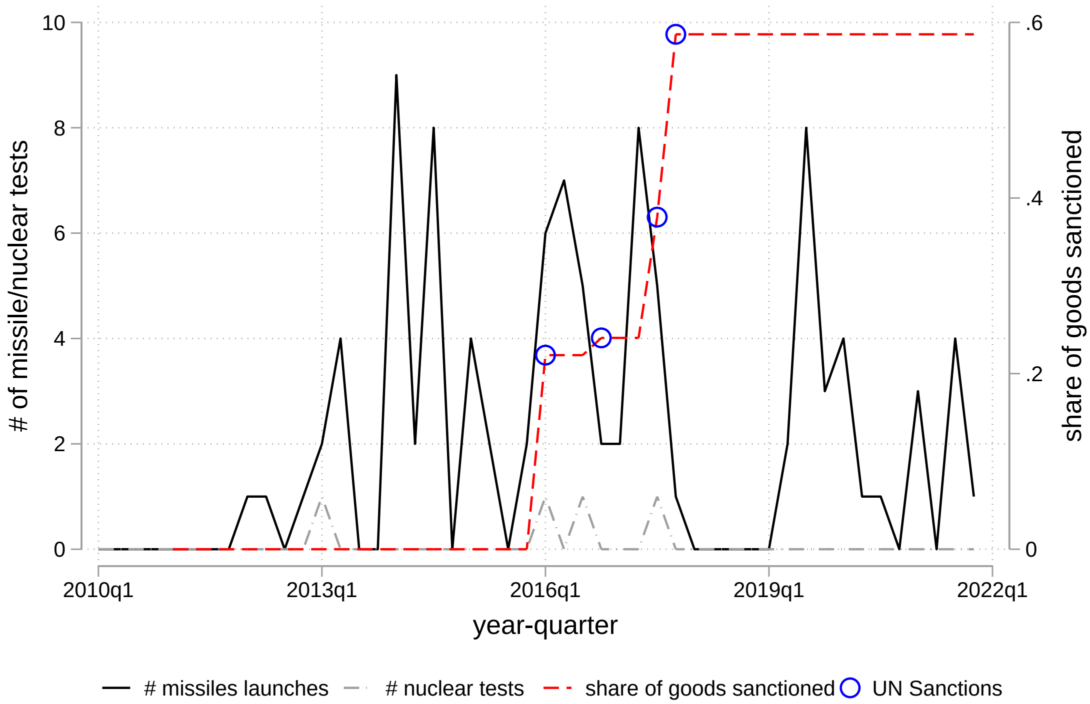
For Online Publication

A Additional Data Descriptions

A.1 Trade Data

A.1.1 Trade Before and After the Sanctions

Figure A-1: Number of Missile Launches/Nuclear Tests and The Share of Goods Sanctioned



Notes: The solid line indicates the number of missile launches and nuclear tests in each quarter from 2010 to 2021. The grey, the dash-dotted line indicates the quarters in which North Korea conducted nuclear tests. The red dashed line shows the share of pre-sanctions exports and imports (2011-2015) that are exposed to UN sanctions up to a particular quarter, representing the cumulative strength of the trade sanctions. The circles indicate quarters in which the UN imposed new trade sanctions: 2016Q1 (UN Resolution 2270), 2016Q3 (UN Resolution 2321), 2017Q3 (UN Resolution 2371 and 2375), 2017Q4 (UN Resolution 2397). For the number of North Korea's missile launches and nuclear tests, we extended the data in Hong (2017), which was up to 2017, to 2021 by cross-checking the database from the Center for Strategic and International Studies (CSIS) and reports from multiple South Korean news media outlets.

Table A-1: Sanctioned Trade Items by UN Resolutions

<table>
<tr><th>Year</th><th>Month</th><th>UN Resolution #</th><th>Ban on Exports from North Korea</th><th>Ban on Imports to North Korea</th></tr>
<tr><td rowspan="3">2006</td><td rowspan="3">Oct</td><td rowspan="3">1718</td><td colspan="2">battle tanks, armoured combat vehicles, large calibre artillery systems, combat aircraft, attack helicopters, warships, missiles or missile systems</td></tr>
<tr><td colspan="2">items, materials, equipment, goods and technology related to ballistic missile or nuclear programs</td></tr>
<tr><td></td><td>luxury goods</td></tr>
<tr><td>2009</td><td>Jun</td><td>1874</td><td></td><td>all arms and related materiel related to the provision, manufacture, maintenance or use of such arms or materiel</td></tr>
<tr><td>2013</td><td>Mar</td><td>2094</td><td></td><td>sanctioned luxury goods are further clarified</td></tr>
<tr><td>2016</td><td>Mar</td><td>2270</td><td>coal, iron, iron ore, gold, titanium ore, vanadium ore
rare earth minerals</td><td>all arms and related materiel, incl. small arms and light weapons and their related materiel,
aviation fuel</td></tr>
<tr><td>2016</td><td>Nov</td><td>2321</td><td>copper, nickel, silver and zinc, statues</td><td>new helicopters and vessels</td></tr>
<tr><td>2017</td><td>Aug</td><td>2371</td><td>coal, iron, and iron ore, lead and lead ore
seafood</td><td></td></tr>
<tr><td>2017</td><td>Sep</td><td>2375</td><td>textiles</td><td>all condensates and natural gas liquids,
all refined petroleum products</td></tr>
<tr><td>2017</td><td>Dec</td><td>2397</td><td>food and agricultural products
machinery, electrical equipment
earth and stone including magnesite and magnesia
wood, vessels</td><td>all refined petroleum products
all industrial machinery
transportation vehicles
iron, steel, and other metals</td></tr>
</table>

