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ABSTRACT

We develop a new algorithm to map confidential firm-level export transactions to their underlying establishments that can be implemented on U.S. microdata. Using this procedure, we construct a novel micro-dataset of U.S. exports at the plant level. Aggregation of these data permits more accurate measurement of exporting at the subnational level (e.g., county, MSA, etc.) than was previously possible. The data reveal exports to be much more geographically concentrated than both employment and manufacturing sales, implying that some regions are heavily reliant on foreign demand. To illustrate the consequences of such exposure, we study the effects of the trade collapse during the Great Recession on local labor markets. Counties experiencing greater declines in foreign demand performed worse in terms of employment, pay, and wages during the Great Recession. A similar analysis implemented with publicly available imputed export data—a common practice in the literature—fails to replicate these estimates.

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1. Introduction

The remarkable expansion in the availability of micro-level data in recent decades has added much to our understanding of U.S. export and import patterns. Yet, despite these advances, relatively little is known about the international trade activity of individual locations in the United States. The reason is that common U.S. datasets contain very limited information on the destination of imports and the geographic origin of exports. Although information on the *port* of exportation or importation is available in U.S. microdata, the travels of goods within the U.S. are typically not known. Firm-level data do generally not solve this problem as large, multi-plant firms account for the vast majority of U.S. trade. As a result, studies that focus on the local effects of trade in the U.S. typically use an imputation approach that pairs the local or regional industrial structure with aggregate product-level data on imports or exports (e.g., Hakobyan and McLaren, 2016; Feenstra, Ma and Xu, 2019).

This paper makes several contributions to improve our understanding of local export patterns in the United States. Our main contribution is to develop an algorithm that maps firm-level export transactions from U.S. customs records to establishments. This algorithm uses datasets commonly available to researchers working with confidential U.S. microdata, and can therefore be applied broadly in such contexts. Doing so allows researchers to identify the precise location of export activity. The methodology provides a promising alternative to imputation strategies and opens the door to a wide range of new empirical analyses.

To illustrate the use of these data, we document several new stylized facts on regional export patterns. In addition, we provide examples of empirical applications that are made feasible by the availability of the new microdata. In our main application, we study the local labor market implications of the Great Trade Collapse of 2008-2009 and show that counties in the U.S. more exposed to foreign demand shocks suffered greater declines in employment, payroll, and wages. This finding highlights both the positive local effects of access to foreign markets and the exposure to fluctuations in foreign demand. We also demonstrate that common approaches of imputing local-area exports using product-level export data and local-industry employment shares cannot replicate directly measured local-area exports. The discrepancy suggests that such imputation-based approaches should be used with caution.

At the core of our analysis is a new algorithm to construct a novel establishment-level dataset of export transactions with information on the destination of each shipment, the product classification, and other details. To distinguish this dataset from alternative sources we call this dataset the plant-level export transactions (or PLEXT) database. Beginning with restricted-access, firm-level export transaction data from the U.S. Census Bureau (Kamal and Ouyang, 2020), we utilize several additional pieces of information to "allocate" each transaction to the appropriate establishment, and hence the precise location from which the transaction originated. This approach is an improvement on plant-level exporting data from the Census of Manufacturers, which excludes certain types of trade and provides no information on the destination of exports or their product classification. It is also an improvement over public-use state-level export data based on an "origin-of-movement" variable, for reasons we describe in detail below. Although a number of important complications remain—the firm of export is not always the firm of production, warehousing, intra-firm export consolidation, and the like—the algorithm we develop provides researchers with a more accurate and more detailed datset to study local export patterns and behavior than was previously available.[1]

Using the novel PLEXT dataset, our second contribution is to document a number of new facts on local-area export activity across the United States. First, we show that geography plays a role in export patterns at the state level, as, for example, states close to the Canadian border tend to export relatively more to Canada. Second, we find that exports are significantly more geographically concentrated than both employment and sales. In addition, we document that the degree to which these variables vary in concentration differs between states. This non-proportionality suggests that problems may arise when using employment or sales shares to impute exports to local areas. Third, we construct measures of export intensity to major U.S. export destinations such as China, Mexico, and Canada. These measures capture how dependent particular local areas are on demand from these destinations and should therefore be of interest to local policymakers.

We then turn to a particular application that illustrates the use of the new PLEXT data for empirical research on the connection between export activity and local labor markets. After aggregating the microdata to the county level, we study the regional heterogeneity in outcomes arising from exporting during the Great Recession and the associated trade collapse. Using an updated version of the World Import Demand instrument (WID, see Hummels et al., 2014) to isolate foreign demand shocks that are plausibly orthogonal to U.S. demand declines and other confounders, we find that counties that were more exposed to negative foreign demand shocks performed worse in terms of employment, pay, and wages during the Great Recession. In our preferred specification, we estimate that a one million dollar decline in exports led to the loss of 17 jobs in the county. Furthermore, county-level payroll declined approximately one for one with a decline in exports, and a one thousand dollar drop in exports per worker led to a 1.9 percent decline in the local wage rate. These

[1] Most of these complications will also affect all publicly available export data.

effects come not just from the direct employment effects of manufacturing exports but also from local, within-county spillovers to non-manufacturing industries.

To make explicit the benefits of our algorithm and the resulting dataset, we assess whether the common approach of "imputing" local exports from county-level employment data and more aggregate export data is problematic or not. To do so, we repeat our analysis of the effects of the Great Trade Collapse during the Great Recession using imputed county-level exports from publicly available data. We find that the resulting estimates are generally statistically insignificant, noisy, and suffer from weak instruments. The discrepancy with our main estimates likely reflects the fact that the imputation relies on the proportionality of employment and exports, which—as we have shown—does not hold in the data. In sum, our evidence shows that imputing local area exports can provide a distorted view of true local exporting patterns, and may imply that this practice is problematic for other analyses as well.[2]

Linking U.S. firm-level export transactions to individual establishments opens up new avenues for analyzing trade patterns and their role in the U.S. economy. One key advancement is that the PLEXT data enable analyses at the establishment level. Previously, U.S. export and import transactions were measured only at the firm level. In contrast, many other surveys and censuses of the U.S. Census Bureau are conducted at the establishment level. To combine trade data with those other datasets from the U.S. Census, researchers often had to aggregate establishment-level data up to the firm level. However, this practice typically introduces measurement error, as most surveys cover only a subset of a firm's establishments. Our algorithm allows researchers to sidestep this issue. Since export transactions can now be measured at the establishment level, the entire analysis can be conducted at that level. Researchers can then also use the appropriate sampling weights from relevant surveys.[3] As an example, Boehm, Flaaen and Pandalai-Nayar (2023) implement this algorithm to build an establishment-level dataset to study export participation by U.S. firms and plants.

In summary, the new algorithm we develop assigns trade transactions with product- and country-level detail to establishments. This allows for new analyses at the establishment level and for more accurate measurement of exports by region.

[2]The practice of imputing trade using employment weights together with national trade data is potentially less problematic for the case of imports, at least for some applications. For example, the employment share of an industry producing an imported good may better capture the exposure to import competition than directly measured imports.

[3]As new datasets constructed with confidential Census Bureau microdata can typically not be easily transferred between researchers, we emphasize our contribution mostly in the form of a detailed algorithm. This algorithm can readily be implemented by other researchers with access to standard confidential microdata and code that can be made available, allowing them to construct these establishment-level export data themselves.

Related Literature. This paper is related to several strands of the literature. A number of previous papers have attempted to measure and study sub-national trade patterns both in the U.S. and other countries. For instance, Santamaría, Ventura and Yeşilbayraktar (2020) create a dataset of regional European trade using a new survey, the European Road Freight Transport Survey (ERFT), from Eurostat. In the U.S., the Commodity Flow Survey (CFS) from the U.S. Census has been used to study intra-U.S. trade (see Allen and Arkolakis (2014) and Atalay, Hortaçsu and Syverson (2014)). Our dataset complements these studies by providing data on foreign exports by product and destination, down to the level of individual establishments and counties.

Our paper is also related to a long line of influential research studying the local labor market effects of trade shocks. Notable papers in this literature include Autor, Dorn and Hanson (2013), Feenstra, Ma and Xu (2019) and many others (China shock); Topalova (2007) (Indian trade liberalization); Kovak (2010) and Dix-Carneiro and Kovak (2017) (Brazilan trade liberalization); Hakobyan and McLaren (2016) (NAFTA); and Benguria and Saffie (2019) and Benguria and Saffie (2020) (U.S.-China trade war). This line of research typically constructs local exposure to a shock by using national or state-level trade data mapped to the local level with employment weights, and often finds large and heterogeneous effects across space. Our main application is most closely related to Feenstra, Ma and Xu (2019), who study the employment effects of exporting. Relative to their paper our focus is on the specific episode of the Great Trade Collapse and we use our novel PLEXT database, which allows for the more accurate measurement of exports. House, Proebsting and Tesar (2020) study the effects of exchange rate shocks on state-level outcomes.[4]

Finally, our paper is related to the large literature studying the trade collapse during the Great Recession. This literature explores reasons for the trade collapse, for instance, the role of intermediate input trade or other demand factors (Levchenko, Lewis and Tesar, 2010; Bems, Johnson and Yi, 2013; Bussière et al., 2013). Alessandria, Kaboski and Midrigan (2010*b*) and Alessandria, Kaboski and Midrigan (2010*a*) study the role of inventories.[5] To the best of our knowledge, no work has directly assessed the local labor market effects of exporting during the trade collapse.

Roadmap. The next section describes the algorithm and datasets we use to construct the new establishment-level dataset of trade transactions. Based on this dataset, we document

[4]Caliendo, Dvorkin and Parro (2019) and Caliendo et al. (2018) study quantitative models with local labor markets or regions. They use employment share-based approaches to motivate their analyses.

[5]The literature on the trade collapse of the Great Recession is vast, including work by Eaton et al. (2016), Ahn, Amiti and Weinstein (2011), Bown and Crowley (2013), and Feenstra, Li and Yu (2014), among many others.

a number of new facts on the local-area incidence of exporting in Section 3. In Section 4 we turn to our main application and study the local labor market effects of the Great Trade Collapse. We subsequently demonstrate in Section 5 that imputed data fails to replicate these results. Section 6 concludes.

2. Constructing A New Dataset of U.S. Export Transactions at the Plant Level

This section describes the methodology and data behind our new establishment-level dataset of export transactions.

2.1 Core Census Ingredients to Establishment Exports

The new dataset we construct builds on a number of restricted-use Census Bureau datasets that have become important resources for economists studying international trade with microdata. Prior to this paper, the most detailed information on establishment-level exports is a survey-based variable of plants' total exports from the Census of Manufacturers (CM). It is available quinquennially in years ending in a 2 or 7 from the CM and from the Annual Survey of Manufacturers (ASM) in intervening years. This variable could ostensibly be tied to a particular labor market.[6] While a long line of research dating back to Bernard and Jensen (1995) and summarized in Bernard et al. (2007*a*) has made important contributions to our understanding of establishments and firms engaged in trade using this variable, it has a number of drawbacks. These are, among others, that it is survey-based, infrequent, and that it contains no information on the product and the destination country.[7] It also lacks other shipment-level details.

A second, related restricted-use Census data product is the "Products Trailer" file of the CM. This extension of the CM additionally asks establishments to separate out their total shipments into detailed product categories. We use this information from the Products Trailer file to match exported products to establishments that are likely to have produced them.

A final component of the restricted-use Census data on export activity—and the primary source for our new dataset—is the Longitudinal Foreign Trade Transactions Dataset (LFTTD).

[6] Another possible source of granular information on export activity comes from the Commodity Flow Survey (CFS). Unfortunately, this survey data relies on a relatively small sample, is infrequently administered, and generally lacks country of destination detail.

[7] Perhaps most importantly, it appears that these surveys stopped asking this export question after 2017.

This dataset, developed through a collaboration between U.S. Customs and the Census Bureau, captures the universe of U.S. export and import transactions in goods (see Kamal and Ouyang, 2020, for details). It includes information on the transaction date, value, quantity, product classification (HS10), and whether the transaction occurred between related parties or at arm's length, among other information. Crucially, these trade transactions have been linked to firms via an Employer Identification Number (EIN) and other information. A major advantage of these data is their ability to be linked with other Census Bureau datasets, most notably the Longitudinal Business Database (LBD), which provides a consistent longitudinal register of establishments and firms, and includes information on employment, payroll, and more.[8]

2.2 Combining Sources of Information for Better Measurement

A key limitation is that the LFTTD export data matches an individual trade transaction to a *firm* identified as the U.S. principal party in interest (USPPI) and not to an individual establishment or location within that firm.[9] Our methodology combines three primary pieces of information to identify the establishment within the firm that most likely produced the goods traded in a given export transaction.[10] Each of these pieces of information has advantages as well as limitations, and thus by combining them we can more accurately assign export transactions to the different production locations of the firm.

First, we utilize a variable in the LFTTD that identifies, for each transaction, the geographic "origin of movement": where the shipment began its journey to the port of export. Of course, this origin of movement need not always be the same as the origin of production, as discussed in some detail in Cassey (2009). The three most salient reasons for a disconnect are:

- Consolidation: if a shipment combines with similar commodities from the same firm then only the location of consolidation is recorded for that shipment. This is most common with agricultural shipments.
- Wholesale/Retail: if the exporter is a wholesaler or retailer, then the location of origin of the wholesaler/retailer is recorded, and not the location of production.
- Warehousing: a shipment could be sent to a storage or warehouse facility and then

[8]We provide additional information on available data sources for U.S. exports and imports in Appendix A.

[9]The USPPI is defined as the the person or legal entity in the United States that receives the primary benefit, monetary or otherwise, from an export transaction.

[10]While firms produce and export goods in most theoretical models, it is important to recognize in the data that there may exist instances in which the act of exporting is undertaken by a non-manufacturing firm (see, e.g., Bernard et al., 2010; Bernard and Fort, 2015).

subsequently exported. If the export process begins at this location, then the origin of movement will be recorded as the warehouse facility, and not the location of production.

Thus, while the origin of movement variable provides useful information for the allocation of export transactions to plants, these examples demonstrate the importance of combining it with other information where relevant. Relative to the publicly available state-level export data that is solely based on the origin of movement variable, we can identify instances where this variable provides misleading information—for instance, because the firm has no plant at the origin of movement.[11]

The second piece of information for identifying the appropriate establishment of a firm's trade transaction comes from linking the exported products to the establishment industries that are typically associated with production of that product. We use the product by industry data from the CM Product Trailer file to construct, for each exported product, a set of "Production-Associated Industries" (PAIs). We create these measures at the industry level rather than linking directly to establishments of a firm because this resource is only available in select years.

