SUB-NATIONAL EMPLOYMENT IMPLICATIONS OF U.S. PHARMACEUTICAL EXPORTS

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Abstract

We develop an industry-specific sub-national model of exports that takes into account international and domestic shipping costs. We generate econometric estimates of these shipping costs by fitting the model to 2017 export data for the U.S. pharmaceutical and medicine manufacturing industry. Then we use the model to estimate the value of exports originating from production in each state and to decompose state-level changes in industry employment between 2012 and 2017 into changes due to exports and changes due to fluctuations in domestic demand. Finally, we compare our model-based estimates to other publicly available estimates of state-level exports of the U.S. pharmaceutical industry. Our model-based method estimates lower export intensity of production in California and higher export intensity for production in New York, North Carolina, Illinois, Florida, Tennessee, and Georgia, compared to the other estimates.

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1 Introduction

Increased access to export markets can create significant new employment opportunities for workers in the United States. However, U.S. export opportunities and associated production and employment gains are not evenly distributed across the country. The location of the production of exports and the employment gains that they support depend in part on domestic and international shipping costs that can create geographic advantages of being close to ports and foreign markets.

It is not difficult to understand how shipping costs can shape the location of export supply. In an industry with large international trade costs but little or no domestic transport costs, exports would be concentrated in the ports closest to the destination country. On the other hand, in an industry with high domestic transport costs and relatively small international trade costs, export ports would more clearly reflect the location of production. In most industries, the distribution of exports across ports reflects a mix of these geographic considerations.

Absent a direct and reliable measure of an industry's domestic shipping costs for its exports, these costs can be inferred from available data using a structural economic model of sub-national trade. Then the location of production for export – or equivalently the export-intensity of production in different parts of the country – can be estimated. In this paper, we develop an industry-specific model of exports for this purpose. The model is designed to utilize available data on export values for each the port district where the exports depart and to overcome limitations on information about sub-national trade and the domestic shipping costs of exported goods.

We calibrate the model to data on the U.S. pharmaceutical and medicines industry in 2017. The U.S. industry exports approximately one quarter of its total shipments, sending them to a large number of countries through many U.S. ports, and there is some pharmaceutical manufacturing in almost every state. Workers in the U.S. pharmaceutical industry are well-paid, with average wages of production workers 47% higher than the average for the U.S. manufacturing sector as a whole in 2017, so increasing pharmaceutical industry employment has the potential to generate significant economic gains.

Section 2 reviews publicly available estimates of state-level exports in the U.S. pharmaceutical industry from the literature. There are limitations of each of the competing estimates that our model-based approach attempts to overcome. At one extreme, estimates of state-level exports from the Brookings Institute are based solely on the national aggregate value of exports and the geographic distribution of industry *production* within the United States, without considering the locations where the exports depart. At the other extreme, estimates from the International Trade Administration in the U.S. Department of Commerce and estimates based on the U.S. Commodity Flow Survey are based solely on the reported origin of movement of the *shipments*, without incorporating information on the location of industry production or the ports where the exports depart.

On the other hand, our model-based estimates combine the data on the geographic distribution of industry production with the data on export departure, and this improves the estimates of states' export shares. Section 3 presents the modeling framework that we have developed for estimating sub-national trade and the location of industry employment that is associated exports.

We apply the model to U.S. pharmaceutical exports after first providing an overview of the industry in Section 4. We report econometric estimates of model parameters for the specific industry in Section 5. The estimates indicate that domestic and international shipping costs were both statistically significant determinants of the distribution of the pharmaceutical industry's exports across U.S. ports in 2017.

Section 6 uses the model to estimate the value of exports originating from production in each state. These estimates indicate that New York, California, Indiana, and Illinois had the largest shares of industry exports, and of these Indiana was the most export-intensive.

Then Section 7 uses the model to decompose state-level changes in pharmaceutical industry employment between 2012 and 2017 into changes due to exports and changes due to fluctuations in domestic demand. This historical decomposition of employment changes demonstrates how the employment effects of exports have been geographically distributed. The states with the largest increases in total industry employment were California, Indiana, Maryland, and Massachusetts. The states with the largest declines were Illinois, Tennessee, Pennsylvania, and Ohio. For most states – including California, New York, Pennsylvania, New Jersey, and Illinois – exports and domestic shipments moved in opposite directions between 2012 and 2017. The states with the largest increases in export-related employment were Indiana, Georgia, Texas, and Illinois.