Table A-2: Top 10 trading commodities, 2011 - 2015

Exports

HS code	Commodity	Trade value (1k USD)	Share (%)	Sanctioned
2701	Coal	6,100,539	35.71	O
2601	Iron Ore	1,165,791	6.82	O
6201	Men's or boys' overcoats	675,585	3.96	O
6203	Men's or boys' suits	643,874	3.77	O
6202	Women's or girls' overcoats	643,290	3.77	O
2710	Petroleum oils	607,053	3.55	X
0307	Molluscs & aquatic invertebrates	452,728	2.65	O
6204	Women's or girls' suits	368,174	2.16	O
7201	Pig iron	337,119	1.97	O
0802	Other nuts	230,102	1.35	O

Imports

HS code	Commodity	Trade value (1k USD)	Share (%)	Sanctioned
2709	Crude oil	1,694,434	8.42	X
2710	Petroleum oils	945,030	4.69	O
8704	Motor vehicles	649,007	3.22	O
5407	Woven fabrics	647,472	3.22	X
1507	Soybean oil	429,324	2.13	X
8525	Transmission apparatus for radio or television	310,826	1.54	O
1101	Wheat or meslin flour	269,577	1.34	X
3102	Mineral or chemical fertilizers	265,992	1.32	X
4011	New pneumatic tyres	257,495	1.28	X
2403	Other manufactured tobacco and substitutes	234,327	1.16	X

Notes: Exports and imports data are reported by North Korea's trading partners in the UN Comtrade Database. Aggregate trade values are from 2011 to 2015. Whether HS code 4-digit items are subject to sanctions is summarized based on Annex 51 of the UN Security Council Sanctions Report of North Korea (S/2021/777). (https://www.un.org/securitycouncil/sanctions/1718/panel_experts/reports)
UNSCR 2397 stipulated the upper limit of crude oil supply to North Korea at 4 million barrels per year. This is the same as the amount of crude oil introduced before sanctions. Therefore, we do not treat crude oil as being sanctioned.

A.1.2 The Effects of Sanctions on North Korea's Trade

In this section, we examine the impact of the sanctions on North Korea's external trade. From the UN Comtrade database, we obtain annual trade statistics of North Korea, which are exclusively reported by its trading partners. As is shown in Table A-3, before the sanctions, China was North Korea's largest trading partner, accounting for 80% of North Korea's exports and 84% of its imports. Besides China, North Korea also trades with India, Russia, and other Asian and European countries, although these partners account for much smaller shares of North Korea's total trade.

Table A-3: Top 5 Trading Partners, 2011 - 2015

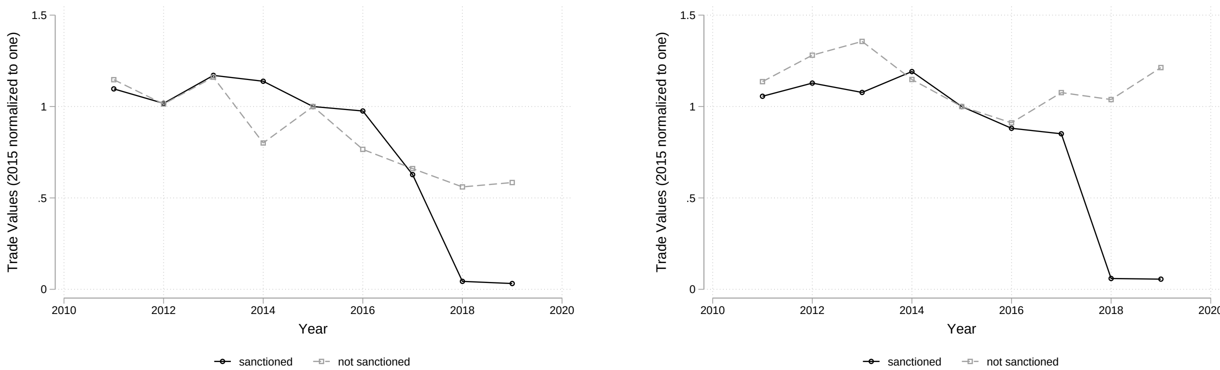
Exports		Imports	
Partner	%	Partner	%
China	79.9	China	84.2
India	1.8	India	4.2
Netherlands	1.4	Russian Federation	2.1
Bahrain	1.4	Thailand	1.7
Pakistan	1.3	Singapore	1.1

Notes: Exports and imports data are reported by North Korea's trading partners in the UN Comtrade Database. Aggregate trade values are from 2011 to 2015.