Finally, we leverage the establishment export variable as reported in the CM or ASM to assist in identifying likely export establishments within a firm. In this last step, where other data are silent, we utilize the shares of overall export activity across a firm's establishments from the CM or ASM to allocate that firm's exports.

2.3 Overview of the Algorithm

The algorithm proceeds sequentially. In each step, it prioritizes certain pieces of information identified above in allocating export transactions to specific establishments. We outline those steps here briefly but highlight that the researcher may want to adapt these criteria based on the specific research question at hand. Additional information on how to prepare the data before applying the algorithm is available in Appendix B.

- **Case 1: Single unit firm.** For firms with only one establishment the allocation is trivial. We set these transactions aside while flagging whether the establishment is classified as a manufacturing or a non-manufacturing plant.

- **Case 2: Unique zip code match: manufacturing.** If the zip code of the origin of movement matches to a unique establishment in manufacturing, then the associated trade is assigned to that establishment. We separately flag whether the establishment records positive export shipments in the ASM/CM.

[11]See https://usatrade.census.gov/ for more information on the state-level exports data.

- **Case 3: Non-unique zip code match to PAI establishment** If there is only one establishment matching the zip code that also matches based on our PAI criteria, then we allocate all trade to the zipcode match that also aligns with the appropriate industry. Given that an HS code can be assigned to multiple PAIs, it is possible for there to be several establishments matching this case. In these cases we use relative export values from the ASM/CM (preferred) or relative employment to split the transaction values.

- **Case 4: No zip code match but unique PAI establishment.** In this case, simply allocate all trade to the unique PAI establishment.

- **Case 5: No zip code match but non-unique PAI establishments.** For multiple establishments matching a PAI, we split the transaction across matching establishments using relative export values from the ASM/CM (preferred) or employment .

- **Case 6: Non-unique zip code match, and no PAI establishments.** We split these cases into those matching manufacturing establishments with those matching non-manufacturing establishments. If there are multiple establishments with the same zip code (which is rare), we continue to use employment shares as weights.

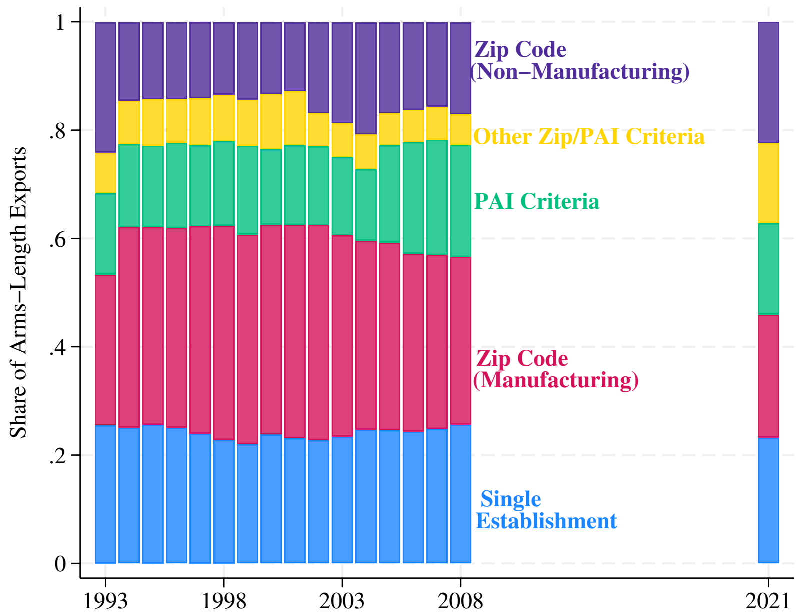
- For any unallocated export transactions at this stage, we loop back through cases 3 through 6 and relax the criteria for PAI establishments to the level of NAICS-5, and then subsequently to NAICS-4.

- **Case 7: No zip code match and no PAI establishments.** For this final case, we first allocate the export transaction to all manufacturing establishments of the associated firm (using either ASM/CM export share weights or employment weights). We next prioritize establishments in the wholesale (NAICS 42) and transportation/warehousing (NAICS 48) industries, based on the distribution of exports from prior matches. If there are no establishments in any of these industries, then the final step allocates the export transaction to all other establishments based on employment shares.[12]

Figure 1 documents the share of overall U.S. exports that is allocated according to the hierarchy of steps as described above. The figure focuses on only arms-length exports – for an analogous figure illustrating allocation shares for related party exports, please see Figure A1. All subsequent analysis uses all exports regardless of whether they are reported as arms-length or related-party.

[12]In practice, for these cases we take the top 20 establishments by employment size, as there are some firms with thousands of establishments.

Figure 1: Share of Exports by Type of Establishment Allocation



Notes: The figure shows the share of total arms-length exports that is allocated to individual establishments based on the criteria described in the text above. The data are from the LFTTD, the CMF, the ASM, and the LBD as explained in the text. Additional years 2009-2020 and beyond are in process for use in subsequent work.

To summarize, the resulting dataset provides greater granularity and detail of U.S. export transactions than has been previously available to researchers. The wealth of details on individual export transactions—such as product, destination, value, quantity, and arms-length status—are mapped to a precise location of origination for the first time.

3. Facts on the Local Geography of Exports

We next document several facts about the incidence of exporting within the U.S. that come out of this data. These facts serve three purposes. First, we aim to compare our new dataset to the extent possible to existing data. Second, since closely comparable datasets are not available, we provide several facts that serve as plausibility checks on our new data. Lastly, some of the facts we document are novel and help further our understanding of the spatial features of exporting in the United States.

3.1 Comparison to State-Level Origin-of-Movement Exports

We begin by aggregating our export data to the state-level. Doing so helps compare them to the more readily available public data from USA Trade Online that is based solely on the

Table 1: State-Level Exports in 2021: Public Use versus PLEXT Data

State	Shares (in percent) Public Data	PLEXT Data	Percentage point Difference	Percent Difference
	Top 5 states: Public Data > PLEXT Data			
Washington	2.4	1.7	0.7	50.7
Tennessee	2.4	1.7	0.7	45.2
New York	6.2	5.6	0.6	15.9
Illinois	4.5	4.0	0.4	16.8
Kentucky	2.1	1.7	0.3	25.6
	Bottom 5 states: Public Data < PLEXT Data			
California	11.1	11.6	-0.5	-0.9
Indiana	2.9	3.4	-0.5	-10.0
Louisiana	2.4	2.9	-0.5	-14.6
Massachusetts	2.2	2.8	-0.6	-16.1
Connecticut	1.0	1.7	-0.7	-37.3

Notes: The table shows the largest discrepancies of state-level exports between the public origin-of-movement data from USA Trade Online and our PLEXT data for the year 2021 together with the export shares of these states from both data sources. State-level exports are measured as a percent of total exports. A positive difference indicates that the public use data attributes more exports to a specific state than the PLEXT data.

origin of movement variable. As our new dataset does not include agricultural and mining products we compare state-level exports to the closest analogue from of the publicly available Census data. The total value of trade is similar, as our methodology accounts for roughly 95 percent of the value identified in the Census public use data in 2021.

The cross-sectional correlation between the PLEXT data and public use Census Bureau data at the state-level is high at 99 percent. The correlations of state exports over time are around 0.87 on average, with the 10th and 90th percentiles being 0.63 and 0.99.

While high correlations at this level of aggregation reflect both an overlap in data sources and the overall skewness of state size, there are significant differences when accounting for variation conditional on state size. Appendix Figure A2 provides a scatter plot of export shares, which highlight the broad overall alignment as well as notable discrepancies. Table 1 shows for the year 2021 the top and bottom five largest measurement gaps in percentage point terms between the public use data and the PLEXT data. Note that this list features both small states such as Connecticut, and large states such as California and New York. For the small states the relative discrepancies between the two measures of state-level exports are large. They exceed 35 percent for Washington, Tennessee, and Connecticut in absolute value. A comparison for all states is available in Appendix Table A1.

3.2 Distance Matters Within the U.S.

The well-known gravity relationship predicts that, all else equal, trade should decrease with distance. For countries other than the United States, research has shown that distance matters for international trade even within country borders.[13] We check this feature in our new data for the U.S.—imperfectly, admittedly, as not all is held equal. Figure 2 displays the intensity of exports to select countries, where we draw out the specialization patterns by reporting the differential share of exports to a particular destination k, relative to the U.S. as a whole ($X_{US,k}$). Specifically, for exports of state i to destination k (x_{ik}) we report:

$$\frac{x_{ik}}{\sum_j x_{ij}} - \frac{X_{US,k}}{\sum_j X_{US,j}}, \tag{3.1}$$

expressed in percent. The figure demonstrates the well-known feature that distance matters. States close to the Canadian border have a higher-than-average share of Canadian exports (Figure 2a). In a similar fashion, exports to Mexico (Figure 2b) tend to be over-represented in states along the southern U.S. border. On the other hand, Figure 2 shows that distance does not explain all important variation in state-level exporting. Exports to China (Figure 2c) are higher than average for some states along the West Coast, but also tend to be high for select states along the East Coast. In addition, the clustering of exports to both Canada and Mexico is evident in parts of the Midwest such as Michigan, Ohio, and Pennsylvania. In Appendix Figure A3 we provide analogous maps for exports to Asia (excl. China), Europe, and the rest of the World.

3.3 Local Area Estimates of Exposure to Export Markets

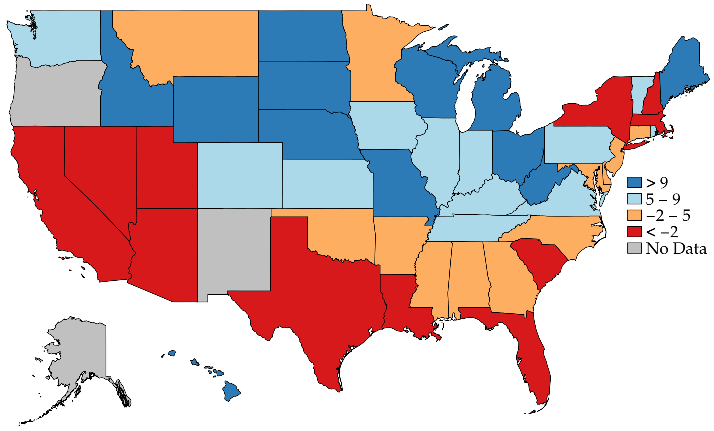
We next turn to the question of which areas in the U.S. are most reliant on foreign export markets. This issue has gained significant attention in early 2025, as the United States imposes a new wave of tariffs, prompting both threatened and actual retaliatory measures from its trading partners. Previous research has shown that exposure to retaliatory tariffs during the 2018–2019 tariff wave was associated with adverse effects on local labor markets and local consumer spending (Flaaen and Pierce, 2024; Autor et al., 2024; Waugh, 2019).

Given the Census disclosure requirements, the most disaggregated geographic area for which we can report exposure statistics is metropolitan statistical areas (MSAs). Our preferred measure divides MSA-level exports to a given destination (aggregated from the PLEXT

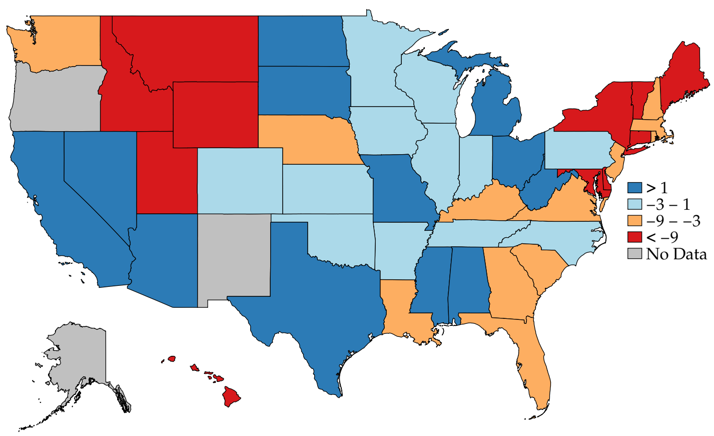
[13]See Crozet and Koenig (2010) for an example with French data, though in their case they use firm-level data and are unable to allocate multi-unit firm exports across *régions* in France.

Figure 2: State-Level Exports to Select Countries, 2021, Percent

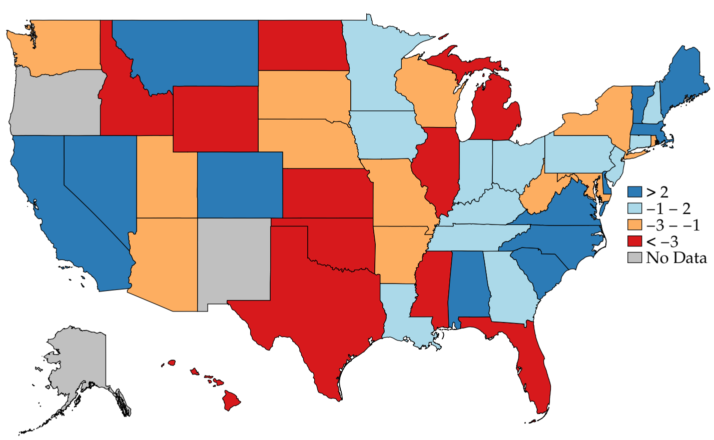
(a) State-Level Exports to Canada



(b) State-Level Exports to Mexico

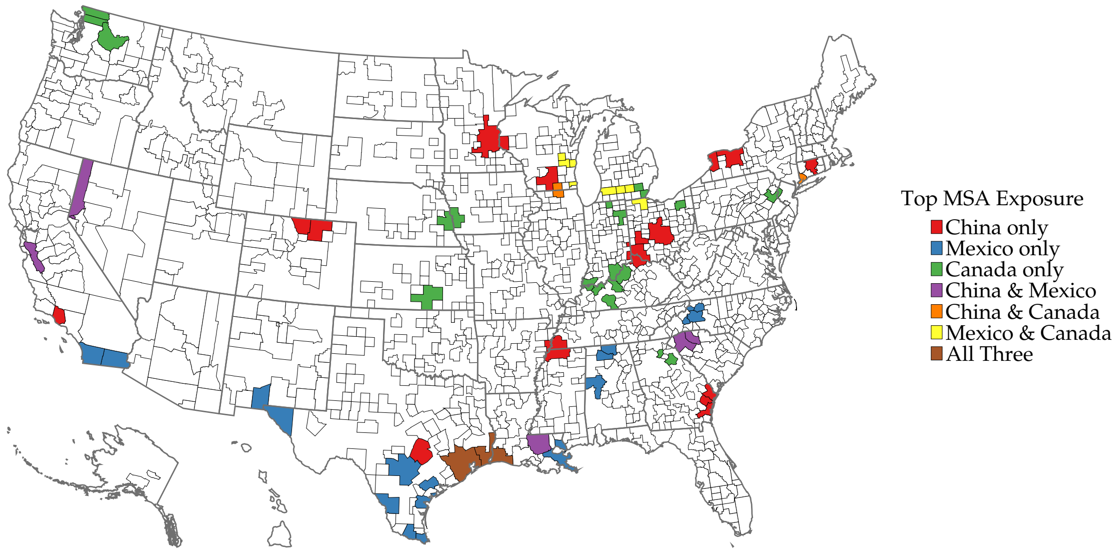


(c) State-Level Exports to China



Notes: Each map shows the state-share of exports to each destination, relative to the national share of exports to that destination (see equation 3.1), expressed in percent. The data are for the year 2021. States with grey coloring have data suppressed due to Census disclosure rules. The differential shading reflects the 25th, 50th, and 75th percentiles of each statistic, among those states with disclosed data.

