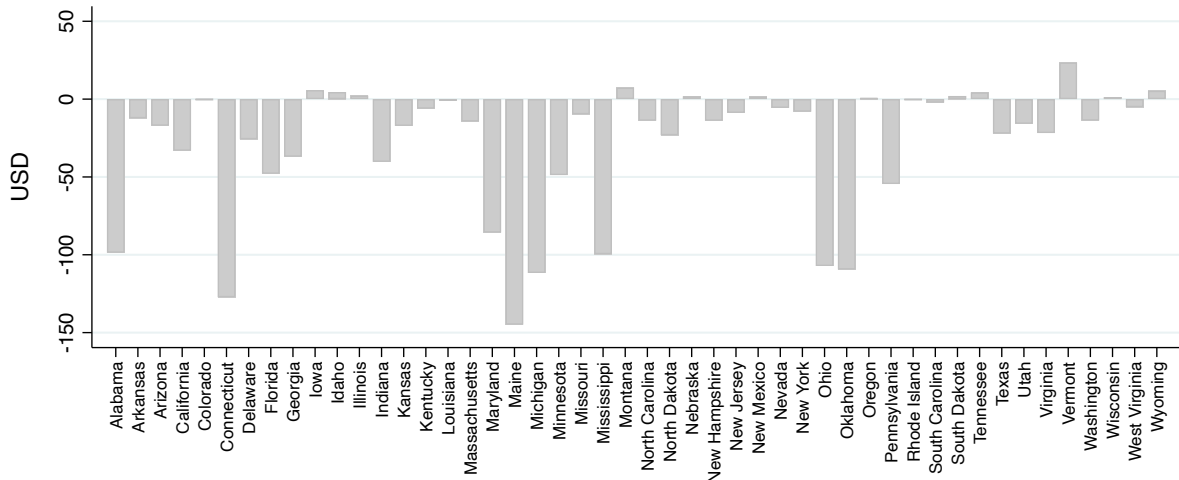
Notes: This figure presents the counterfactual changes in employment to working age population ratio across states resulting from an increase in the required domestic share of component inputs for G production to 75%.

Figure F.6: Percentage Changes in Wages: Increase the Required Domestic Share of Component Inputs for G to 75%



Notes: This figure presents the counterfactual percentage changes in wages across states resulting from an increase in the required domestic share of component inputs for G production to 75%.

Figure F.7: Consumption Equivalent Variation (Alternative Formulation of Welfare): Increase the Required Domestic Share of Component Inputs for G to 75%



Notes: This figure presents the counterfactual changes in welfare across states resulting from an increase in the required domestic share of component inputs for G production to 75%. The welfare changes are measured by consumption equivalent variation. The calculation assumes that consumers only have access to the locally produced public goods.

Table F.1: Procurement Demand Shock and Labor Market Outcomes
(Simulated Regressions, With EES)

Dependent Variable:	Δ Mfg empl/ working-age pop $\Delta\left(\sum_{s \in mfg} \pi_{os}\right)$ (1)	Δ Total wage and salary empl/ working-age pop Δe_o (2)	Δ Log personal income per capita $\Delta \ln w_o$ (3)
Panel A: $\kappa = 1.5$			
Δx_o^G	0.0020*** (0.0003)	0.0021*** (0.0002)	0.0056*** (0.0006)
Observations	48	48	48
R-squared	0.7653	0.7586	0.7485
Panel B: $\kappa = 3$			
Δx_o^G	0.0033*** (0.0003)	0.0035*** (0.0003)	0.0049*** (0.0004)
Observations	48	48	48
R-squared	0.8303	0.8255	0.8126

Notes: All regressions are weighted by state working age population in 2014. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table F.2: Procurement Demand Shock and Labor Market Outcomes
(Simulated Regressions, Without EES)

Dependent Variable:	Δ Mfg empl/ working-age pop $\Delta\left(\sum_{s \in mfg} \pi_{os}\right)$ (1)	Δ Total wage and salary empl/ working-age pop Δe_o (2)	Δ Log personal income per capita $\Delta \ln w_o$ (3)
Panel A: $\kappa = 1.5$			
Δx_o^G	0.0020*** (0.0003)	0.0020*** (0.0002)	0.0056*** (0.0006)
Observations	48	48	48
R-squared	0.7721	0.7649	0.7554
Panel B: $\kappa = 3$			
Δx_o^G	0.0034*** (0.0003)	0.0036*** (0.0003)	0.0050*** (0.0004)
Observations	48	48	48
R-squared	0.8382	0.8323	0.8073

Notes: All regressions are weighted by state working age population in 2014. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table F.3: Remove the BAA Wedges on Final Goods Accounting for National Security Considerations