However, North Korea's trade was seriously disrupted by the trade sanctions in 2016 and 2017, at least according to the statistics reported by the trading partners. Figure A-2 shows the trade values from 2011 to 2019, for products that are ever sanctioned in the 2016/2017 UN resolutions and those that are not sanctioned, respectively, with 2015 values normalized to one. North Korea's imports from the rest of the world (RoW) declined by 94% from 2015 to 2018 in the product categories that were sanctioned by the UN in 2016/2017, while there is no such trend for imports of non-sanctioned products. On the export side, the value of trade declined by 96% from 2015 to 2018 among the sanctioned products, while there is also a small but declining trend in export activities among the non-sanctioned products up to 2018.[37] We see similar patterns in Figure A-3, where we only plot the trade values between North Korea and China.

[37] We are agnostic about the causes of the decline in non-sanctioned products. It could be because of a spillover effect of the sanctions, but it could also reflect a long-term deterioration of trade relations between North Korea and other countries. Notably, we do not see such a trend for North Korea's exports to China in non-sanctioned products (see Figure A-3).

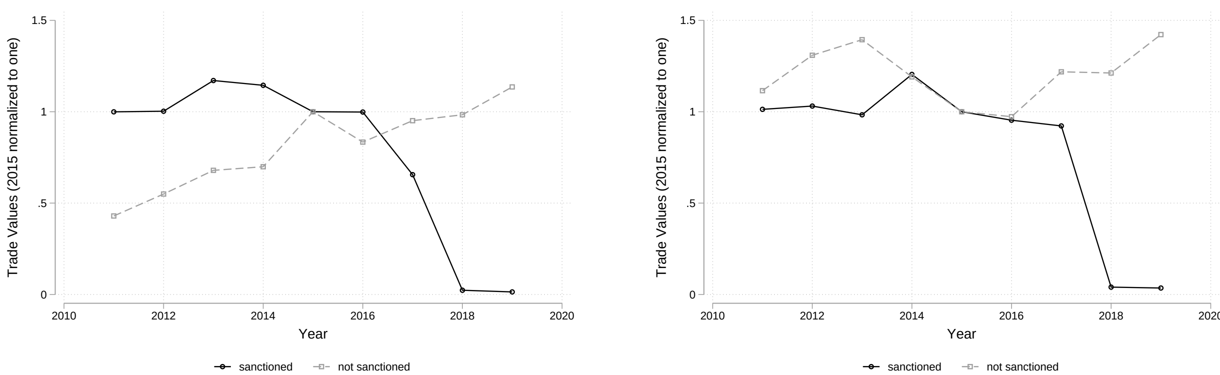
Figure A-2: Total Trade in Sanctioned and Non-sanctioned Categories



(a) Exports (b) Imports

Notes: Data are normalized by the 2015 trade values for each category of products.

Figure A-3: Total Trade with China in Sanctioned and Non-sanctioned Categories



(a) Exports (b) Imports

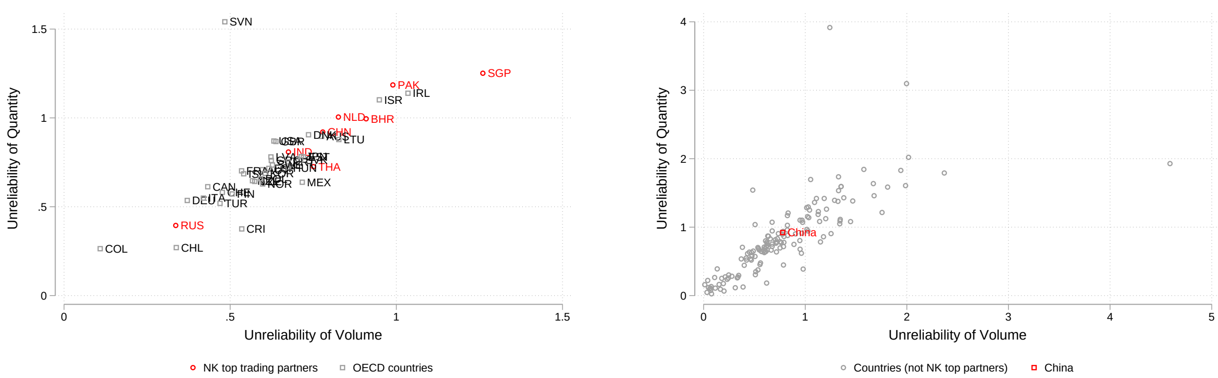
Notes: Data are normalized by the 2015 trade values for each category of products.

A.1.3 Quality of UN Comtrade Data

In this section, we investigate the quality of North Korea's top trading partners' trade data in general. A potential concern is that North Korea's trading partners may not have the capacity to produce high-quality trade data and the trade data they report are prone to measurement errors. We obtain indices of data unreliability from BACI. The indices of data unreliability are created by cross-checking the FOB export data reported by the exporting country and the CIF import data reported by the importing country for the same trade flow (with proper adjustment of the gap between FOB and CIF prices). Guillaume and Zignago (2010) provide more details about the methodology. We use the indices computed based on the 2020 version of the BACI data under HS 2012 classifications. For each country, the dataset reports the unreliability of quantities and volumes.