Figure 3: MSA-level Export Exposure by Destination Country, 2021

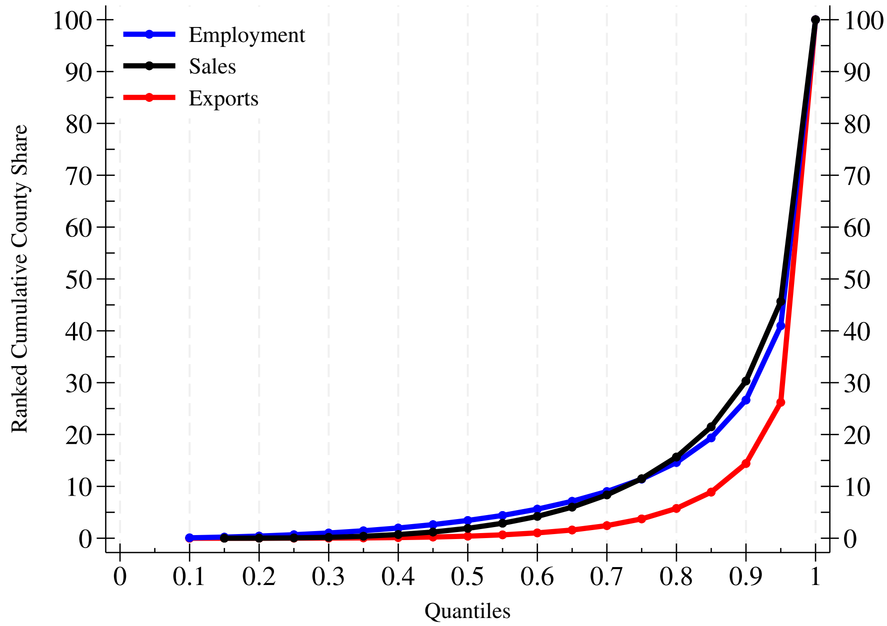


Notes: The map shows the MSAs with the highest export exposure to Canada, Mexico, and China. Export exposure is constructed as MSA exports (aggregated from PLEXT database) divided by the number of workers (from the LBD). Data is for the year 2021. The underlying data is available in Appendix Tables A2, A3, and A4.

data) by the number of workers employed in that geographic area (from the LBD, see Chow et al., 2021). We report data for roughly the top 20 MSAs and focus on exports to Canada, Mexico, and China. The data are from 2021, the most recent year for which our PLEXT data are currently available.

Figure 3 reports these highly exposed MSAs for each export destination. Note that it is often the case that a particular MSA is among the top 20 MSAs for multiple export destinations. It is evident from the figure that high rates of exposure to Mexico cluster near the border, consistent with the gravity relationship just discussed. However, the role of geography is less clear for the cases of Canada and China. For Canada, the highest exposure occurs in several areas of the Midwest historically associated with the concentration of motor vehicle production. The geographies with high concentrations to China are harder to summarize, but it is notable that several areas tied to high-tech and research universities have high degrees of China export exposure (San Jose, CA; Austin, TX; Madison, WI; Rochester, NY; Columbus, OH; etc.). Given the local spillovers associated with foreign demand shocks that we document below, these MSAs will warrant close scrutiny if trade tensions continue to increase. Appendix Tables A2, A3, and A4 report the MSA names and export-per-worker numbers for Canada, Mexico, and China, respectively. It is notable that some MSAs are highly reliant on demand from specific destinations. For instance, several MSAs export between \$10,000 and \$35,000 worth of goods per worker to Mexico.

Figure 4: County-level Concentration in 2021: Exports, Manufacturing Sales, Employment



Notes: The figure shows the cumulative shares of employment, manufacturing sales, and exports after ranking U.S. counties in ascending order for each variable. The data come from the PLEXT database and are for the year 2021. Values below the first decile are suppressed due to Census disclosure rules. For the underlying data, see Appendix Table A5.

3.4 Exports are Highly Concentrated Across Space

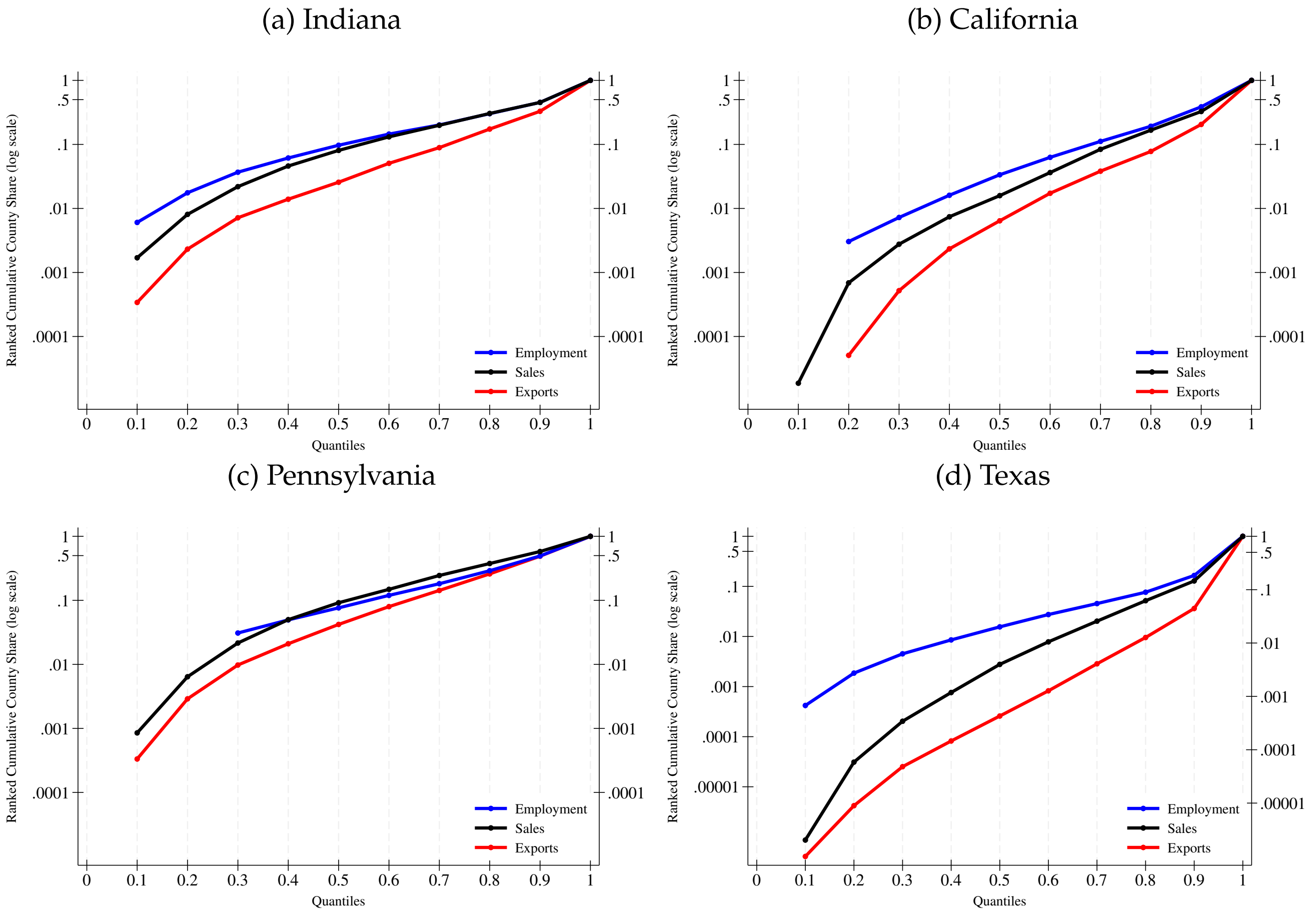
The new PLEXT data also reveal aspects of exporting at the local level that were previously impossible to study with any confidence. One novel fact which we document next is the remarkable concentration of export activity in the United States. Although it is well known that economic activity is highly concentrated across space (see Axtell, 2001; Gabaix, 1999, 2011) and that export activity is concentrated in a small number of firms (see, for example, Bernard et al., 2007*b*), the geographic concentration of exporting has received less attention.

As one way to highlight this concentration, we aggregate our data to the roughly three thousand counties in the United States, rank counties by their share in aggregate exports, and then calculate the cumulative share by quantile. For comparison, we conduct a similar exercise for both employment and manufacturing sales, noting that an individual county's rank generally differs for each measure.[14] The resulting Figure 4 is similar to a Lorenz curve, but has the cumulative *share* of exports, sales, and employment on the vertical axis.

Figure 4 not only confirms the extreme skewness of overall economic activity at this level of geography, but also highlights that export activity is even more concentrated than both

[14]None of the results in this section are informative about the relationship between a county's ranks of, for example, employment and exporting, but we document evidence for a substantial positive correlation between these objects in Figure 6 below.

Figure 5: County-level Concentration by State in 2021: Exports, Manufacturing Sales, Employment



Notes: The figure shows the cumulative shares of employment, manufacturing sales, and exports for different states after ranking each states' counties in ascending order for each variable. The data come from the PLEXT database and are for the year 2021. Values below the first few deciles are suppressed due to Census disclosure rules.

employment and sales.[15] While the top 5 percent of counties by employment account for a little over 55 percent of employment, the top 5 percent of counties by export volume account for over 70 percent of total exports.

An additional and related fact revealed by the PLEXT data is that much of the variation in exporting actually occurs *within* states. In Figure 5 we perform a similar exercise to Figure 4 but within states rather than across the entire country. Although disclosure limitations prevent a full presentation of all states, we report results for four large states covering different geographic areas of the United States. Given the smaller number of overall counties for a given state, we report these ranked shares by decile, and improve legibility by using a log scale.

Figure 5 reveals several notable features. The greater concentration of exports relative

[15]The shares of counties below the first few deciles are so low that disclosure rules prevent us from reporting them.

Table 2: Proportion of Activity in Top Decile of Counties in 2021: Selected States

	Employment	Sales	Exports
Pennsylvania	50.7%	42.1%	51.1%
Indiana	54.7%	54.7%	67.1%
California	61.4%	67.3%	79.5%
Texas	81.5%	85.4%	96.4%
Georgia	67.8%	58.1%	80.8%

Notes: The table reports the proportion of employment, manufacturing sales, and exports in the top decile of counties in each state, where the deciles are calculated separately for each measure. The data com from the PLEXT database and are for the year 2021.

to employment or manufacturing sales holds for all states shown, though the degree of this gap differs by state; for example, the proportions track more closely in Pennsylvania than in Texas. Second, the degree of export concentration also differs markedly across states. This point is more clearly visible in Appendix Figure A4, which plots just the export concentration across states. For yet another perspective, Table 2 focuses on the variation in the top decile for five selected states (the four states from Figure A4 along with Georgia) with as little as 42 percent of activity in the top decile (sales in Pennsylvania), to above 96 percent (exports in Texas). In each case, exports are more concentrated than either manufacturing sales or employment.

The stylized facts documented in this section illustrate the high degree of variation in exports across counties across the United States, and within individual states. This variation does not always align with other indicators of economic activity, with exports typically more highly concentrated than both employment and sales. In the context of evaluating the local labor market effects of trade, this feature is particularly salient in light of the common practice of using county-level employment shares to impute the effects of export activity to local areas. As our new dataset shows, such a practice could lead to the inaccurate assessment of a local area's export exposure. In addition, and as discussed earlier in this section, this high concentration implies that some areas in the U.S. benefit substantially from access to foreign markets.

4. Local-Area Effects of Exports: Evidence from the 2008-2009 Great Trade Collapse

During the Great Recession U.S. real imports and exports both declined by around 20 percent from peak to trough—a much larger drop than overall economic activity. While a sizeable literature has analyzed the factors contributing to this "Great Trade Collapse" (e.g., Levchenko, Lewis and Tesar, 2010; Alessandria, Kaboski and Midrigan, 2010*b*), data limitations have thus far prevented researchers from studying the effects on U.S. local labor market outcomes. In this section we illustrate the advantages of the new dataset constructed by our algorithm and study how the Great Trade Collapse affected county-level employment, payroll, and wages.

To isolate exogenous variation in foreign demand we employ a version of the World Import Demand (WID) instrument as used, for instance, in Hummels et al. (2014). However, doing so poses the challenge that the Great Recession also adversely affected demand in the U.S. and hence declines in foreign demand of a counties' products may be correlated with declines in domestic demand. We therefore adapt the WID instrument to only use variation in destination-specific declines in the imports of a counties' product—and not variation that was common across destinations. This correction implies that our version of the WID instrument is plausibly uncorrelated with changes in domestic demand.

We use this variation to estimate to what extent counties more exposed to foreign demand declines experienced greater employment, payroll, and wage declines between 2007-2009. Our main results are as follows. A one million dollar drop in exports, induced by a drop in foreign demand, led, on average, to the loss of 17 jobs. Further, the pass-through from exports to payroll was approximately one-for-one so that a one dollar drop in exports reduced payroll in the county by also one dollar. Lastly, a one thousand dollar drop of exports per worker reduced wages, on average, by 1.9 percent.