Section 8 places our model-based estimates next to other available estimates of state export shares. This state-by-state comparison suggests that it is important to consider domestic shipping costs and to incorporate information on the ports where the exports depart as well as information on the geographic distribution of industry production. Section 9 concludes.

2 Estimates of Exports by State in the Literature

Before explaining our model-based approach to estimating the location of production and employment associated with industry exports, we first discuss the competing methods for estimating state exports in the literature, with a focus on their estimates for the U.S. pharmaceutical industry in 2017.

2.1 Public Use File for the Commodity Flow Survey

The Public Use File for the Commodity Flow Survey (CFS) provides data on individual shipments of commodities within the United States in Economic Census year 2017.[1] Pharmaceutical products are reported under Standard Classification of Transported Goods (SCTG) code 21. Approximately 4.5% of the total value of the SCTG code 21 shipments are designated as exports of the United States. Among these export shipments, 56.6% are shipments from chemical manufacturers in NAICS code 325, and the rest are shipments from wholesalers and other types of distributors from unknown production locations. The main limitation of this rich micro-data set is that the individual shipments that are reported do not necessarily record the full path from production to port.[2] For example, a shipment to an interim domestic distributor might be ultimately destined for export but might not be reported as an export in the shipments micro-data set. Or it could be a shipment from a distributor that is recorded as an export but that identifies the location of the distributor, rather than the location of production, as the origin of movement.

With these caveats in mind, it is still possible to use these data to generate an estimate of U.S. pharmaceutical exports from each state. Export shipments in SCTG code 21 from manufacturers in North American Industrial Classification System (NAICS) code 325 were relatively concentrated in a small number of states in 2017: 20.8% of the national total value of exports originate in manufacturers in California, 21.0% in North Carolina, 11.6% in Pennsylvania, 7.9% in Michigan, 7.3% in Illinois, and 6.9% in Texas.[3]

[1]The data are publicly available at `https://www.census.gov/data/datasets/2017/econ/cfs/historical-datasets.html`.

[2]Other limitations of the CFS data are that they are only available every five years when there is an Economic Census, and the Public Use File introduces additional noise in the individual shipment records to mask the identities of shipping parties.

[3]On the other hand, export shipments from distributors have a different pattern of concentration. 43.1% are from California, 27.6% from New York, 3.2% from Tennessee, 2.9% from Illinois, and 2.8% from New Jersey. As we note above, these products are not necessarily manufactured in these states.

2.2 ITA Estimates of Exports by State

Estimates from the International Trade Administration (ITA) in the U.S. Department of Commerce have a similar focus on the origin of the shipments rather than the location of production. International Trade Administration (2021) publishes a dataset on exports by state, based on origin-of-movement designations in the export declarations collected by the U.S. Census Bureau. ITA's data set has the advantage that it records declarations of export origin from the market participants; however, its limitation, like the Commodity Flow Survey, is that the data do not measure the location of production, and so the ITA estimates are a noisy indicator of the location of export-related employment. It is possible that ITA's estimated state exports are larger than reported industry production in a particular state. For example, the ITA estimates of 2017 state exports from Idaho, Kentucky, and Oregon significantly exceed the total value of NAICS code 3254 production in each of these states according to the 2017 Economic Census.

2.3 Brookings Estimates of Exports by State

The Brookings Institute publishes an annual data set with estimates of exports from each state at the level of four-digit NAICS codes, including NAICS code 3254.[4] Their estimates are constructed by attributing the national aggregate exports of each industry to each state in proportion to the state's estimated share of the total value of U.S. production in the industry.[5] The Brookings estimates are not based on origin-of-movement designations. The Brookings calculation would be appropriate if domestic shipping costs were insignificant, but the econometric analysis in Table 4 challenges that simplifying assumption.

The Brookings estimates of 2017 exports in NAICS code 3254 are concentrated in three states with double-digit shares: California accounts for 23.76%, Indiana for 10.92%, and

[4]The data are publicly available at `https://www.brookings.edu/research/export-monitor-2018/`.
[5]The Brookings method is similar to earlier estimates in Testa, Klier and Zelenev (2003).