In Figure A-4, we plot the unreliability index of quantity against unreliability index of volume for each country. Panel (a) focuses on two groups of countries: North Korea's top trading partners listed in Table A-3 and OECD countries. As one might expect, data reported by OECD countries are in general more reliable. However, North Korea's top trading partners' data quality is not that far behind. Panel (b) highlights the position of China, North Korea's most important trading partner, among all other countries in terms of data quality (excluding the other top trading partners of North Korea in panel (a)). There are 87 countries with better export data quality (as reporters) than China and 67 countries with worse data quality. China's data quality is around the 56th percentile. China's data quality is close to Denmark and Australia, and not very far behind the United States. Overall, we do not find trade data reported by North Korea's major trading partners are significantly worse than the other countries in the UN Comtrade data.

Figure A-4: Unreliability of Comtrade export data based on BACI



(a) Top NK trading partners v.s. OECD countries
(b) China v.s. other countries

Notes: both panels plot the unreliability indices according to BACI based on UN Comtrade data (Guillaume and Zignago (2010)). Panel (a) focuses on two groups of countries: North Korea's top trading partners listed in Table A-3 and OECD countries. Panel (b) highlights the position of China among all countries that are not North Korea's top trading partners.

A.1.4 Monthly Trade with China

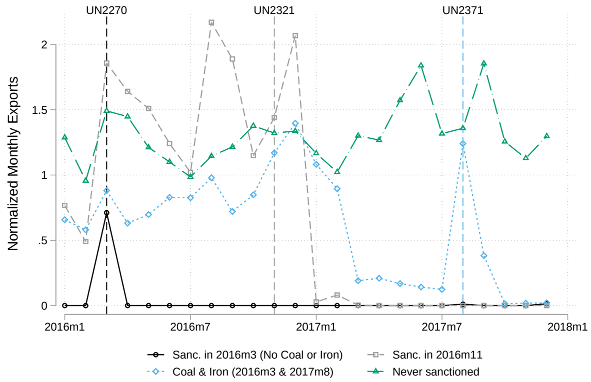
In this section, we describe the monthly trade patterns between North Korea and China and present suggestive evidence that exports of sanctioned products increase temporarily before the corresponding sanctions are imposed. We obtain the monthly trade data reported by China to the UN Comtrade database. Unfortunately, such data are reported on a voluntary basis, and we only have data for 2016 and 2017.[38]

Panels (a) and (b) of Figure A-5 plot North Korean exports to China in different groups of products, normalized by the average monthly exports of the corresponding products in 2015 (dividing the yearly exports by 12). The two panels focus on products that were sanctioned in 2016 and 2017, respectively. Each line represents a group of products, often sanctioned by one particular UN resolution. We use a vertical line with the same color to represent the timing of the most relevant sanction. Coal and iron products are sanctioned twice, once by UN2270 (2016 March) and once by UN2371 (2017 August). Therefore, we isolate these products from the relevant sanctions and plot their trade values in both panels. The green dash-dotted line with triangle markers indicates the goods that are never sanctioned. Other than the fourth sanction (UN2375 in 2017 September), we either see elevated exports for several months leading to the sanction (UN2321) or temporary spikes in exports before or at the time of the sanctions. This suggests either that North Korean firms were able to ramp up production whenever the sanctions were announced, or that they expected the sanctions and increased their inventories and were able to ship out products when the sanctions drew near. The second interpretation is consistent with our evidence of temporary nightlight increases in regions that were more exposed to the export sanctions in 2016.

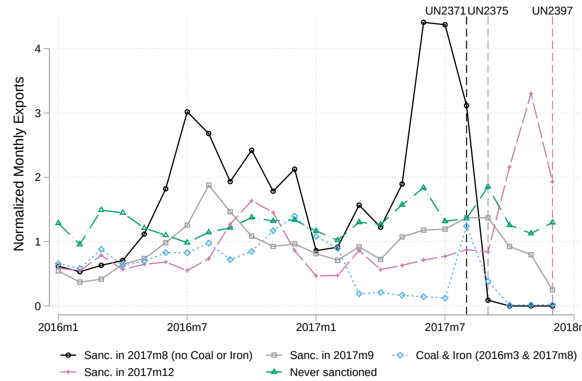
In contrast, we do not observe such temporary growth in trade on the import side. In Panel (c), we isolate three groups that are affected: vessels (sanctioned twice in Nov 2016 and Dec 2017), petroleum products (sanctioned twice in Sep 2017 and Dec 2017) and products sanctioned in Dec 2017, excluding vessels and petroleum products. We do not see large increases in imports of the sanctioned products leading up to the corresponding sanctions. We see large declines in the imports of vessels right after the first relevant sanction (UN2321). For refined petroleum products, the decline started before the first relevant sanction (UN2375) was imposed.

[38]China also reported monthly trade in 2011 and 2012, but we do not use them for the analysis here.