We perform our analysis at the county level as opposed to alternative levels of aggregation (e.g., an establishment or state-level analysis). The main reason is that a key object of interest to policymakers is the net number of jobs gained or lost in a given labor market. To the extent that a county roughly aligns with the local labor market, a county-level analysis is informative about this object.[16] In contrast, an establishment-level analysis would measure a gross flow, that is, the number of jobs lost in exporting establishments without taking into

[16] Another commonly used definition of a local labor market is a Commuting Zone (CZ) (see, e.g., Autor, Dorn and Hanson, 2013, among others). We use counties in our analysis as they are the geographic unit that is used in publicly available datasets such as the County Business Patterns database. A disadvantage of this approach is that we cannot directly link our results to previous work using CZs. Future researchers can readily implement our algorithm and approach at the CZ-level.

account that workers might find jobs elsewhere in the local labor market. While a state-level analysis would also measure the net change in jobs, it would provide very limited variation. A second reason is that a county-level analysis aligns our application with a common level of aggregation used in previous work that studies the effects of shocks on local labor markets (e.g., Serrato and Wingender, 2016).

We first discuss our main estimating equation in Section 4.1. Threats to identification and the instrument are discussed in Section 4.2 and we present the results in Section 4.3. Lastly, we consider extensions in Appendix D.1 and present robustness exercises in Appendix D.2.

4.1 Regression Specification

Let c index counties and t time. We estimate specifications of the form

$$\frac{y_{c,2009} - y_{c,2007}}{\text{emp}_{c,2007}} = \alpha + \beta \frac{\text{exp}_{c,2009} - \text{exp}_{c,2007}}{\text{emp}_{c,2007}} + \text{controls} + \varepsilon_c, \tag{4.1}$$

where $y_{c,t}$ is an outcome of interest, $\text{exp}_{c,t}$ denotes the value of exports, and $\text{emp}_{c,t}$ employment. All variables are aggregated up from establishment-level data in the county. To account for the fact that counties differ in size, we divide both the change in the outcome of interest and the change in exports by the counties' employment in 2007. Notice that this division only affects the interpretation of the constant α; it does not affect the interpretation of the coefficient of interest β.

Our primary outcome variables $y_{c,t}$ are employment and payroll. Employment is measured as the number of workers, and payroll and exports are measured in millions of U.S. dollars. Hence, when the outcome variable of interest is employment, β captures the number of jobs lost due to a drop in exports of one million U.S. dollars. When the outcome variable of interest is payroll, the coefficient β measures the dollars worth of payroll lost after a drop in exports of one dollar. We also estimate equation (4.1) after replacing the left-hand side with the relative change in the average county-level wage $\frac{\text{wage}_{c,2009} - \text{wage}_{c,2007}}{\text{wage}_{c,2007}}$, expressed in percent. In this case we measure exports in thousands of U.S. dollars and hence β measures the percent change in the wage rate attributable to one thousand dollar change in exports per worker.

Specification (4.1) contains a constant and is estimated at the county level. This implies that any aggregate variation over the period from 2007 to 2009 is purged and we estimate the coefficient of interest β entirely from cross-county variation. Note that this coefficient does capture local (general) equilibrium effects such as wage adjustments which may follow a change in foreign demand. As discussed earlier, county-level employment changes following the trade shock reflect *net* changes in the sense that they reflect laid off workers who do not subsequently find jobs elsewhere in the county.

When interpreting the coefficient β, it is important to note that equation (4.1) subsumes changes in domestic demand (both from the county and the remainder of the U.S.) into the error term. Our objective is to estimate the labor market impact of a decline in foreign import demand on a counties' labor market outcomes relative to a county which did not experience this decline in foreign demand. Since domestic demand is not kept constant in equation (4.1), the coefficient β measures the effect of a decrease in foreign demand, which could partially be offset (or enhanced) by selling more (or less) domestically.

While we expect that the sign of β is positive so that a decline in foreign demand adversely affects employment, payroll, and wages, we do not have a strong prior regarding its magnitude. In the presence of only the direct effect—that exporting firms lay off workers following the drop in foreign demand—β captures the inverse of the marginal product of labor. However, this effect may either be attenuated or enhanced. Some work suggests, for instance, that selling domestically and abroad are substitutes, so firms that were adversely affected by the collapse in trade may have been able to compensate for part of this decline by selling more domestically.[17] Further, some laid-off workers may subsequently find work elsewhere in the county, which could partially offset the direct effect at the plant level. Both of these mechanisms would suggest that β is relatively small. Alternatively, any initial layoffs may be aggravated due to local multiplier effects. Such a mechanism would raise the size of β. Taken together, the magnitude of β is influenced by multiple different mechanisms and their relative importance is ex-ante not clear.

We control throughout for the 2007 ratio of exports to employment $\frac{\text{exp}_{c,2007}}{\text{emp}_{c,2007}}$. This control aims to address the possibility that counties which differ in their exposure to foreign demand may differ in other dimensions that could be correlated with developments in their labor market between 2007 and 2009. To address the concern that the outcome variable of interest is trending over time, we further present specifications in which we control for the lagged change in the dependent variable $\frac{y_{c,2007}-y_{c,2005}}{\text{emp}_{c,2005}}$. Lastly, we also present specifications with state fixed effects. In this case the coefficient β is identified entirely from within state variation.

4.2 Identification

The objective of the empirical analysis in this section is to identify the causal effect of a decline in exports—induced by a drop in foreign demand—on counties' local labor markets. This

[17]See, e.g., Vannoorenberghe (2012) for a discussion of this mechanism and evidence at the firm-level.

effect is measured relative to counties that did not experience a decline in exports. Of course, the change in exports on the right-hand side of equation (4.1) and the outcome variable of interest are both endogenously determined and potentially affected by many different shocks. For instance, an adverse local supply shock may reduce both exports and employment and thus bias the estimate of β upwards. On the other hand, a decline in domestic demand could raise exports by lowering their price while also reducing local employment. Hence, such shocks would lead to a downward bias. In Appendix E we develop a stylized model and show that the direction of the bias that arises under OLS estimation depends on the composition of shocks and is generally ambiguous.

To identify β we employ an instrumental variable strategy. Specifically, we use a version of the World Import Demand (WID) instrument (Hummels et al., 2014) to isolate variation in foreign demand that is plausibly orthogonal to other shocks that affect county-level exports and employment over this period. Our version of the WID instrument is

$$\text{inst}_c^{\text{WID}} = \frac{\text{exp}_{c,2007}}{\text{emp}_{c,2007}} \cdot \sum_{d,p} s_{c,d,p,2007}^{\text{exp}} \left(\Delta \ln \text{imp}_{d,p} - \overline{\Delta \ln \text{imp}_p} \right). \tag{4.2}$$

In this expression $s_{c,d,p,2007}^{\text{exp}} = \frac{\text{exp}_{c,d,p,2007}}{\text{exp}_{c,2007}}$ is county c's export share of product p to destination d and $\Delta \ln \text{imp}_{d,p}$ denotes country d's change in total imports of product p between years 2007 and 2009. Further, $\overline{\Delta \ln \text{imp}_p} = \frac{1}{D} \sum_d \Delta \ln \text{imp}_{d,p}$ denotes the product-specific average of the change in foreign imports, where the average is taken across all possible destinations $d = 1, \dots, D$.

At its core, the WID instrument is a weighted sum of changes in foreign imports. It varies by county because different counties are differentially exposed to changes in foreign imports—as captured by the predetermined shares $s_{c,d,p,2007}^{\text{exp}}$. The fraction on the right-hand side of equation (4.2), $\frac{\text{exp}_{c,2007}}{\text{emp}_{c,2007}}$, simply scales the weighted change in foreign imports to account for the fact that some counties export more than others.

A key difference relative to alternative implementations of the WID instrument is that we subtract the product-specific average in imports ($\overline{\Delta \ln \text{imp}_p}$) from the destination and product-specific change in imports ($\Delta \ln \text{imp}_{d,p}$). This adjustment applies and extends the idea of Boehm and Pandalai-Nayar (2022) to purify the WID instrument of undesired components, and addresses the following concern. Since the Great Recession was essentially global in nature, and since downturns affect the demand for products differentially, a version of the WID instrument without this adjustment could be correlated with domestic declines in demand. It is well-known, for instance, that the demand for durable goods declines more during downturns than the demand for nondurable goods. It is also known that a disproportionate share of traded goods is durable. Hence, without purging the instrument of the average decline in demand for products, it likely that the instrument would be correlated with changes in the U.S. demand for a counties' products. Our adjustment implies that the instrument as constructed in equation (4.2) uses destination-specific and destination-product-specific variation, but not purely product-specific variation in foreign demand. Intuitively, a county's demand from abroad was disproportionately affected by the collapse in trade if it exported to destinations whose import demand for its products declined by more than the average global demand for its products during the Great Trade Collapse.

Our research design connects to a recent literature formalizing the properties of shift-share instruments and establishing sufficient conditions for consistent estimation. Our identification argument particularly relates to Borusyak, Hull and Jaravel (2022) and—adopting their terminology—relies on the quasi-random assignment of "shocks", which in our setting are $\Delta \ln \text{imp}_{d,p} - \overline{\Delta \ln \text{imp}}_{p}$. An important feature of our analysis is that these shocks vary by product *and* destination. A sufficient condition for instrument validity is that these shocks are uncorrelated with other shocks that drive appropriately constructed averages of counties' employment or payroll changes that vary at the destination and product level. Subtracting the product-specific average of the growth rate of imports from the shock is analogous to a "shock-level control" and ensures that shock-level confounders that vary purely at the product level—such as a decline of domestic demand for a product—do not pose a problem for identification. Further, our setup features "incomplete shares" since our exposure weights for a given county c, $\frac{\text{exp}_{c,2007}}{\text{emp}_{c,2007}} s^{\text{exp}}_{c,d,p,2007} = \frac{\text{exp}_{c,d,p,2007}}{\text{emp}_{c,2007}}$, do not sum to unity, but to exports per worker $\frac{\text{exp}_{c,2007}}{\text{emp}_{c,2007}}$. Since it is undesirable to use this variation for identification, we include exports per worker as a control in our preferred specifications—as discussed above. In additional checks suggested by Borusyak, Hull and Jaravel (2022), we establish that the effective sample size of shocks, computed as the inverse Herfindahl index of normalized exposure shares, is large (greater than 180) and that the largest exposure share to shocks is smaller than 0.06.[18] The number of shocks is around 23,500. Since the structure of the shift-share instrument implies that conventional formulas for computing standard errors do often not apply, we follow the recommendation of Borusyak, Hull and Jaravel (2022) and report standard errors, which are clustered by product and destination in all results below. We also report the shock-level F-statistics for the first stages for each regression. These are typically lower than conventional first stages, and so provide a conservative assessment of the strength of our instrument.

We use annual imports from the United Nations Comtrade database to construct the WID

[18] Both of these conditions support the asymptotic thought experiment required for consistent estimation—an appropriate law of large numbers at the shock level.

instrument. A product in equation (4.2) is measured at the Harmonized System (HS) 3-digit level. The change in imports, $\Delta \ln \text{imp}_{d,p}$, is constructed as the relative change in imports from all partner countries except for the U.S.[19]

4.3 Baseline estimates

Panel A of Table 3 presents the effects on employment. We begin with specification (1), which reports estimates with only the exports-per-worker control. The estimated coefficient on the change in exports is around 17, implying that a one million dollar decline in exports to foreign countries led to the loss of 17 jobs in the county. This estimate is significant at the one percent level. Little changes when we include the lagged change in employment to account for pre-trends (specification (2)). The coefficient estimate on the change in exports remains stable near 17 and highly significant.

In specification (3) we additionally add state fixed effects and therefore identify the coefficient of interest only from within-state variation across counties. The estimate remains near 17. We note that the first-stage F statistics exceed the conventionally applied threshold of 10 by a large margin for all specifications reported in Panel A of Table 3. This suggests that the instrument is uniformly strong.

We next turn to the effects on payroll, which are reported in Panel B of Table 3. Specification (1) reports the estimate with only the exports-per-worker control. This estimate is 1.04. In specification (2) we add the lagged change in payroll. The coefficient of interest remains stable. A coefficient of 1.04 implies that a one dollar decline in exports reduces payroll by 1.04 dollars or, put differently, that the decline in exports is passed through to payroll approximately one-for-one. Again the estimate remains stable when we include state fixed effects, as reported in specification (3).

Table 4 reports the effects on a measure of wages, which we construct by dividing payroll by the number of workers – thereby capturing the average pay per worker. We refer to this measure henceforth as wages. More specifically, the dependent variable is now the relative change in wages from 2007 to 2009, expressed in percent. Further, for ease of interpretation, exports are now measured in thousands of U.S. dollars. The estimate of interest in specification (1) with only the exports-per-worker control is 1.85, implying that a decline in exports per worker by 1000 U.S. dollars reduces the county-level wage by 1.85 percent. This estimate is quite stable when we add the lagged change in wages as a control. When we add state fixed effects in specification (3) the estimate falls slightly.

[19]We have alternatively constructed the instrument at the HS 4-digit level in undisclosed results.

Table 3: Baseline Estimates: Employment and Payroll

Panel A: Employment

Dependent variable: $\frac{\text{emp}_{c,2009} - \text{emp}_{c,2007}}{\text{emp}_{c,2007}}$

	(1)	(2)	(3)
$\frac{\text{exp}_{c,2009} - \text{exp}_{c,2007}}{\text{emp}_{c,2007}}$	16.9***	16.4***	17.7***
	(4.78)	(4.65)	(6.51)
	[4.89]	[4.77]	[6.47]
$\text{exp}_{c,2007}/\text{emp}_{c,2007}$	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
$\frac{\text{emp}_{c,2007} - \text{emp}_{c,2005}}{\text{emp}_{c,2005}}$		0.01	-0.01
		(0.01)	(0.01)
State fixed effects	no	no	yes
First stage F	37.57	37.42	31.27
Shock-level first stage F	25.29	25.18	21.84

Panel B: Payroll

Dependent variable: $\frac{\text{pay}_{c,2009} - \text{pay}_{c,2007}}{\text{emp}_{c,2007}}$

	(1)	(2)	(3)
$\frac{\text{exp}_{c,2009} - \text{exp}_{c,2007}}{\text{emp}_{c,2007}}$	1.04***	0.96***	0.96***
	(0.35)	(0.34)	(0.44)
	[0.35]	[0.34]	[0.45]
$\text{exp}_{c,2007}/\text{emp}_{c,2007}$	0.06	0.05	0.07
	(0.05)	(0.04)	(0.06)
$\frac{\text{pay}_{c,2007} - \text{pay}_{c,2005}}{\text{emp}_{c,2005}}$		0.04***	0.02
		(0.02)	(0.02)
State fixed effects	no	no	yes
First stage F	37.57	36.89	31.28
Shock-level first stage F	25.29	24.62	21.81

Notes: The table displays two-stage least squares estimates based on equation (4.1), where we use the WID instrument (4.2) to address the endogeneity of exports. Exports and payroll are measured in millions of dollars and employment in numbers of workers. The number of observations—rounded to the closest 100 to comply with Census disclosure requirements—is 3000 in all specifications. The number of shocks, also rounded, is 23,500. We report two types of standard errors. First, we report standard errors clustered by state in parentheses. Second, we report in square brackets standard errors from the "shock-level" specification and clustered by product and destination using the approach by Borusyak, Hull and Jaravel (2022). ***, **, and * indicate significance at the 1, 5, and 10 percent level. Significance is based on the "shock-level" standard errors where available.