North Carolina for 10.18%. Seventeen states in the Brookings database have shares above 1%.

Brookings Institute (2018) argues that the origin-of-movement designations used in the ITA estimates provide a "distorted" view of regional employment effects, pointing out that origin-of-movement exports sometimes exceed that state's total production; however, they also acknowledge that their own method relies on the restrictive assumption that producers in all sub-national locations throughout the country have the same export intensity.

3 Modeling Framework

Our model-based estimates improve on the competing approaches in the literature by combining data on the location of shipments with data on the location of production. In this section, we present the structural model that we use to analyze the data. The industry-specific model of sub-national trade assumes that foreign consumer demand for the products of the industry has the constant elasticity form in equation (1), with products differentiated by state of manufacture and by the convenience of their distribution path. Different distribution routes have different domestic and international shipping costs. x_{sdc} is the free along-side (FAS) value of industry exports from state s that depart through port district d and are shipped to foreign country c.[6]

$$x_{sdc} = Y_c \, Z_s \, e^{\alpha \, r_{sd} \, + \, \beta \, r_{dc}} \tag{1}$$

The value of exports depends on a state-specific factor Z_s that reflects state-specific production costs and any differences in preferences for the products of different states. Y_c is a country-specific factor that reflects total expenditure on the industry's products in country c

[6] This is the value of the exports as they depart from the port, before adding the costs of international trade.

as well as its price index for the industry. There are multiple distribution routes (indexed by d) from each state s to each foreign country c. The domestic transport cost factor depends on the domestic distance from state s to district d, measured by remoteness indicator r_{sd}. This indicator is equal to zero if one of the ports included in district d is located in state s, and is equal to one otherwise, so we expect that $\alpha < 0$. The international trade cost factor depends on the international distance from district d to country c, represented by the remoteness indicator r_{dc}. This indicator is equal to zero if the coast or border where district d is located is closest to the continent where country c is located, and is equal to one otherwise, so we expect that $\beta < 0$. We explicitly derive the export demand model in (1) from CES preferences in the Appendix.

Equation (2) is a log-linear transformation of (1).

$$ln\ x_{sdc} = \alpha\ r_{sd}\ +\ \beta\ r_{dc}\ + ln\ Y_c\ +\ ln\ Z_s \tag{2}$$

The total value of exports to country c departing from district d, x_{dc}, is the sum across the exports from d to c that originate in each of the states indexed by s.

$$x_{dc} = \sum_s x_{sdc} \tag{3}$$

We approximate (3) using a first-order log-linear Taylor series expansion around an equilibrium with symmetric domestic transport costs.[7]

$$ln\ x_{dc} = \sum_s \theta_s\ ln\ x_{sdc} \tag{4}$$

[7] The log-linear approximation in (4) is similar to the bonus vetus OLS approach in Baier and Bergstrand (2009). Their model focuses on international trade, rather than sub-national trade, so their log-linear expansion is around an equilibrium with symmetric international trade costs, rather than symmetric domestic transport costs.

$\theta_s = \frac{Z_s}{\sum_{s'} Z_{s'}}$ is the share of state s in national production of the industry. Finally, equation (5) by substitutes (2) into (4).

$$ln\ x_{dc} = \alpha \sum_s \theta_s\ r_{sd}\ +\ \beta\ r_{dc}\ + ln\ Y_c\ +\ \sum_s \theta_s\ ln\ Z_s \tag{5}$$

Equation (5) is the basis for our econometric specification.

4 Industry Data and Attributes

We apply the model to the exports of the U.S. pharmaceutical industry. Before turning to the econometric analysis, we first provide a brief overview of the industry. We apply the model to 2017 data for the pharmaceutical and medicine manufacturing industry, defined by NAICS code 3254. In 2017, exports accounted for 24.2% of the total value of shipments of this U.S. industry. We analyze export data that are disaggregated by port district, destination country, and year.[8] Table 1 lists the top twelve port districts with U.S. pharmaceutical exports in 2017, along with the FAS value of exports that they reported.[9] An export district is an aggregate of neighboring ports of departure. There are 37 export districts in the model.