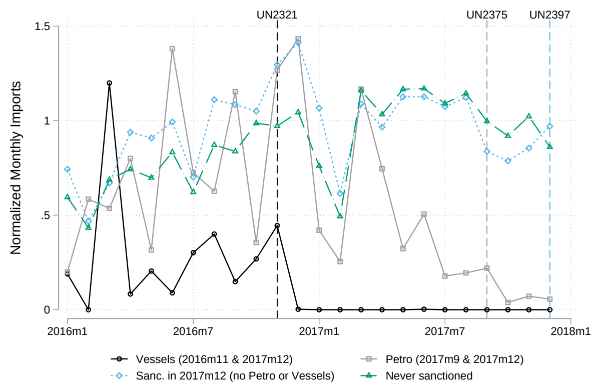
Figure A-5: North Korean monthly exports to and imports from China



(a) Exports affected by 2016 sanctions



(b) Exports affected by 2017 sanctions



(c) Imports affected by sanctions

Notes: Panel (a) plots North Korean monthly exports to China normalized by average monthly exports of the corresponding goods in 2015 (yearly exports divided by 12). Three groups of goods are highlighted: sanctioned by UN2270 (2016M3) but excluding coal and iron products, sanctioned by UN2321 (2016M11) and coal and iron products (sanctioned both in 2016M3 and 2017M8. The green dash-dot line indicates the goods that are never sanctioned. Panel (b) also plots monthly exports, but focuses on goods that are mostly affected by the 2017 sanctions, i.e., those sanctioned by UN2371 in 2017M8 (excluding coal and iron), those sanctioned by UN2375 in 2019M9, and those sanctioned by UN2397 in 2017M12. Coal and iron products and goods that are never sanctioned are also plotted for ease of comparison. Panel (c) plots North Korean monthly imports from China (normalized by the average monthly imports in 2015) for different groups of products. We isolate three groups that are affected: vessels (sanctioned twice in 2016M11 and 2017M12), petroleum products (sanctioned twice in 2017M9 and 2017M12) and products sanctioned in 2017M12, excluding vessels and petroleum products.

A.1.5 Transportation Mode for North Korea's Trade with China

In our baseline calibration, we assume that the international trade costs of each North Korean county is determined by its distance to the North Korea-China border. In this section, we examine the validity of this assumption by checking the major transportation modes between North Korea and China. To obtain statistics regarding trade by transportation modes, we use transaction-level trade data from the Chinese customs between 2000 and 2006.

In Table A-4, we report the fraction of China's export (North Korea's import) and the fraction of China's import (North Korea's export) by transportation mode in 2006, the latest year for which we have data. Truck transportation accounts for 55% of China's export to NK and 51% of China's import from NK. Combined with rail transportation, transportation over land accounts for 76% of China's export to NK and 63% of China's import from NK, respectively. Therefore, we conclude that the majority of China's trade with North Korea is through the North Korea-China border.

Table A-4: Percentage of Trade between China and Korea by Transportation Mode, 2006

Transportation Mode	China's export to NK (%)	China's import from NK (%)
Truck	54.6	51.4
Waterborne	23.6	36.7
Rail	21.5	11.7
Air	0.2	0.3

Notes: Authors' calculation based on transaction-level data from the Chinese Customs. "Transportation by mail" and "Other transportation modes" are omitted from the calculation.

A.2 North Korean Company Database

In this section, we discuss additional explanations of North Korea's company data not covered in the main text. KIET, a South Korean government research institute, collected data on North Korean companies through North Korea's official media and classified them into industries following the Korean Standard Industrial Classification (KSIC) Rev. 10. We further map the KSIC industry codes to ISIC (Rev. 3) two-digit industries. The concordance map can be found in Table A-5.

There are several concerns about this company list. First, this list is limited to companies that can be identified through North Korea's official newspaper, so the data may not include all North Korean companies. However, in the absence of reliable data on North Korean companies, the data are meaningful in that they are the most comprehensive data providing regional and industrial information for North Korean companies. A second concern is that our list may include companies that may have shut down and are no longer in operation. However, given that all companies are state-owned in North Korea, we believe that company or factory closure is rather rare in the country. We deal with this problem by conducting robustness tests with various measures.

We present examples of how North Korean companies were mentioned in the official media in subsection B.1. Articles from the *Rodong Sinmun* related to production and investment are presented. *Rodong Sinmun* is North Korea's representative daily newspaper and is the official newspaper of the Workers' Party of North Korea. In addition, the distribution of the number of company mentions and the log values of mentions are presented as graphs in B.2.

A.2.1 Examples of production and investment of North Korean companies in the official newspaper

1) May 16, 2016.

Title: Research achievements that will contribute to the development of the machine manufacturing industry

Article summary: *Guseong Construction Machinery Design Research Institute* made an effort to manufacture CNC equipment. They ensured high speed and the best quality in part processing and assembly. By rapidly increasing the proportion of localization of parts, it has been confirmed that the newly developed CNC tooling machine and CNC inner/outer grinding machine sufficiently guarantees the precision of machining products as required by design.

2) July 21, 2019.

Title: Install facilities at power plant construction sites on time at *Daean Heavy Machinery Federation*

Article summary: Workers and technicians in the assembly part are shortening the assembly period of equipment based on the detailed assembly schedule for each part. Due to the dedicated struggle of the workers in the company, it is predicted that the production of power generation equipment to be sent to the *Eorangcheon No. 4 Power Plant* will be possible in July.

3) Dec 15, 2015.

Title: Let's vigorously accelerate the struggle to realize the modernization and localization of our own style as the Party intended

Article summary: The successful modernization of major industrial processes, including the hot rolling process of the *Kimchaek Steel Federation*, has enabled the production of high-quality rolled steel while saving enormous amounts of electricity and materials.