Table 4: Baseline Estimates: Wage

	Dependent variable: $\frac{\text{wage}_{c,2009}-\text{wage}_{c,2007}}{\text{wage}_{c,2007}}$ (in percent)		
	(1)	(2)	(3)
$\frac{\text{exp}_{c,2009}-\text{exp}_{c,2007}}{\text{emp}_{c,2007}}$	1.85***	1.92***	1.56**
	(0.87)	(0.77)	(0.75)
	[0.86]	[0.77]	[0.75]
$\text{exp}_{c,2007}/\text{emp}_{c,2007}$	0.02	0.02	0.00
	(0.12)	(0.10)	(0.10)
$\frac{\text{wage}_{c,2007}-\text{wage}_{c,2005}}{\text{wage}_{c,2005}}$		-0.21***	-0.22***
		(0.02)	(0.02)
State fixed effects	no	no	yes
First stage F	37.57	37.37	31.29
Shock-level first stage F	25.29	25.06	21.82

Notes: The table displays two-stage least squares estimates based on equation (4.1), where we use the WID instrument (4.2) to address the endogeneity of exports. The dependent variable is the relative change in the wage from 2007 to 2009, expressed in percent. Exports are measured in thousands of dollars and employment in numbers of workers. The number of observations—rounded to the closest 100 to comply with Census disclosure requirements—is 3000 in all specifications. The number of shocks, also rounded, is 23,500. We report two types of standard errors. First, we report standard errors clustered by state in parentheses. Second, we report in square brackets standard errors from the "shock-level" specification and clustered by product and destination using the approach by Borusyak, Hull and Jaravel (2022). ***, **, and * indicate significance at the 1, 5, and 10 percent level. Significance is based on the "shock-level" standard errors where available.

OLS estimates. For comparison Table 5 shows OLS estimates. For all three dependent variables, these estimates are positive. While they typically remain statistically significant, the estimates tend to be smaller than our 2SLS estimates. As discussed in Appendix E such a downward bias can arise from domestic demand shocks. A decline in U.S. demand for a countries' goods could reduce their price and thus raise exports abroad. At the same time, the decrease in demand could reduce local employment. Hence, such shocks can lead to a negative correlation between local employment and the counties' exports, biasing OLS estimates downward. A second plausible explanation for smaller OLS estimates is classical measurement error in counties' exports. Since this variable is differenced in our specification, the attenuation bias could be sizable despite the relatively accurate measurement of county-level exports.

Extensions and robustness. Appendix D.1 considers extensions of our application, as well as robustness checks. We show that the decline in foreign demand during the Great Recession adversely affected both the manufacturing and the non-manufacturing sectors (see Table A6).

Table 5: OLS Estimates: Employment, Payroll and Wages

Dependent variable:	$\frac{\text{emp}_{c,2009}-\text{emp}_{c,2007}}{\text{emp}_{c,2007}}$		$\frac{\text{pay}_{c,2009}-\text{pay}_{c,2007}}{\text{emp}_{c,2007}}$		$\frac{\text{wage}_{c,2009}-\text{wage}_{c,2007}}{\text{wage}_{c,2007}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{\text{exp}_{c,2009}-\text{exp}_{c,2007}}{\text{emp}_{c,2007}}$	4.38***	3.80***	0.18***	0.15***	0.15**	0.08
	(0.68)	(0.71)	(0.03)	(0.03)	(0.09)	(0.07)
$\text{exp}_{c,2007}/\text{emp}_{c,2007}$	0.00	0.00***	-0.04***	-0.03*	-0.20***	-0.18***
	(0.00)	(0.00)	(0.02)	(0.02)	(0.04)	(0.04)
Lagged dep. variable	0.01	-0.01	0.05***	0.02	-0.20***	-0.21***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
State fixed effects	no	yes	no	yes	no	yes
R^2	0.01	0.13	0.05	0.19	0.09	0.17

Notes: The table displays ordinary least squares estimates based on equation (4.1). In specifications (1)-(4) exports and payroll are measured in millions of dollars and employment in numbers of workers. In specifications (5) and (6) exports are expressed in thousands of dollars. The change in wages between 2007 and 2009 is expressed in percent. The number of observations—rounded to the closest 100 to comply with Census disclosure requirements—is 3000 in all specifications. Standard errors are clustered by state. ***, **, and * indicate significance at the 1, 5, and 10 percent level.

We also discuss the effects of employment weights and confirm the robustness of our results when using publicly available employment measures.[20]

5. Estimates using Imputed Data

To further validate the benefits of our algorithm and the resulting PLEXT database, we illustrate in this section how an alternative approach for identifying the local employment effect of exporting during the Great Trade Collapse is likely problematic. We do so by replicating the analysis in the previous section, but instead of using our new data on county-level exports, we impute these series from publicly available sources. All else, most notably the sample, is kept the same. The imputation follows common approaches in the literature and pairs more aggregate trade data with county-level employment shares.

We highlight that there are different imputation approaches in the literature, and we illustrate results from one strategy where we impute county-level exports from county-level employment and state-level exports. The findings of this exercise do not imply that all the varied imputation strategies of the prior literature are flawed in some way, but simply show

[20]In additional robustness checks we have also implemented the estimation after deflating exports with the export price indexes from the Bureau of Labor Statistics. Since this deflation has essentially no effect on the estimates, we do not report them here.

how the specific imputation approach we implement here performs relative to using the PLEXT data.

5.1 Imputation of County-Level Exports

To use the maximum amount of information available and therefore give this approach the best possible chance to provide accurate estimates, we use state-level export data from the U.S. Census Bureau for the imputation. This data is the most geographically disaggregated data with comprehensive coverage that is publicly available and provides exports from state s of product p to destination d at time t.[21] The imputation further uses the share of county c employment in industry p of overall state-level employment in industry p—again measured at time t.[22] We use County Business Patterns data (CBP, also from the U.S. Census Bureau) with adjustments for missing values as detailed in Eckert et al. (2020). Formally, the imputed value of county-level exports is

$$\widehat{\exp}_{c,d,p,t} = \frac{\text{emp}^{\text{CBP}}_{c,p,t}}{\sum_{c' \in s} \text{emp}^{\text{CBP}}_{c',p,t}} \cdot \exp_{s(c),d,p,t}, \tag{5.1}$$

where $s(c)$ denotes the state s of county c.

Figure 6 shows a binned scatterplot of the quantiles of county-level exports, aggregated over products and destinations, between the imputed data and our new dataset on county-level exports. While the figure demonstrates a strong positive correlation, it also highlights the troubling feature that imputed exports systematically exceed measured exports for all but the largest counties. Note that this imputation error is consistent with the high concentration of exports documented above.

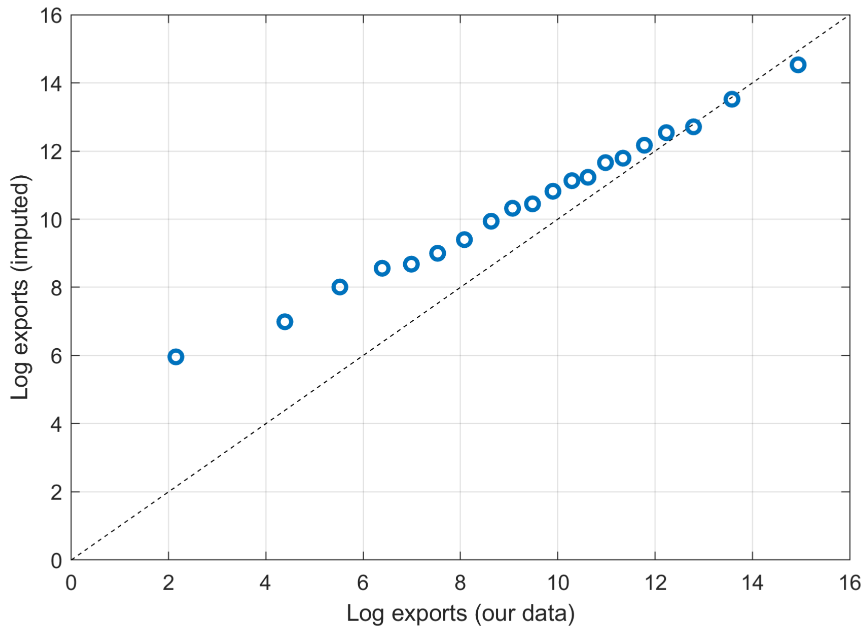
5.2 Estimates using Publicly Available Data

We next repeat the analysis from the previous section, replacing measured exports with imputed exports, but keeping all else equal. Imputed exports enter the estimation of equation (4.1) in three distinct places. First, they enter the change in exports on the right-hand side of the estimating equation. Second, they enter into the exports per worker control. Third, they

[21]We access this dataset via the USA Trade Online database (see https://usatrade.census.gov/). As described in detail above, the state-level attribution relies on the "origin of movement" identified in Customs records and therefore may have some error relative to true source of export activity.

[22]Note that we are defining product and industry to be identical in this application, which follows from the classification of Census products according to a NAICS classification. At the level of available detail—3-digit NAICS—the industry and product-level classifications coincide.

Figure 6: Binned Scatterplot of PLEXT vs. Imputed County-Level Exports



Notes: County-level exports from the PLEXT database and exports imputed with equation (5.1) are aggregated into 20 quantiles and then plotted against one another. The imputation requires data from the CBP and USA Trade Online. Exports are measured in thousands of U.S. dollars.

enter into the construction of the instrument: the exposure weights as well as the scaling of exports per worker are now constructed from the imputed data (see equation 4.2).

Table 6 collects the results of this exercise. In all columns the change in exports on the right-hand side and the exports-per-worker control are constructed using imputed exports. Further, columns (1)-(3) use our version of the WID instrument, constructed as described in Section 4.2, but where county-level exposure shares are constructed using imputed county-level exports. Hence, these columns reflect how a researcher would proceed without access to our new PLEXT dataset (hence the label "public"). The estimates tend to be large and imprecise. Most importantly, the first stage is so weak that this research design does not appear viable and the estimates are not informative.

In columns (4)-(6), we continue to use imputed exports to construct all variables—except the instrument. Although this research design is not feasible without access to our data, this exercise provides a tentative answer as to whether the discrepancy between our main estimates and the estimates in columns (1)-(3) of Table 6 results from measurement error in the change in exports or whether the imputation introduces too much noise for the instrument to have a strong first stage (or both). As columns (4)-(6) show, the instrument strength improves and the estimates rise, suggesting that the imputation is a problem for the instrument's first

Table 6: Estimates using Public Data

	Dependent variable: $\frac{\text{emp}_{c,2009}-\text{emp}_{c,2007}}{\text{emp}_{c,2007}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{\widehat{\text{exp}}_{c,2009}-\widehat{\text{exp}}_{c,2007}}{\text{emp}_{c,2007}}$	21.9	22.4	29.9	39.9***	40.9***	76.4**
	(27.7)	(28.6)	(28.8)	(12.7)	(13.0)	(43.1)
	[21.4]	[22.1]	[27.7]	[9.63]	[10.2]	[36.9]
$\widehat{\text{exp}}_{c,2007}/\text{emp}_{c,2007}$	0.00	0.00	0.00	0.00***	0.00***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\frac{\text{emp}_{c,2007}-\text{emp}_{c,2005}}{\text{emp}_{c,2005}}$		-0.03	-0.03		-0.04	-0.02
		(0.03)	(0.02)		(0.03)	(0.03)
State fixed effects	no	no	yes	no	no	yes
Instrument	Public	Public	Public	Baseline	Baseline	Baseline
Shock-Level First stage F	0.11	0.11	0.02	8.33	7.68	3.23

Notes: The table displays two-stage least squares estimates based on equation (4.1), where we use publicly available trade data to impute export growth at the county-level as described in the text. In columns (1)-(3) the WID instrument (4.2) is constructed using exposure shares based on the imputed data to address the endogeneity of exports. In columns (4)-(6) the instrument is simply our baseline instrument used in Section 4.3. The dependent variable is the relative change in CBP employment from 2007 to 2009, expressed in percent. Exports are measured in millions of dollars and employment in numbers of workers. The number of observations—rounded to the closest 100 to comply with Census disclosure requirements—is 3000 in all specifications. The number of shocks, also rounded, is 23,500. We report two types of standard errors. First, we report standard errors clustered by state in parentheses. Second, we report in square brackets standard errors from the "shock-level" specification and clustered by product and destination using the approach by Borusyak, Hull and Jaravel (2022). ***, **, and * indicate significance at the 1, 5, and 10 percent level. Significance is based on the "shock-level" standard errors where available.

stage.

This exercise provides an example of the value of using an establishment-level dataset on exports that can be tied to geography and local labor markets over using firm-level data (which underlie the state-level export measure used for the imputation). We note that establishment-level data also has the potential to improve industry-level data, for instance, the measurement of industry-level exports. The degree of mis-measurement of regions' or industries' exports when constructed from alternative sources – whether they are created by using firms' industries, by imputation strategies, or other approaches – will depend on a variety of factors. For instance, a firm might have spatially concentrated establishments, in which case the implied geography of exports will correspond well to the location of the firm headquarters. At the same time, the firm might have establishments in multiple different industries. In this case, using the firm headquarters' industry as the origin industry of the exports will lead to mis-measured industry exports.

6. Concluding Remarks

This paper presents a new method to map firm-level export data from customs records to the underlying establishments. Applying it to microdata from the U.S. Census Bureau results in a new dataset, the PLEXT data, which offers researchers greater detail about the origin of export transactions. We then use this dataset to document a number of new stylized facts. We show that export activity is more geographically concentrated than both employment and sales. We further document that the degree of concentration varies substantially across U.S. states—and differentially so for employment, sales, and exports. This nonproportionality implies that conventional imputation methods that construct exports of local areas based on industry-level employment shares suffer from systematic error and can—as in our application—prevent identification of the effect of interest.