Table 2 reports the destination countries that accounted for the largest shares of industry exports in 2017, based on the FAS value of industry exports. Several EU countries are at the top of this list. Exports to each of these countries were shipped from dozens of different U.S. port districts.

The sub-national model includes the lower 48 states and the District of Columbia.[10] Data on the total shipments and employment of U.S. pharmaceutical producers in each state are

[8] The source for the export data is the USITC/DOC Trade Dataweb at `https://dataweb.usitc.gov/`.

[9] The model does not analyze U.S. exports from geographically separate Puerto Rico.

[10] The model does not include Alaska, Hawaii, or the U.S. territories, which are geographically disconnected from the rest of the U.S. market.

Table 1: Top Twelve Export Districts

Export District	States with Ports in the District	Value of Exports in 2017 in Billions of Dollars
Chicago	IL, IN	8.75
New York	NY	6.12
Cleveland	OH, IN, KY, PA	3.54
Los Angeles	CA	2.82
Miami	FL	2.56
Norfolk	VA, WV	2.24
New Orleans	LA, MS, TN	2.22
San Francisco	CA, NV	2.17
Savannah	GA	1.66
Buffalo	NY	1.33
Houston-Galveston	TX	1.32
Boston	MA, NM	1.26

Table 2: Major Export Destination Countries in 2017

Destination Country	Value of Exports in Billions of Dollars	Number of Districts with Exports
Belgium	3.90	27
Netherlands	3.89	30
Germany	3.89	31
Italy	3.77	28
Japan	3.69	33
Canada	3.67	38
Ireland	3.45	25
United Kingdom	3.08	33
China	3.04	33
Austria	2.02	23
France	2.00	30
Switzerland	2.00	28
Spain	1.79	25
Mexico	1.25	30
Brazil	1.21	26
Korea	1.12	31

from the 2017 U.S. Economic Census.[11] Table 3 reports the states with the largest share of domestic production in 2017. California, New York, North Carolina, and Pennsylvania are at the top of the list.

Table 3: Shipments of Top States in 2017

	Total Value of Shipments (Billion $)
California	63.52
New York	20.61
North Carolina	19.40
Pennsylvania	12.72
New Jersey	10.41
Illinois	8.66
Indiana	8.64
Florida	5.97
Massachusetts	5.72
Michigan	5.09
National	211.21

Having established the location of international trade (the U.S. port districts where U.S. the products were exported) and the location of domestic production (the states where the products were manufactured), we use the economic model to link the two types of data in order to estimate the states where the U.S. industry's exports were produced.

5 Econometric Estimates

We estimate the domestic shipping cost parameter α and the international trade cost parameter β using a 2017 cross section of U.S. export values for the industry. The econometric specification in (6) is based on (5), with the addition of a normally distributed error term

[11] The value of shipments and employment in each industry are reported in the 2017 Economic Census database, at `https://www.census.gov/programs-surveys/economic-census/data/tables.html`.

ϵ_{dc} and consolidation of several factors into the country fixed effects γ_c.

$$ln\ x_{dc} = \alpha \sum_{s} \theta_s\ r_{sd}\ +\ \beta\ r_{dc}\ + \gamma_c\ +\ \epsilon_{dc} \tag{6}$$

The first term on the right-hand side of (6) measures the remoteness of district d from producers in the individual states. It is an average of the remoteness of the states from district d, weighted by the value of total shipments originating in each state. All of the terms in (5) that do not vary across districts are absorbed in the country fixed effects in (6), γ_c, and this reduces the data requirements of the econometric model. This specification is a practical solution to the problem that we do not observe the domestic shipments of exports from s to d; if we had complete data on the shipment of U.S. exports between states, we could estimate domestic transport costs using a standard gravity model of s-to-d trade.[12]

As an indicator of international proximity, we define groups of countries and coast/border groups of port districts. The country groups include five continents (Africa, Asia, Europe, South and Central America, and Oceania) and two individual countries (Canada and Mexico). The four coast or border groups are Atlantic (East), Pacific (West), Gulf (South), and Canada (North). r_{dc} is equal to zero if c is the closest country group to the coast or border group of d, and is equal to one if it is not the closest.

If all exports were produced in the state where they leave the country, then α would be very large. At the other extreme, if the location of production within the United States were irrelevant to the district of export, then α would be zero. We test both these hypotheses by estimating the value of α using industry data for 2017.