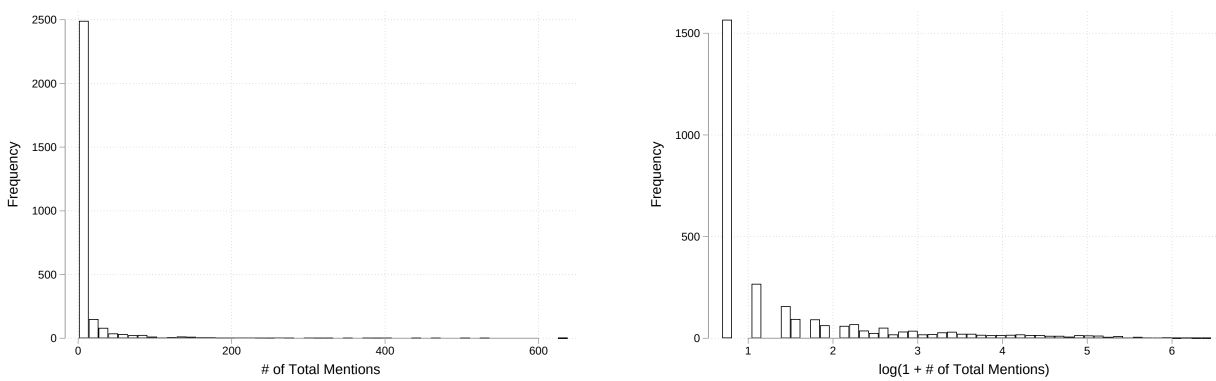
4) July 21, 2019.

Title: The reward of putting energy into facility remodeling: At the *Buryeong Paper Factory*

Article summary: Recently, the *Buryeong Paper Factory* has been making progress in improving the quality of paper. The workers pooled their wisdom and strength to produce a cylindrical crushing machine. As a result of the technical remodeling of the crusher, the quality of the pulp has been significantly improved compared to the previous one.

A.2.2 Distribution of Company Mentions

Figure A-6: Histograms of companies' total mentions, 2000 – 2015



(a) # of total mentions (b) log(1 + # of total mentions)

Notes: Calculated based on the North Korean Company List Database provided by KIET. The total number of firms is 2960.

Table A-5: concordance between KIET industry codes (KSIC Rev. 10) and ISIC Rev. 3

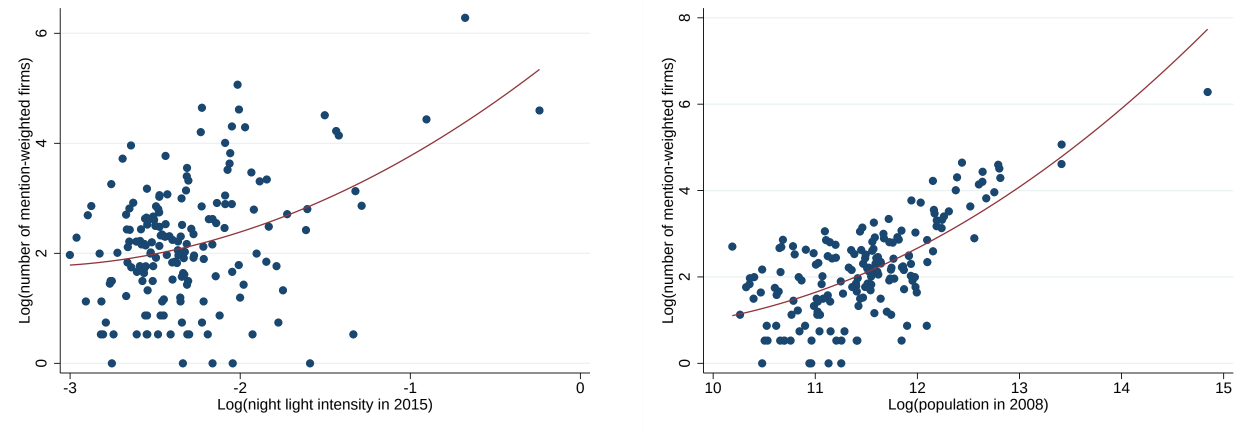
KSIC code	KSIC description	ISIC
10000	Manufacture of food products	15
10600	Manufacture of grain mill products, starches and starch products	15
10700	Manufacture of other food products	15
10800	Manufacture of prepared animal feeds and feed additives	15
11100	Manufacture of alcoholic beverages	15
11200	Manufacture of ice and non-alcoholic beverages; production of mineral waters	15
12000	Manufacture of tobacco products	16
13000	Manufacture of textiles, except apparel	17
13100	Spinning of textiles and processing of threads and yarns	17
13200	Weaving of textiles and manufacture of textile products	17
13300	Manufacture of knitted and crocheted fabrics	17
13900	Manufacture of other made-up textile articles, except apparel	17
14100	Manufacture of sewn wearing apparel, except fur apparel	18
14200	Manufacture of articles of fur	18
14400	Manufacture of apparel accessories	18
15100	Manufacture of leather, luggage and similar products	19
15200	Manufacture of footwear and parts of footwear	19
16000	Manufacture of wood and of products of wood and cork; except furniture	20
17100	Manufacture of pulp, paper and paperboard	21
17200	Manufacture of corrugated paper, paper boxes and paper containers	21
18000	Printing and reproduction of recorded media	22
19000	Manufacture of coke, briquettes and refined petroleum products	23
20000	Manufacture of chemicals and chemical products; except pharmaceuticals and medicinal chemicals	24
20100	Manufacture of basic chemicals	24
20200	Manufacture of plastics and synthetic rubber in primary forms	24
20300	Manufacture of fertilizers, pesticides, germicides and insecticides	24
20400	Manufacture of other chemical products	24
20492	Manufacture of processed and refined salt	24
20500	Manufacture of man-made fibers	24
21000	Manufacture of pharmaceuticals, medicinal chemical and botanical products	24
22000	Manufacture of rubber and plastics products	25
23100	Manufacture of glass and glass products	26
23200	Manufacture of refractory and non-refractory ceramic products	26
23300	Manufacture of cement, lime, plaster and its products	26
23900	Manufacture of other non-metallic mineral products	26
24100	Manufacture of basic iron and steel	27
24200	Manufacture of basic precious and non-ferrous metals	27
25000	Manufacture of fabricated metal products, except machinery and furniture	28
27000	Manufacture of medical, precision and optical instruments, watches and clocks	33
28000	Manufacture of electrical equipment	31
29000	Manufacture of other machinery and equipment	29
29200	Manufacture of special-purpose machinery	29
30000	Manufacture of motor vehicles, trailers and semitrailers	34
31100	Building of ships and boats	35
31200	Manufacture of railway locomotives and rolling stock	35
31900	Manufacture of other transport equipment	35
32000	Manufacture of furniture	36
33000	Other manufacturing	36
33200	Manufacture of musical instruments	36
35100	Electric power generation, transmission and distribution	40