The resulting new dataset makes possible a diverse array of additional research applications. These include, in particular, analyses with detailed information on exports at the plant level. They also include analyses that require export information for different sub-state geographies, such as zip codes, counties, or MSAs. To illustrate such an application, we studied the collapse in trade during the Great Recession and showed that exposure to falling foreign demand exacerbated employment, payroll, and wage declines in local labor markets. This application makes clear both the exposure to fluctuations in foreign demand and the general benefits of accessing foreign markets through exporting.

Future research could tackle other questions using this data. First, the connection between exporting and business dynamics is much more direct using establishment data, when one can differentiate between new greenfield investments versus firm growth that is driven by mergers and acquisitions. Second, export promotion programs are a common goal of public policy, but the genesis of such efforts are often local governments with local goals for employment and investment outcomes. Hence, this data offers perhaps the only method to evaluate these policy efforts. Finally, the application highlighted here has only scratched the surface of agglomeration economies in the context of exporting and future research could further study how the presence of exporting establishments in a region may boost the export propensity or productivity of neighboring establishments. With establishment level data, one could build establishment-to-establishment measures of distance to understand how such spillovers exist and evolve.

We hope that the availability of our algorithm to researchers with access to U.S. census data helps stimulate new research that improves our understanding of the local role of export activity. One dimension of the PLEXT data that we have not yet explored is that they contain separate information on related party and non-related party exports. Such data are particularly useful for studying the role of multinational activity on U.S. local labor markets (e.g., Boehm, Flaaen and Pandalai-Nayar, 2020; Kovak, Oldenski and Sly, 2021). For questions in international macro focusing on the transmission of shocks, our dataset has the advantage of containing monthly or even daily export transactions. Ultimately, we hope that the PLEXT database will prove useful for future research and, in turn, to policymakers eager to understand the role of trade for local areas in the U.S.

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Appendix

A. Sources of U.S. Data on Firm and Establishment Level Exports

The original source for firm and establishment level export data from the U.S. Census Bureau comes from the quinquennial Census of Manufacturers (as well as the annual supplement, the Annual Survey of Manufacturers). This survey asks establishments to report the dollar value of their shipments that are destined for foreign countries. The advantage of this survey-based question is the tight mapping between export values and a particular manufacturing plant ostensibly involved with the actual production of that exported product. There are numerous disadvantages of this source, however. There is no product or destination-level detail, it is only an annual measure of total exports, there are concerns of reliability due to the survey basis of the reporting, there is no information on the import side, and the longitudinal nature of the data is limited.

Detailed information on trade transactions are compiled by U.S. Customs for purposes of enforcing trade laws, documenting trade flows, and monitoring border security. The administrative documentation attached to these transactions offers rich detail, including the value, quantity, detailed product, country of export/import, port location, type of transaction, and more. Beginning with Bernard, Jensen and Schott (2009), the U.S. firm associated to these trade transactions was linked to other Census datasets, thus improving the dimensions of information on firm-level trade for study by economists. The principal method of linkage was the employer identification number (EIN), as it was recorded by Customs Bureau documents accompanying individual shipments and also existed as part of the establishment/firm register in the Census Bureau.[23] The resulting Linked/Longitudinal Foreign Trade Transactions (LFTTD) database has been a very useful resource for trade economists studying import/export patterns by U.S. firms. One disadvantage, however, is that the EIN-based matching does not allow exports or imports to be assigned to individual establishments (plants) of the firm. The drawbacks of this limitation are discussed further below.

The final major resources for firm-level trade are the surveys of multinational firms collected by the Bureau of Economic Analysis. The level of aggregation is a mix between the firm and establishment (affiliate), depending on the direction of trade, size of the firm, or

[23]On the export side, the EIN is listed on the "Shippers Export Declaration. The exception are shipments to Canada, which do not contain EINs but rather a field listing the firm name. On the import side, the Customs Forms (7501 and 7503) record the EIN representing the "ultimate consignee" of the imported goods.

whether a particular year falls under the BEA's benchmark survey period. Like the survey-based information from the Census Bureau, the BEA data do not have extensive information on products or high-frequency detail of shipments. And while the focus on multinational firms provides for useful splits between arms-length and related-party trade, the BEA data do not have any information on non-multinational firms.

B. Details on Dataset Cleaning Procedures

B.1 Cleaning Procedures for CM Product Trailer File

There are several data issues that must be addressed before using the CM-Products file to infer information about the relative value of product-level shipments by a particular firm. First, the trailer file contains product-codes that are used to "balance" the aggregated product-level value of shipments with the total value of shipments reported on the base CM survey form. We drop these product codes from the dataset. Second, there are often codes that do not correspond to any official 7-digit product code identified by Census. (These are typically products that are self-identified by the firm but do not match any of the pre-specified products identified for that industry by Census.) Rather than ignoring the value of shipments corresponding to these codes, we attempt to match at a more aggregated level. Through an iterative process we try to find a product code match at the 6, 5, and 4 digit product code level, and use the existing set of 7-digit matches as weights to allocate the product value among the 7-digit product codes encompassed by the more aggregated level.

The final step involves linking the product codes from the export data (the Schedule B product classification) to the SIC/NAICS/NAPCS product codes through what are referred to as a SIC/NAICS "base" codes. These base codes are up to 8 alphanumeric characters long, with shorter base codes representing more highly aggregated products. Depending on the SIC or NAICS linkages, the first four to six digits of the basecodes are called the baseroot. Each HS code has a single baseroot, while a baseroot might be associated with multiple HS codes. We use the NAICS (or SIC) to HS concordance from Pierce and Schott (2012), to map the information from the CM-Products file to the LFTTD trade data.

We now describe how we construct the set of "Production-Associated Industries (PAIs)" associated with a given product. Formally, let x_{pij} denote the value of shipments of product p by establishment i in industry j during a census year. Then the total output of product p

in industry j can be written as:

$$X_{pj} = \sum_{i=1}^{I_{pj}} x_{pij},$$

where I_{jp} is the number of establishments producing p in industry j. Total output of product p is then:

$$X_p = \sum_{j} X_{pj}.$$

The share of product output accounted for by a given industry j is therefore:

$$S_{pj} = \frac{X_{pj}}{X_p}.$$

Because of reporting errors and aggregation of products, we designate an industry as a PAI of product p provided that its share S_{pj} passes a certain threshold – which we set at 5 percent [24]. Hence, the set of PAI industries for product p is $\{j : S_{pj} > 0.05\}$.

B.2 Cleaning Procedures for LFTTD

We match individual years of the LFTTD data to the closest available Census year. This procedure allows one to attach a set of industries to each exported product from the LFTTD; the industry detail of establishments in the LBD can then be used to match products to establishments.

We clean the geographic indicators of zipcode and state, which are used comparatively less by researchers. Although uncommon, some trade transactions in the LFTTD record a missing or incomplete zipcode. For these observations, we fill in missing zip-codes iteratively by replacing missing values with the largest zip-code value within the firm, country, month, HS code and baseroot observation. By attaching a U.S. location to an export transaction, this method may also assist in identifying the relevant establishment of export, though subject to the limitations outlined in the main text.

B.3 Preparatory Steps for Iterative Allocation

To retain as much detail as possible, we take the raw LFTTD export data and aggregate only up to the firm, product, country, month, zipcode, port, export-method (rail, air, etc), and related-party status. Next we take the cartesian product of these firm-level transactions to the full set of firm-establishments from the LBD in each associated year – essentially making

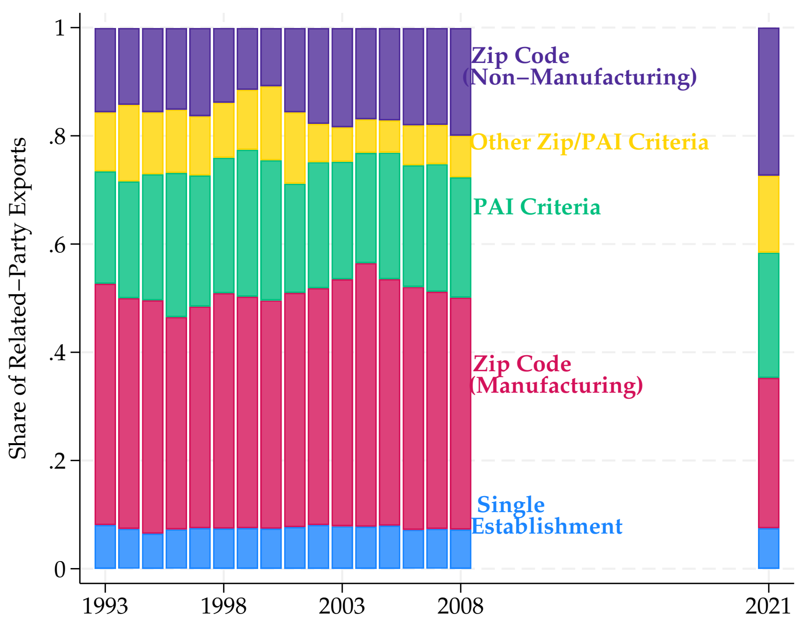
[24] We have varied this threshold without affecting our results

copies of each export observation to attach to all of the firm's establishments. Because the LBD only registers a firm if it existed on March 12th of a particular year, some firms could be trading in the LFTTD but not exist in the LBD. To remedy this issue, we match the trade data not found in the LBD for that period with samples from the year prior and the year following. Using this large dataset, we retain the most likely establishment for each trade observation according to an iterative set of rules, decreasing in the degree of confidence in the establishment match.

Once this dataset is available, we apply the iterative allocation steps outlined in Section 2.3.

Figure 1 in the main text illustrates the shares of arms-length exports according to the type of matching criteria used in the allocation procedure described above. Below we provide a similar illustration for the related-party exports. The results are very similar, with the unsurprising difference that single-establishment shares of allocation are quite a bit smaller for related-party exports.

Figure A1: Share of Exports by Type of Establishment Allocation: Related-Party Exports



Notes: The figure shows the share of total related-party exports that is allocated to individual establishments based on the criteria described in the text above. The data are from the LFTTD, the CMF, the ASM, and the LBD as explained in the text. Additional years 2009-2020 and beyond are in process for use in subsequent work.

C. Additional Figures and Tables

Figure A2: Scatterplot of Public Use versus PLEXT Data in 2021

Notes: The figure plots the share of state-level exports in the national total from USA Trade Online against the same share from the PLEXT data for the year 2021. Note that both axes use a log scale.

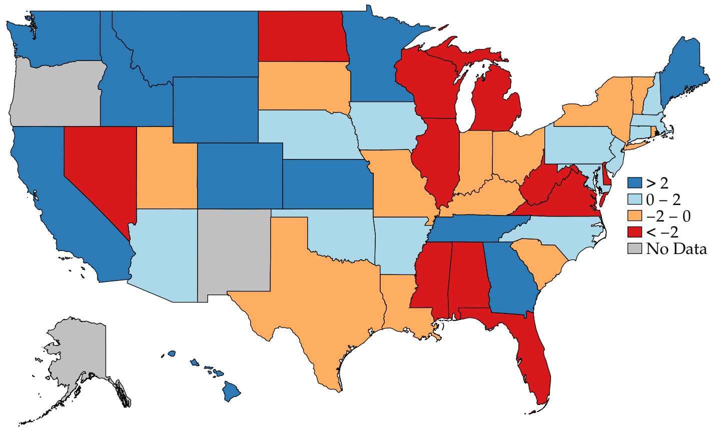
Table A1: State-Level Exports in 2021: Public Use Data vs. PLEXT Data

State	Shares (in percent) Public Data	PLEXT Data	Percentage point Difference
Washington	2.4	1.7	0.7
Tennessee	2.4	1.7	0.7
New York	6.2	5.6	0.6
Illinois	4.5	4.0	0.4
Kentucky	2.1	1.7	0.3
Iowa	0.9	0.6	0.3
Florida	3.8	3.5	0.3
New Jersey	3.4	3.1	0.3
Arizona	1.5	1.2	0.2
Pennsylvania	2.9	2.7	0.2
South Carolina	2.0	1.9	0.2
Maryland	1.0	0.8	0.2
Alabama	1.4	1.2	0.2
New Mexico	0.4	0.2	0.1
North Dakota	0.3	0.2	0.1
New Hampshire	0.4	0.3	0.1
Virginia	1.0	1.0	0.1
Mississippi	0.8	0.8	0.1
Wyoming	0.1	0.0	0.0
West Virginia	0.3	0.2	0.0
Georgia	2.8	2.8	0.0
Arizona	0.4	0.4	0.0
South Dakota	0.1	0.1	0.0
Vermont	0.2	0.2	0.0
Maine	0.2	0.2	0.0
Nevada	0.7	0.7	0.0
Hawaii	0.0	0.0	0.0
Missouri	1.0	1.0	0.0
North Carolina	2.3	2.3	0.0
Oklahoma	0.4	0.4	0.0
Rhode Island	0.2	0.3	-0.1
Montana	0.1	0.2	-0.1
Delaware	0.3	0.4	-0.1
Utah	1.2	1.3	-0.1
Alaska	0.1	0.2	-0.1
Wisconsin	1.7	1.8	-0.1
Nebraska	0.5	0.6	-0.1
Idaho	0.2	0.3	-0.1
Colorado	0.6	0.7	-0.1
Kansas	0.7	0.8	-0.1
Texas	18.4	18.5	-0.1
Michigan	3.8	4.0	-0.2
Ohio	3.3	3.5	-0.2
District of Columbia	0.1	0.4	-0.3
Minnesota	1.5	1.8	-0.3
Oregon	2.0	2.3	-0.4
California	11.1	11.6	-0.5
Indiana	2.9	3.4	-0.5
Louisiana	2.4	2.9	-0.5
Massachusetts	2.2	2.8	-0.6
Connecticut	1.0	1.7	-0.7

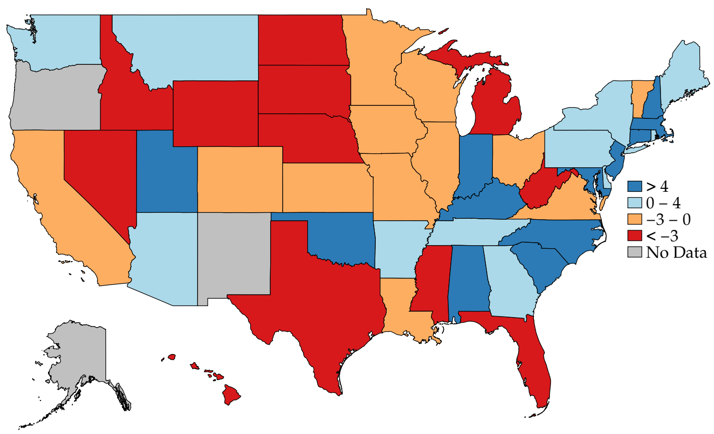
Notes: The table shows export shares by state and the discrepancies of state-level exports between the public origin-of-movement data from USA Trade Online and our PLEXT data for the year 2021. State-level exports are measured as a percent of total exports. A positive difference indicates that the public use data attributes more exports to a specific state than the PLEXT data.