We estimated the parameters in (6) using ordinary least squares (OLS) and then two-stage least squares (2SLS), with a sample that includes the 2,373 combinations of districts and countries that reported U.S. pharmaceutical exports in 2017. Table 4 reports the estimated

[12] There is some information on domestic shipments of exports from the U.S. Commodity Flow Survey. However, there are limitations on these data, which we discussed in Section 2.

model parameters, with standard errors in parentheses. The first column of numbers reports the OLS estimates when 2017 domestic shipment values are used to construct θ_s. The second column reports 2SLS estimates when domestic shipment values from 2012 are used to create an instrumental variable for $\sum_s \theta_s r_{sd}$. The second version addresses potential simultaneity bias. For both specifications, t tests indicate that α and β are each significantly less than zero, consistent with the theoretical model, and F test rejects the hypothesis that the country fixed effects are jointly equal to zero. A Hausman specification test indicates that the consistent 2SLS estimate is preferrable.

Table 4: Econometric Estimates

	OLS	2SLS
Domestic Shipping	-4.7221	-6.3311
α	(0.5010)	(0.5096)
International Shipping	-0.8557	-0.8570
β	(0.1072)	(0.1025)
Country	F Test	χ^2 Test
Fixed Effects	p=0.000	p=0.000
Number of Observations	2,373	2,373
R^2	0.4579	0.4553
Hausman Specification Test		p=0.000

As a sensitivity analysis, Table 5 reports an additional set of estimates that define r_{sd} differently. In this case, r_{sd} is equal to one if state s is in the same BEA region as district d, and is equal to zero otherwise. The estimates of α in the two tables are similar. The estimates in Table 4 appear to fit the data better, based on the R^2 statistics, so we focus on the 2SLS estimate in Table 4 ($\alpha = -6.3311$) in the simulations that follow.

Table 5: Sensitivity Analysis: Regional Blocks

	OLS	2SLS
Domestic Shipping	-3.3011	-6.9794
α	(0.5704)	(0.7037)
International Shipping	-0.7544	-0.6457
β	(0.1098)	(0.1066)
Country	F Test	χ^2 Test
Fixed Effects	p=0.000	p=0.000
Number of Observations	2,373	2,373
R^2	0.4442	0.4335
Hausman Specification Test		p=0.000

6 Attribution of Exports to Individual States

Calculating each state's share of U.S. pharmaceutical exports requires an estimate of the value of industry exports at a finer level – by state, port district, and destination country. Since the state of manufacture of the exports is not reported in official trade statistics, we estimate the state where the exports are produced using the econometric model in Section 5. Equation (7) is the modeled exports from district d to country c that are produced in state s, as a share of reported exports from the port district to the foreign country.[13]

$$\frac{x_{sdc}}{x_{dc}} = \frac{\theta_s \; e^{\;\alpha \; r_{sd}}}{\sum_{s'} \; \theta_{s'} \; e^{\;\alpha \; r_{s'd}}} \tag{7}$$

We calculate x_{sdc} by multiplying observed x_{df} by the ratio in (7).

To better understand this ratio, consider the extreme case where domestic transport costs are *not* increasing in domestic distance, so $\alpha = 0$. In this case, the geographic distribution of production for export would be determined solely by the state production shares θ_s. When domestic transport costs increase with domestic distance, export shares diverge from these production shares according to (7).

With an estimate of x_{sdc} in hand, we sum across districts and foreign countries to calculate total industry exports from production in each state s.

$$x_s = \sum_d \; \sum_c \; x_{sdc} \tag{8}$$

Table 6 reports the resulting shares of U.S. pharmaceutical exports originating in the 25 states with the largest shares of U.S. pharmaceutical manufacturing in 2017. The table reports each state's share of the total value of U.S. manufacturing as well as the state's

[13]To simplify the notation, we have canceled several terms that would be included in both the numerator and the denominator of the ratio.

modeled share of industry exports.

The states' shares of production are quite different from their shares of exports. There is lower export intensity in states with production shares that significantly exceed their export shares (including California, North Carolina, and Pennsylvania), and higher export intensity in states with export shares that significantly exceed their production shares (including New York, New Jersey, Indiana, Illinois, Florida, Texas, Tennesee, and Georgia). These differences are missed in the Brookings estimates, which assume the same export intensity of production throughout the United States.