Notes: Descriptions of KSIC codes are obtained from Statistics Korea (http://kssc.kostat.go.kr/ksscNew_web/ekssc/main/main.do).

A.2.3 North Korea Company Data Validation Exercise

We construct the regional industry shares based on the North Korean company data which is admittedly a subsample of all companies in North Korea. One potential concern of using this data is that there may still exist a large number of firms that are important for the regional economy but not observed due to the lack of news reports. As a validation exercise of the KIET company data, we exploit cross-county variation in the number of mention-weighted firms and examine its correlation with night light intensity and population, respectively. The idea is to check whether the number of observed firms in the KIET company data is positively correlated with proxies of regional economic development; if a sizeable number of important firms are not included in the data, then it is likely to have no systematic relationship. County-level number of mention-weighted firms is obtained by adding the log-scaled total number of mentions between 2000 and 2015 for all firms in the county. Figure A-7 presents scatter plots showing the cross-county relationship between total number of firms and night light intensity in 2015 (panel (a)) and population in 2008 (panel (b)). Both panels suggest that the number of firms, weighed by the number of mentions between 2000 and 2015, reasonably captures the difference in economic and demographic characteristics across counties. In Tables A-6 and A-7, we report results from regressing nightlight intensity in 2015 on aggregate number of company mentions, which can be considered as a proxy for output, and regional characteristics. The results show a strong positive correlation between company mentions and nightlight intensity.

Figure A-7: Cross-county relationship between total number of firms and night light intensity and population



(a) Night light intensity 2015

(b) Population 2008

Notes: This figure presents scatter plots of county-level total number of firms and night light intensity (panel (a)) and population (panel (b)). The red line indicates the quadratic fit of the data. The vertical axis shows the log of the sum of firms where firms are weighted by the total number of mentions from 2000 to 2015. The horizontal axis in panel (a) is the log of night light intensity in 2015 and in panel (b) is the log of population in 2008.

The analysis above suggests that the number of mentions aggregated at the county level is a good proxy of local manufacturing activities. Since we use them to compute industry shares within a county, we also need to examine their performance in predicting industry output. Unfortunately, we do not have county-level information on industry output – otherwise, we would have used them instead of using the number of mentions as a proxy. Instead, we aggregate the number of company mentions (transformed by the functional form $\log(1+M_f)$) at the industry level and compare them with other proxies of nationwide industry-level output.

Panel (a) of Figure A-8 plots the share of exports of each industry in total exports during the period 2011-2015 against the share of the number of mentions of companies in each industry (we transform the number of mentions of each company by $\log(1+M_f)$ before aggregation). We see a weak and positive correlation of 0.29. In our calibration, we assume that the North Korean consumption shares, ξ_j, are the same as the ones of China in 2002. In panel (b), we see that the consumption shares, ξ_j, are much closer to the share of total company mentions by industries, with a correlation coefficient of 0.83. Finally, we plot the share of gross output in each industry j in our calibrated model against the share of company mentions and find an even higher correlation (0.90). Our model calibration takes into account both imports and exports as well as input-output linkages, which provides a better approximation to industry-level output than the consumption shares. For example,