Figure A3: State-Level Exports to Select Regions, 2021, Percent of Total

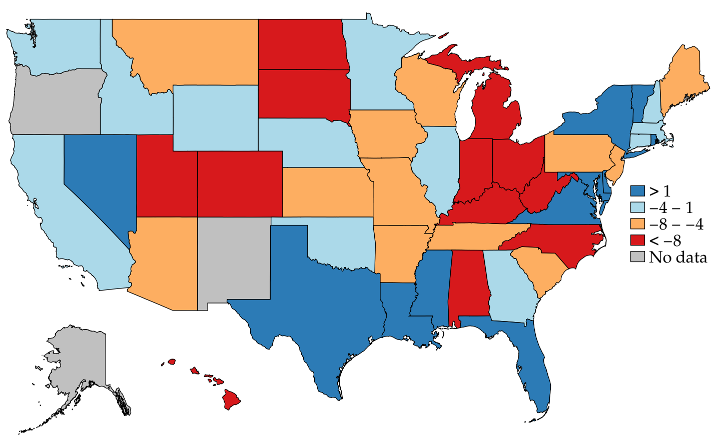
(a) State-Level Exports to Asia (excl. China)



(b) State-Level Exports to Europe



(c) State-Level Exports to Rest of World



Notes: Each map shows the state-share of exports to each destination, relative to the national share of exports to that destination (see equation 3.1), expressed in percent. Exports come from the PLEXT database and are for the year 2021. States with grey coloring have data suppressed due to Census disclosure rules. The differential shading reflects the 25th, 50th, and 75th percentiles of each statistic, among those states with disclosed data. Europe is the EU-27 plus UK. Asia excluding China includes Cambodia, Japan, Malaysia, Mongolia, Myanmar, Papua New Guinea, Philippines, Singapore, South Korea, Taiwan, Thailand, Timor-Leste, and Vietnam. Rest of World excludes EU-27 (plus UK), Canada, Mexico, and Asia (including China).

Table A2: Export Exposure to Canada: Top MSAs

Rank	Name of MSA	Exports per Worker
3	Detroit-Warren-Dearborn, MI Metro Area	$11,640
4	Elkhart-Goshen and Fort Wayne, IN Metro Areas	$11,180
7	Racine, Sheboygan, Oshkosh, and Fond du Lac, WI Metro Areas	$9,004
13	Kalamazoo, Battle Creek, Jackson, MI Metro Areas plus Allegan County	$6,739
16	Toledo, OH Metro Area	$6,025
19	Evansville, Elizabethtown, Bowling Green and Owensboro, IN-KY Metro Areas	$5,115
21	Bellingham-Mount Vernon-Wenatchee plus Clallam County and Jefferson County	$4,899
22	Louisville/Jefferson County, KY-IN Metro Area	$4,873
23	Omaha-Council Bluffs, NE-IA Metro Area	$4,596
24	Wichita, KS Metro Area	$4,545
25	Gainesville and Athens, GA Metro Areas plus Jackson-Habersham-Stephens Counties	$4,542
26	Bridgeport-Stamford-Norwalk, CT Metro Area	$4,388
27	Monroe and Ann Arbor, MI Metro Areas plus Lenawee County	$4,274
33	Houston-The Woodlands-Sugar Land, TX Metro Area	$3,565
36	Allentown-Bethlehem-Easton, PA-NJ Metro Area	$3,311
39	Akron, OH Metro Area	$3,226
43	Beaumont-Port Arthur, TX plus Lake Charles, LA Metro Areas	$3,060
44	Rockford, IL plus Janesville-Beloit, WI Metro Areas plus Stephenson-Walworth Counties	$3,054

Notes: This table shows the top geographies in terms of export exposure to Canada, as measured by the exports per worker employed in that geography. In some cases two or more MSAs are combined in order to align with geography-based disclosure rules. Data on exports are from the PLEXT database and employment comes from the LBD.

Table A3: Export Exposure to Mexico: Top MSAs

Rank	Name of MSA	Exports per Worker
3	El Paso, TX plus Las Cruces, NM Metro Areas	$35,160
4	Beaumont-Port Arthur, TX plus Lake Charles, LA Metro Areas	$31,900
6	Corpus Christi and Laredo and Victoria Metro Areas plus Bee/Kleberg County	$17,520
9	McAllen-Edinburg-Mission, TX plus Brownsville-Harlingen, TX	$12,880
10	Houston-The Woodlands-Sugar Land, TX Metro Area	$11,700
14	Reno plus Carson City, NV Metro Areas	$7,463
23	San Diego-Carlsbad, CA plus El Centro, CA Metro Areas	$4,807
24	San Antonio-New Braunfels, TX Metro Area	$4,762
25	Detroit-Warren-Dearborn, MI Metro Area	$4,631
26	Racine, Sheboygan, Oshkosh, and Fond du Lac, WI Metro Areas	$4,428
27	New Orleans-Metairie, LA Metro Area	$4,265
31	Tuscaloosa, Huntsville, and Decatur, AL Metro Areas	$3,513
32	Toledo, OH Metro Area	$3,347
34	Kalamazoo, Battle Creek, and Jackson, MI Metro Areas plus Allegan County	$3,266
35	Spartanburg plus Greenville-Anderson-Mauldin, SC Metro Areas	$3,241
36	San Jose-Sunnyvale-Santa Clara, CA Metro Area	$3,221
38	Baton Rouge, LA Metro Area	$2,918
39	Hickory-Lenoir, NC Metro Area plus Wilkes-Surry-Wautaga-McDowell County	$2,874

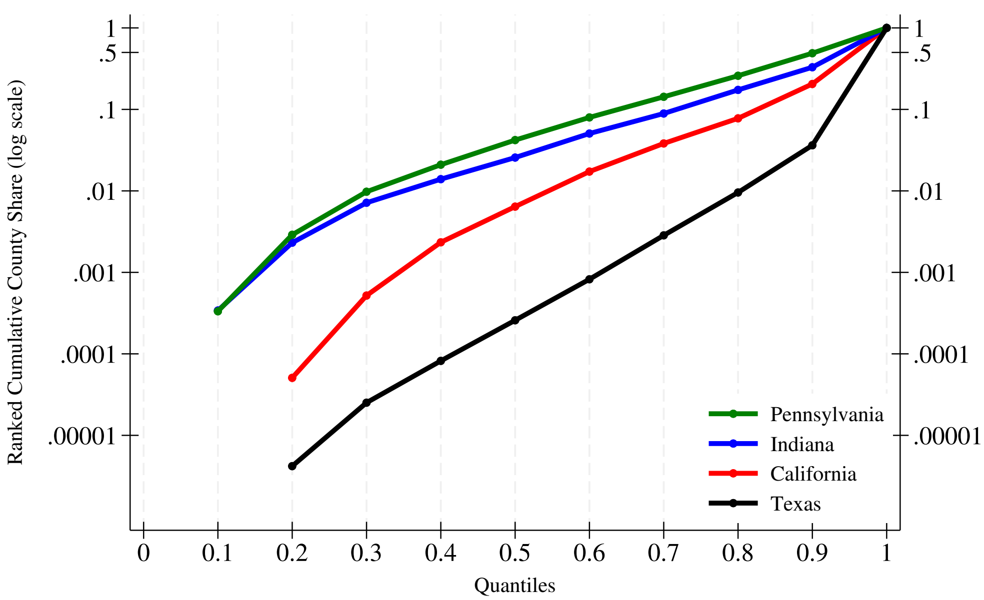
Notes: This table shows the top geographies in terms of export exposure to Mexico, as measured by the exports per worker employed in that geography. In some cases two or more MSAs are combined in order to align with geography-based disclosure rules. Data on exports are from the PLEXT database and employment comes from the LBD.

Table A4: Export Exposure to China: Top MSAs

Rank	Name of MSA	Exports per Worker
1	Beaumont-Port Arthur, TX plus Lake Charles, LA Metro Areas	$14,130
4	Spartanburg plus Greenville-Anderson-Mauldin, SC Metro Areas	$6,047
18	Reno plus Carson City, NV Metro Areas	$2,769
19	San Jose-Sunnyvale-Santa Clara, CA Metro Area	$2,680
23	Dayton, OH Metro Area	$2,121
24	Brunswick, Savannah and Hinesville, GA Metro Areas	$2,114
27	Hartford-West Hartford-East Hartford, CT Metro Area	$2,019
28	Austin-Round Rock, TX Metro Area	$2,009
29	Houston-The Woodlands-Sugar Land, TX Metro Area	$1,984
30	Cincinnati, OH-KY-IN Metro Area	$1,951
31	Greeley and Fort Collins, CO Metro Areas	$1,916
32	Baton Rouge, LA Metro Area	$1,913
33	Rockford, IL and Janesville-Beloit, WI Metro Areas plus Stephenson-Walworth Counties	$1,851
36	Oxnard-Thousand Oaks-Ventura, CA Metro Area	$1,693
42	Rochester, NY Metro Area	$1,341
44	Memphis, TN-MS-AR Metro Area	$1,281
45	Minneapolis-St. Paul-Bloomington, MN-WI Metro Area	$1,268
55	Buffalo-Cheektowaga-Niagara Falls, NY Metro Area	$1,086
56	Bridgeport-Stamford-Norwalk, CT Metro Area	$1,064
60	Columbus, OH Metro Area	$1,015
61	Madison, WI Metro Area	$1,011

Notes: This table shows the top geographies in terms of export exposure to China, as measured by the exports per worker employed in that geography. In some cases two or more MSAs are combined in order to align with geography-based disclosure rules. Data on exports are from the PLEXT database and employment comes from the LBD.

Figure A4: County-level Export Concentration by State in 2021



Notes: The figure shows the cumulative shares of exports for different states after ranking each states' counties in ascending order. The data come from the PLEXT database and are for the year 2021. Values below the first few deciles are suppressed due to Census disclosure rules.

Table A5: Cumulative Shares by Quantile of U.S. Counties (in ascending order)

Percentile	Employment	Payroll	Mfg. Sales	Exports
5	(D)	0.0001	(D)	(D)
10	0.0008	0.0005	(D)	0.00000
15	0.0022	0.0013	0.00002	0.00001
20	0.0042	0.0025	0.0002	0.00006
25	0.0068	0.0041	0.0007	0.00014
30	0.0102	0.0062	0.0018	0.0003
35	0.0144	0.0090	0.0038	0.0007
40	0.0197	0.0125	0.0071	0.0013
45	0.0263	0.0169	0.0120	0.0023
50	0.0343	0.0223	0.0191	0.0040
55	0.0440	0.0290	0.0289	0.0065
60	0.0561	0.0373	0.0421	0.0103
65	0.0713	0.0479	0.0600	0.0159
70	0.0901	0.0613	0.0836	0.0244
75	0.1140	0.0791	0.1148	0.0373
80	0.1460	0.1036	0.1566	0.0575
85	0.1935	0.1408	0.2149	0.0889
90	0.2665	0.1999	0.3032	0.1441
95	0.4098	0.3252	0.4566	0.2621
100	1.0000	1.0000	1.0000	1.0000

Notes: The table displays the cumulative sums of the column variable after sorting all U.S. counties in ascending order for each variable. The data are from the U.S. Census. Mfg. abbreviates manufacturing and (D) signifies suppressed due to disclosure protocol.

D. Application: Extensions and robustness

In this appendix we explore how the foreign demand shock during the Great Recession affected the manufacturing and the non-manufacturing sector separately. We subsequently discuss additional robustness checks.

D.1 Manufacturing versus non-manufacturing

We begin with studying the degree to which the foreign demand shock affected manufacturing sectors and non-manufacturing sectors differentially. Since the manufacturing sector produces the large majority of traded goods, 78 percent in 2007 (see Census, 2008, p.1 of FT-900 Supplement), one would expect that a decline in foreign demand affects this sector disproportionately. On the other hand, lost income of manufacturing workers may trigger declines in the demand for locally produced goods and services, thereby leading to contractions in the non-manufacturing sectors through local equilibrium effects. This section aims to estimate the magnitudes of these effects.

To do so we consider the same outcome variables as before—i.e. employment, payroll, and wages—but construct them separately for manufacturing and non-manufacturing industries within each county. We identify manufacturing plants based on their 2-digit NAICS classifications (31, 32, and 33) and refer to aggregates over the manufacturing industries as the manufacturing *sector* and to aggregates of non-manufacturing industries as the non-manufacturing sector.

Table A6 presents the results. We report coefficient estimates of our preferred specifications, which include the the 2007 ratio of exports per worker as well as a lagged dependent variable (from 2005 to 2007) as controls, but do not include state fixed effects.[25] Specifications (1) and (2) show that employment was impacted by similar magnitudes in the manufacturing and non-manufacturing sectors. More precisely, the estimates suggest that a decline of exports of one million U.S. dollars reduced manufacturing employment by 9.72 jobs while it reduced non-manufacturing employment by 7.95 jobs. Both estimates are significantly different from zero at conventional levels, but the effect for the non-manufacturing sector is estimated with somewhat lower precision. While the large magnitude of the effect on employment for non-manufacturing may seem at first surprising, recall that the level of manufacturing employment is considerably lower than non-manufacturing employment in most counties.

[25] These results are also robust to including state fixed effects.