7 Decomposition of Changes in Industry Employment

Next, we use our model-based estimates of state exports for 2017 and similarly constructed estimates for 2012 to decompose the state-level changes in industry employment between these two years into changes associated with exports and changes associated with domestic shipments to U.S. consumers.

The share of state s employment in the industry that is attributable to exports from s in year t is the export intensity ratio, defined as the ratio of the value of exports ($x_{s,t}$) to the value of total shipments from production in the state ($v_{s,t}$), as long as each firm exports approximately the same products that it sells domestically or if the products have similar labor requirements per dollar of output.

We calculate the total change in industry employment in state s between 2012 and 2017, the change in industry employment in state s associated with exports, and the change in industry employment in state s associated with domestic shipments based on (9), (10), and (11).

$$\Delta L_s = L_{s,2017} \; - \; L_{s,2012} \tag{9}$$

Table 6: State Shares in 2017

	Share of U.S. Manufacturing (%)	Share of Exports Estimated in the Model (%)
α	0.0000	-6.3311
California	30.1	13.5
New York	9.8	14.4
North Carolina	9.2	5.0
Pennsylvania	6.0	5.7
New Jersey	4.9	6.0
Illinois	4.1	10.4
Indiana	4.1	13.3
Florida	2.8	5.9
Massachusetts	2.7	2.7
Michigan	2.4	2.6
Texas	2.2	4.5
Delaware	1.7	0.4
Utah	1.6	0.2
Colorado	1.5	0.2
Maryland	1.5	0.4
Ohio	1.4	1.1
Missouri	1.4	0.1
Tennessee	1.1	3.9
West Virginia	1.1	0.6
South Carolina	1.1	0.3
Rhode Island	1.0	0.0
Kansas	1.0	0.0
Wisconsin	0.9	0.1
Virginia	0.8	1.6
Georgia	0.8	3.2
Top 25 States	95.2	96.1

$$\Delta LX_s = \sum_d \sum_f \left(\left(\frac{x_{s,2017}}{v_{s,2017}} \right) \ L_{s,2017} \quad - \ \left(\frac{x_{s,2012}}{v_{s,2012}} \right) \ L_{s,2012} \right) \tag{10}$$

$$\Delta LD_s = \Delta L_s \ - \ \Delta LX_s \tag{11}$$

Table 7 lists the reported change in U.S. employment in the industry between 2012 and 2017 by state, along with the modeled employment changes associated with exports and domestic shipments, for the 25 top pharmaceutical manufacturing states in Table 6. Total industry employment moved in different directions across the 25 states, and there is significant variation in the magnitude of these changes. The states with the largest increase in total industry employment were California, Indiana, Maryland, and Massachusetts. The states with the largest decline were Illinois, Tennessee, Pennsylvania, and Ohio. For most states – including California, New York, Pennsylvania, New Jersey, and Illinois – exports and domestic shipments moved in opposite directions during the time period. The states with the largest increase in export-related employment were Indiana, Georgia, Texas, and Illinois.

8 Side-by-Side Comparison of Estimates

Table 8 compares 2017 state export shares for the U.S. pharmaceutical industry from the ITA and Brookings datasets to teh state export shares estimated using our econometric model, for each of the 25 top pharmaceutical manufacturing states.

The estimates of export shares are very different across the columns, state by state. The table of correlation coefficients in Table 9 shows that our modeled-based estimates with $\alpha = -6.3311$ are closer to the ITA estimates, while the estimates setting α equal to zero (and using only information about the location of production) are closer to the Brookings production-based estimates.