Welfare Measure	\hat{V}_{US}	Distribution of \hat{V}_o			EV _{US} (USD)	Δ Mfg. Jobs	Costs per Mfg. Job	Δ Jobs	Costs per Job
		Mean	Min	Max					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: EES									
(a) Nationwide Public Goods ($\kappa = 1.5$)	0.0781	0.0711	0.0007	0.1270	57.04	-91,590	122,848	-96,747	116,299
(b) Local Public Goods Only ($\kappa = 1.5$)	0.0877	0.0682	-0.0771	0.6099	62.61	-91,590	134,859	-96,747	127,670
(c) Nationwide Public Goods ($\kappa = 3$)	0.0764	0.0703	0.0082	0.1176	55.83	-169,623	64,931	-180,301	61,085
(d) Local Public Goods Only ($\kappa = 3$)	0.0865	0.0679	-0.0698	0.6104	61.80	-169,623	71,879	-180,301	67,622
Panel B: Without EES									
(a) Nationwide Public Goods ($\kappa = 1.5$)	0.0809	0.0736	0.0033	0.1287	59.04	-88,076	132,246	-93,104	125,103
(b) Local Public Goods Only ($\kappa = 1.5$)	0.0904	0.0707	-0.0759	0.6109	64.61	-88,076	144,723	-93,104	136,906
(c) Nationwide Public Goods ($\kappa = 3$)	0.0810	0.0745	0.0193	0.1214	59.14	-159,787	73,011	-169,949	68,646
(d) Local Public Goods Only ($\kappa = 3$)	0.0910	0.0721	-0.0673	0.6127	65.07	-159,787	80,341	-169,949	75,537

Notes: This table shows the effects of the policy experiment that removes the “Buy American” wedges on final goods that are not subject to NS concerns on welfare and employment. In Row (a), welfare changes are calculated according to (F.8), assuming consumers have access to the composite public goods from different states. In Row (b), welfare changes are calculated according to (F.9), assuming consumers only have access to the locally produced public goods. Rows (c) and (d) report the corresponding results with an alternative labor supply elasticity. Column (1) shows the aggregate welfare effect for the US, in percentage terms $100(\sum_o \frac{L_o}{L_{US}} \hat{V}_o - 1)$. Columns (2)-(4) present the summary statistics of the distribution of \hat{V}_o across states: Column (2) shows the mean welfare effect $100(\frac{1}{N_o} \sum_o \hat{V}_o - 1)$; and Columns (3) and (4) show the minimum and maximum of $100(\hat{V}_o - 1)$, respectively. Column (5) displays the consumption equivalent variation (EV) per worker measured by USD. Column (6) shows the counterfactual change in the number of manufacturing jobs for the US. Column (7) displays the cost per manufacturing job saved due to the BAA wedge on final goods that are not subject to national security concerns. Column (8) shows the counterfactual change in the number of jobs for the US. Column (9) displays the cost per job saved due to the BAA wedge on final goods that are not subject to national security concerns.

Table F.4: Remove the BAA Wedges on Imports of both Final Goods and Component Inputs

Welfare Measure	\hat{V}_{US}	Distribution of \hat{V}_o			EV _{US} (USD)	Δ Mfg. Jobs	Costs per Mfg. Job	Δ Jobs	Costs per Job
		Mean	Min	Max					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: With EES									
(a) Nationwide Public Goods ($\kappa = 1.5$)	0.0945	0.0867	0.0094	0.1516	68.95	-101,759	133,668	-107,572	126,445
(b) Local Public Goods Only ($\kappa = 1.5$)	0.1011	0.0782	-0.0760	0.7218	72.43	-101,759	140,421	-107,572	132,833
(c) Nationwide Public Goods ($\kappa = 3$)	0.0923	0.0855	0.0181	0.1397	67.38	-188,201	70,627	-200,142	66,413
(d) Local Public Goods Only ($\kappa = 3$)	0.0995	0.0776	-0.0677	0.7225	71.35	-188,201	74,785	-200,142	70,324
Panel B: Without EES									
(a) Nationwide Public Goods ($\kappa = 1.5$)	0.0974	0.0893	0.0120	0.1535	71.09	-98,038	143,048	-103,713	135,220
(b) Local Public Goods Only ($\kappa = 1.5$)	0.1040	0.0808	-0.0750	0.7229	74.56	-98,038	150,028	-103,713	141,819
(c) Nationwide Public Goods ($\kappa = 3$)	0.0972	0.0900	0.0291	0.1442	70.97	-177,694	78,796	-189,078	74,052
(d) Local Public Goods Only ($\kappa = 3$)	0.1044	0.0821	-0.0653	0.7250	74.88	-177,694	83,136	-189,078	78,131

Notes: This table shows the effects of the policy experiment that removes the “Buy American” wedges on both final and intermediate goods on welfare and employment. In Row (a), welfare changes are calculated according to (F.8), assuming consumers have access to the composite public goods from different states. In Row (b), welfare changes are calculated according to (F.9), assuming consumers only have access to the locally produced public goods. Rows (c) and (d) report the corresponding results with an alternative labor supply elasticity. Column (1) shows the aggregate welfare effect for the US, in percentage terms $100(\sum_o \frac{L_o}{L_{US}} \hat{V}_o - 1)$. Columns (2)-(4) present the summary statistics of the distribution of \hat{V}_o across states: Column (2) shows the mean welfare effect $100(\frac{1}{N_o} \sum_o \hat{V}_o - 1)$; and Columns (3) and (4) show the minimum and maximum of $100(\hat{V}_o - 1)$, respectively. Column (5) displays the consumption equivalent variation (EV) per worker measured by USD. Column (6) shows the counterfactual change in the number of manufacturing jobs for the US. Column (7) displays the cost per manufacturing job saved due to the BAA wedge on final goods τ_s^{fG} and on intermediate goods τ_k^{iG} . Column (8) shows the counterfactual change in the number of jobs for the US. Column (9) displays the cost per job saved due to the BAA wedge on final goods τ_s^{fG} and on intermediate goods τ_k^{iG} .