Table A6: Effects on Manufacturing and non-Manufacturing Sectors

Dependent variable	Employment		Payroll		Wages	
	Mfg.	Non-Mfg.	Mfg.	Non-Mfg.	Mfg.	Non-Mfg.
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{\text{exp}_{c,2009}-\text{exp}_{c,2007}}{\text{emp}_{c,2007}}$	9.72***	7.95***	0.52***	0.87	2.08***	0.90
	(2.76)	(4.49)	(0.12)	(0.60)	(0.79)	(0.88)
	[3.90]	[3.70]	[0.19]	[0.62]	[0.86]	[0.92]
$\text{exp}_{c,2007}/\text{emp}_{c,2007}$	0.00	0.00	0.02	0.09	-0.04	-0.00
	(0.00)	(0.00)	(0.02)	(0.08)	(0.09)	(0.11)
Lagged dep. variable	-0.01	-0.01	-0.09***	0.01	-0.19***	-0.21***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.04)
State fixed effects	no	no	no	no	no	no
Shock-level first stage F	25.02	25.26	24.65	25.12	25.27	24.89

Notes: The table displays two-stage least squares estimates based on equation (4.1), where we use the WID instrument (4.2) to address the endogeneity of exports. Abbreviations: Mfg.—Manufacturing; Non-Mfg.—Non-manufacturing. In specifications (1) and (2) the dependent variable is $(\text{emp}^s_{c,2009} - \text{emp}^s_{c,2007})/\text{emp}_{c,2007}$, where $s \in \{\text{Mfg.}, \text{Non-Mfg.}\}$ indexes the sector. In specifications (3) and (4) the dependent variable is $(\text{pay}^s_{c,2009} - \text{pay}^s_{c,2007})/\text{emp}_{c,2007}$. In specifications (1) through (4) exports and payroll are measured in millions of dollars and employment in numbers of workers. In specifications (5) and (6) the dependent variable is $(\text{wage}^s_{c,2009} - \text{wage}^s_{c,2007})/\text{wage}^s_{c,2007}$, expressed in percent, and exports are measured in thousands of dollars. *Lagged dep. variable* refers to the dependent variable from 2005 to 2007. The number of observations —rounded to the closest 100 to comply with Census disclosure requirements—is 3000 in all specifications. The number of shocks, also rounded, is 23,500. We report two types of standard errors. First, we report standard errors clustered by state in parentheses. Second, we report in square brackets standard errors from the "shock-level" specification and clustered by product and destination using the approach by Borusyak, Hull and Jaravel (2022). ***, **, and * indicate significance at the 1, 5, and 10 percent level. Significance is based on the "shock-level" standard errors where available.

Specifications (3) and (4) show the effects on payroll. The estimates suggest that for every dollar decline in exports, payroll fell by 52 cents in manufacturing sectors and by 87 cents in non-manufacturing sectors. Although the latter effect is very large, it is imprecisely estimated. Specifications (5) and (6) show—as expected—that the impact on wages is greater in the manufacturing sector.

D.2 Robustness

As our findings in Section 3 illustrated, counties differ substantially in their export behavior and hence in their exposure to declines in foreign demand. In particular, we showed that over 70 percent of exports are accounted for by just five percent of counties. While this differential exposure implies that the trade collapse during the Great Recession provides a useful source of variation for our exploration, it also raises the concern that our results could be driven by a relatively small number of counties. To ensure that our estimates are not driven by extreme observations we winsorize all variables used in our empirical analysis.

Employment weights. We have re-estimated the effect of a drop in foreign demand on employment, payroll, and wages, weighing counties with their employment share. In this case, the coefficient estimates, in particular for employment, shrink and become insignificant (estimates not reported). This exercise may suggest that our main estimates are driven by a set of relatively small counties with large changes in exports per worker. We note, however, that it is unclear whether to use employment weights in the estimation. As discussed in Solon, Haider and Wooldridge (2015), in the presence of heterogeneous effects, neither weighted nor unweighted estimation generally ensure consistent estimation of the average partial effect in the population. Instead, they recommend directly exploring the source of heterogeneity. As our goal here is to illustrate a possible application of our algorithm, we leave this to future research.

CBP employment. As additional robustness, to ensure our employment results are not driven by changes in the vintage of the LBD or other Census products, we also estimate the effect of a foreign demand shock on county-level employment using the publicly available County Business Patterns (CBP) dataset to measure employment. The estimated declines in employment per million dollars of foreign export declines are greater and range from 24 workers in the specification with only the exports-per-worker control to 26.9 workers in the specification with state fixed effects. This helps assuage any concerns about the cleaning process we implement on the establishment-level employment data while aggregating to county-level within the Census.

E. Model

To understand our estimating equation, the bias that arises with OLS estimation, and more generally the identification argument in Section 4, consider the following stylized model.

E.1 Setup

The county under study is modeled as a small open economy. Consumers in the county consume goods that are produced domestically and a quasi-linear good m_t that is produced abroad and serves as the numeraire. Trade is balanced. The county also sells its domestically-produced good abroad. It sells to the remainder of the U.S. and to foreign countries. Note that although the model is static, we use time subscripts to make a tighter connection to the estimation in Section 4.

E.1.1 Households

The representative household takes prices p_t and w_t as given and solves

$$\max_{c_t, m_t, l_t} \delta_t^{\frac{1}{\sigma}} \frac{c_t^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} + m_t - \frac{l_t^{1+\frac{1}{\eta}}}{1+\frac{1}{\eta}}$$

subject to the budget constraint

$$p_t c_t + m_t = w_t l_t. \tag{A1}$$

Here, c_t is consumption of the domestically-produced good, l_t is employment, and δ_t a local demand shock. Optimal behavior implies a demand function for the domestically-produced consumption good c_t,

$$c_t = \delta_t p_t^{-\sigma}, \tag{A2}$$

and a labor supply curve

$$l_t = w_t^{\eta}. \tag{A3}$$

We assume in our baseline calibration that the demand elasticity σ satisfies $\sigma > 1$. η is the Frisch labor supply elasticity.

E.1.2 Firms

The representative firm takes prices as given, operates a linear technology,

$$y_t = z_t l_t, \tag{A4}$$

where z_t is total factor productivity, and maximizes

$$\max_{y_t, l_t} p_t y_t - w_t l_t$$

subject to the technology (A4).

Optimal behavior requires that in any equilibrium with strictly positive and finite employment the following relationship holds:

$$p_t z_t = w_t. \tag{A5}$$

E.1.3 Foreign demand

The county faces a downward-sloping demand curve from the remainder of the U.S.,

$$x_{2t} = p_t^{-\sigma} X_{2t}, \tag{A6}$$

where x_{2t} is the quantity demanded, and X_{2t} is a demand shifter.

The quantity demanded from foreign countries (outside the U.S.) is denoted by x_{3t}, and nominal exports to foreign countries are

$$x_{3t}^n := p_t x_{3t}. \tag{A7}$$

We treat x_{3t}^n and X_{2t} as exogenous when solving the model, but allow for correlations between them and with other shocks in the estimation.

E.1.4 Market clearing

The market for output clears:

$$y_t = c_t + x_{2t} + x_{3t}. \tag{A8}$$

E.2 Equilibrium

Given the exogenous shocks $\{z_t, X_{2t}, x^n_{3t}, \delta_t\}$, an equilibrium in this economy consists of the sets of quantities $\{l_t, y_t, m_t, c_t, x_{2t}, x_{3t}\}$ and prices $\{w_t, p_t\}$, such that equations (A1) through (A8) hold.

Note that z_t is a local productivity shock, δ_t is a local demand shock, X_{2t} is a demand shock arising from changes in demand in the remainder of the U.S., and x^n_{3t} is a demand shock from abroad.

E.3 Model solution

It is straightforward to show that in equilibrium and up to a first order approximation around the steady state, labor l_t, the price of the domestically-produced good p_t, and exports to the remainder of the U.S. satisfy:

$$d\ln l_t = \frac{\eta}{\eta+\tilde{\sigma}}\frac{c}{y}d\ln\delta_t + \frac{\eta\,(\tilde{\sigma}-1)}{\eta+\tilde{\sigma}}d\ln z_t + \frac{\eta}{\eta+\tilde{\sigma}}\frac{x_2}{y}d\ln X_{2t} + \frac{\eta}{\eta+\tilde{\sigma}}\frac{x_3}{y}d\ln x^n_{3t}, \tag{A9}$$

$$d\ln p_t = \frac{1}{\eta+\tilde{\sigma}}\frac{c}{y}d\ln\delta_t - \frac{1+\eta}{\eta+\tilde{\sigma}}d\ln z_t + \frac{1}{\eta+\tilde{\sigma}}\frac{x_2}{y}d\ln X_{2t} + \frac{1}{\eta+\tilde{\sigma}}\frac{x_3}{y}d\ln x^n_{3t}, \tag{A10}$$

$$d\ln x_{2t} - \frac{\sigma}{\eta+\tilde{\sigma}}\frac{c}{y}d\ln\delta_t + \sigma\frac{1+\eta}{\eta+\tilde{\sigma}}d\ln z_t + \left(1-\frac{\sigma}{\eta+\tilde{\sigma}}\frac{x_2}{y}\right)d\ln X_{2t} - \frac{\sigma}{\eta+\tilde{\sigma}}\frac{x_3}{y}d\ln x^n_{3t}, \tag{A11}$$

where $\frac{c}{y}$, $\frac{x_2}{y}$, and $\frac{x_3}{y}$ are the steady-state shares of consumption, exports to the remainder of the U.S., and exports to foreign countries in domestic production, respectively, and

$$\tilde{\sigma} := \sigma\left(\frac{c}{y} + \frac{x_2}{y}\right) + \frac{x_3}{y}.$$

Note that $\tilde{\sigma} > 1$ if and only if $\sigma > 1$.

In addition, it is useful to note that nominal exports to the remainder of the U.S. satisfies

$$d\ln x^n_{2t} = -\frac{\sigma-1}{\eta+\tilde{\sigma}}\frac{c}{y}d\ln\delta_t + \frac{\sigma-1}{\eta+\tilde{\sigma}}d\ln z_t + \left(1-\frac{\sigma-1}{\eta+\tilde{\sigma}}\frac{x_2}{y}\right)d\ln X_{2t} - \frac{\sigma-1}{\eta+\tilde{\sigma}}\frac{x_3}{y}d\ln x^n_{3t}. \tag{A12}$$

E.4 Estimation

Our estimation aims to identify the effect of a change in foreign demand dx^n_{3t} on local employment dl_t. From equations (A9) and (A7) it follows that

$$\frac{dl_t}{l} = \frac{\eta}{\eta + \tilde{\sigma}} \frac{l}{py} \frac{dx^n_{3t}}{l} + u_t, \tag{A13}$$

where

$$u_t = \frac{\eta}{\eta + \tilde{\sigma}} \frac{c}{y} d \ln \delta_t + \frac{\eta (\tilde{\sigma} - 1)}{\eta + \tilde{\sigma}} d \ln z_t + \frac{\eta}{\eta + \tilde{\sigma}} \frac{x_2}{y} d \ln X_{2t}.$$

Hence, in the model at hand, the coefficient of interest is $\frac{\eta}{\eta+\tilde{\sigma}} \frac{l}{py}$. It is a function of the supply and demand elasticities in the market for output, η and $\tilde{\sigma}$, as well as output per worker, py/l. The error term contains the local demand shock $d \ln \delta_t$, the local productivity shock $d \ln z_t$, and the demand shock from the remainder of the U.S., $d \ln X_{2t}$.

E.4.1 OLS estimation

Estimating equation (A13) with OLS in the population yields the following coefficient estimate:

$$\begin{aligned}
\frac{Cov\left(\frac{dl_t}{l}, \frac{dx^n_{3t}}{l}\right)}{V\left(\frac{dx^n_{3t}}{l}\right)} &= \frac{\eta}{\eta + \tilde{\sigma}} \frac{l}{py} + \frac{Cov\left(u_t, \frac{dx^n_{3t}}{l}\right)}{V\left(\frac{dx^n_{3t}}{l}\right)} \\
&= \frac{\eta}{\eta + \tilde{\sigma}} \frac{l}{py} + \frac{l}{py} \frac{\eta}{\eta + \tilde{\sigma}} \frac{c}{x_3} \frac{Cov\left(d \ln \delta_t, d \ln x^n_{3t}\right)}{V\left(d \ln x^n_{3t}\right)} \\
&\quad + \frac{l}{py} \frac{\eta (\tilde{\sigma} - 1)}{\eta + \tilde{\sigma}} \frac{y}{x_3} \frac{Cov\left(d \ln z_t d \ln x^n_{3t}\right)}{V\left(d \ln x^n_{3t}\right)} + \frac{l}{py} \frac{\eta}{\eta + \tilde{\sigma}} \frac{x_2}{x_3} \frac{Cov\left(d \ln X_{2t}, d \ln x^n_{3t}\right)}{V\left(d \ln x^n_{3t}\right)}.
\end{aligned}$$

Hence, the following biases arise with OLS estimation (recall that we assume as a baseline that $\sigma > 1$):

- Domestic demand shocks, $d \ln \delta_t$: Positive domestic demand shocks lower nominal exports (see equation A12), because they raise prices (see equation A10). One would therefore expect that $Cov\left(d \ln \delta_t, d \ln x^n_{3t}\right) < 0$. Domestic demand shocks therefore lead to a downward bias in the OLS estimate.

- Local productivity shocks, $d \ln z_t$: Positive local productivity shocks raise nominal exports (see equation A12), because they lower prices (see equation A10). One would therefore expect that $Cov\left(d\ln z_t, d\ln x_{3t}^n\right) > 0$. Local productivity shocks therefore lead to an upward bias of the OLS estimate.

- Demand shocks in the rest of the U.S., $d\ln X_{2t}$: Positive foreign demand shocks lower nominal exports (see equation A12), because they raise prices (see equation A10). One would therefore expect that $Cov\left(d\ln X_{2t}, d\ln x_{3t}^n\right) < 0$. Foreign demand shocks therefore lead to a downward bias in the OLS estimate.

Hence, demand shocks that are specific to either consumers in the county of interest or the remainder of the U.S. lead to downward biases of the OLS estimate while productivity shocks lead to upward biases. If demand shocks were positively correlated so that $Cov\left(d\ln \delta_t, d\ln x_{3t}^n\right) > 0$ and $Cov\left(d\ln X_{2t}, d\ln x_{3t}^n\right)$, then they would also lead to an upward bias.

Recall that we assumed that $\sigma > 1$ for the discussion above. If instead $\sigma < 1$, then the biases of both demand and productivity shocks change signs. In this case, productivity shocks lead to a downward bias, and demand shocks to an upward bias of the OLS estimate. Importantly, there is also the possibility that the OLS estimates is biased downward when $\sigma < 1$.

E.4.2 IV estimation

Suppose now that there is an instrument s_t, which is relevant, $Cov\left(d\ln x_{3t}^n, d\ln s_t\right) \neq 0$, and exogenous, $Cov\left(d\ln \delta_t, d\ln s_t\right) = Cov\left(d\ln z_t, d\ln s_t\right) = Cov\left(d\ln X_{2t}, d\ln s_t\right) = 0$. The IV estimate in the population is then:

$$\frac{Cov\left(d\ln l_t, d\ln s_t\right)}{Cov\left(\frac{dx_{3t}^n}{l}, d\ln s_t\right)} = \frac{\eta}{\eta + \tilde{\sigma}}\frac{l}{py}.$$

This is the object we aimed to identify.