Table 7: Change in Industry Employment, 2012 to 2017

	Total Employment	Export Related	Domestic Shipments
California	6,583	-275	6,858
New York	1,192	-2,665	3,857
North Carolina	1,044	637	406
Pennsylvania	-1,384	284	-1,668
New Jersey	-232	-2,769	2,537
Illinois	-2,535	1,373	-3,908
Indiana	5,425	5,882	-457
Florida	-419	-1,732	1,313
Massachusetts	4,458	1,141	3,317
Michigan	365	-591	956
Texas	1,004	1,398	-394
Delaware	723	-15	738
Utah	2,399	79	2,320
Colorado	-32	5	-37
Maryland	5,256	288	4,968
Ohio	-1,330	177	-1,507
Missouri	-88	0	-88
Tennessee	-1,844	213	-2,057
West Virginia	0	124	-124
South Carolina	1,016	34	982
Rhode Island	424	7	417
Kansas	-83	-1	-82
Wisconsin	1,861	25	1,836
Virginia	-405	444	-849
Georgia	1,207	1,720	-513

Table 8: Side-by-Side Estimates

Source	ITA Estimates (%)	Brookings Estimates (%)	Model-Based Estimates (%)
California	14.5	23.8	13.5
New York	3.0	5.4	14.4
North Carolina	10.8	10.2	5.0
Pennsylvania	7.1	5.8	5.7
New Jersey	3.7	7.2	6.0
Illinois	7.4	5.2	10.4
Indiana	16.4	10.9	13.3
Florida	1.5	1.3	5.9
Massachusetts	4.6	3.0	2.7
Michigan	1.9	1.6	2.6
Texas	4.0	6.3	4.5
Delaware	1.9	0.1	0.4
Utah	0.7	0.9	0.2
Colorado	0.4	0.7	0.2
Maryland	2.0	2.7	0.4
Ohio	1.6	1.5	1.1
Missouri	1.5	1.8	0.1
Tennessee	1.4	0.4	3.9
West Virginia	0.1	0.3	0.6
South Carolina	0.3	0.5	0.3
Rhode Island	0.3	0.3	0.0
Kansas	0.6	0.6	0.0
Wisconsin	1.9	1.0	0.1
Virginia	0.7	0.6	1.6
Georgia	0.9	0.7	3.2
Top 25 States	89.0	92.8	96.1

Table 9: Correlation of Estimates

Model-Based Estimates	Brookings	ITA
$\alpha = -6.3311$	0.74	0.76
$\alpha = 0.0000$	0.92	0.68

The model-based estimates in the final column of Table 8 have advantages over the Brookings estimates, because the econometric analysis explicitly rejects the restriction that α is equal to zero. They have advantages over the ITA estimates, because the ITA numbers do not incorporate data on the location of industry production, and the origin-of-movement designations are not a close substitute. Compared to the other estimates, our method estimates lower export intensity of production in California and higher export intensity of production New York, North Carolina, Illinois, Florida, Tennessee, and Georgia.

9 Conclusions

In this paper, we have estimated an econometric model that allows us to trace U.S. pharmaceutical exports back to the state where they were produced. In this way, we link export opportunities to industry employment in each state and identify the workers most exposed to fluctuations in demand in foreign markets and most directly benefiting from increased access to these markets.

The model overcomes significant limitations on data on sub-national trade by constructing a structural framework that estimates domestic shipping costs based on data that are readily available: the geographic distribution of total industry production across states and the geographic distribution of industry exports across port districts. In this way, the model provides a practical tool for analyzing the impact of exports on labor markets in different parts of the United States.

10 Appendix

The export demand function in (1) can be derived from the CES model of export demand in (12) and (13).

$$x_{sdc} = \gamma \ E_c \ (P_c)^{\sigma \ - \ 1} \ (p_s \ t_{sdc})^{1 \ - \ \sigma} \ \mu_s \tag{12}$$

$$t_{sdc} = e^{\alpha_0 \ r_{sd} \ + \ \beta_0 \ r_{dc}} \tag{13}$$

E_c is aggregate expenditure in country c, γ is the expenditure share of the industry, and μ_s is a CES preference asymmetry parameter for products from state s. Exports are differentiated by the location of production (state s) and their distribution path (district d).

Equations (14) through (17) define the factors in (1) in terms of the structural parameters in (12) and (13).

$$Y_c = \gamma \ E_c \ (P_c)^{\sigma \ - \ 1} \tag{14}$$

$$Z_s = \mu_s \ (p_s)^{1 \ - \ \sigma} \tag{15}$$

$$\alpha = (1 \ - \ \sigma) \ \alpha_0 \tag{16}$$

$$\beta = (1 \ - \ \sigma) \ \beta_0 \tag{17}$$

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