Table A-6: Regional Predictors of Night Light Intensity

	Log(Nightlight intensity 2015)		
	(1)	(2)	(3)
Sum of log-weighted number of company mentions	0.003***	0.004***	0.003***
	(0.000)	(0.000)	(0.001)
Log (population in 2008)			0.106
			(0.130)
Log (road length in 2017)			0.024
			(0.083)
Log (building area in 2014)			-0.025
			(0.137)
Log distance to border			-0.197**
			(0.079)
Log distance to major port			-0.016
			(0.019)
Log distance to Pyeongyang (NK Capital)			0.146
			(0.097)
Special economic zone - agriculture development			-0.174
			(0.121)
Special economic zone - tourism development			0.068
			(0.146)
Log (number of major mines)			-0.130**
			(0.054)
Log (total area of markets in 2015)			0.006
			(0.027)
Province FE	No	Yes	Yes
R-squared	0.64	0.71	0.82
Observations	174	174	174

Notes: Total company mentions is the sum of all mentions for companies in each county between 2000 and 2015. Robust standard errors are reported in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

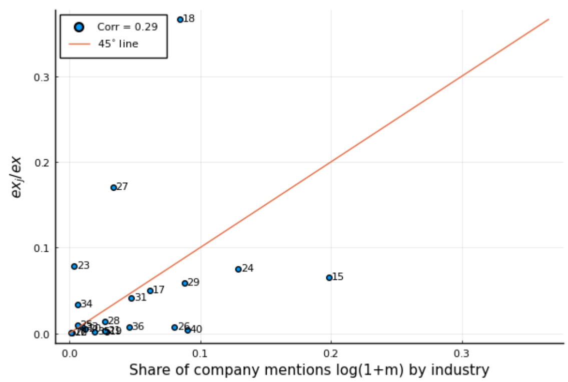
the consumption share of the Manufacturing of Food (Sector 15) is much higher than its share of company mentions, but the model implied share of output is closer to the company mention share, largely due to the large net imports in this sector. Though we are not directly comparing the share of total company mentions to industry shares in the raw data in panels (b) and (c), the use of company mentions to approximate industry shares is at least consistent with industry shares implied by the quantitative model.

Table A-7: Regional Predictors of Night Light Intensity

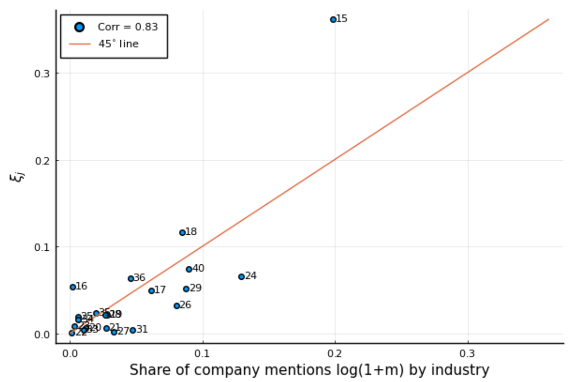
	Log(Nightlight intensity 2015)		
	(1)	(2)	(3)
Total company mentions in 2000-2015 (unit: 1,000)	0.435***	0.453***	0.337***
	(0.014)	(0.066)	(0.113)
Log (population in 2008)			0.104
			(0.120)
Log (road length in 2017)			0.052
			(0.100)
Log (building area in 2014)			-0.025
			(0.130)
Log distance to border			-0.206***
			(0.074)
Log distance to major port			-0.009
			(0.020)
Log distance to Pyeongyang (NK Capital)			0.038
			(0.069)
Special economic zone - agriculture development			-0.150
			(0.110)
Special economic zone - tourism development			0.079
			(0.155)
Log (number of major mines)			-0.158***
			(0.056)
Log (total area of markets in 2015)			0.003
			(0.026)
Province FE	No	Yes	Yes
R-squared	0.65	0.72	0.82
Observations	174	174	174

Notes: Total company mentions is the sum of all mentions for companies in each county between 2000 and 2015. Robust standard errors are reported in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

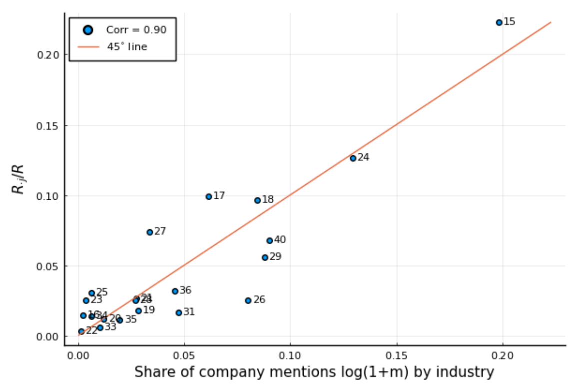
Figure A-8: Compare share of company mentions to industry-level exports, consumption and output



(a) Export by Industry



(b) (Chinese) consumption by Industry



(c) Output by Industry in the Baseline Model

Notes: panel (a) plots the share of exports of each industry in total exports during the period 2011-2015 against the share of the number of mentions of companies in each industry (we transform the number of mentions of each company by $\log(1 + M_f)$ before aggregation). Panels (b) and (c) uses the nationwide consumption shares and output shares in the calibrated model instead of shares of exports, respectively.

A.3 How does the Bank of Korea estimate North Korea's GDP?

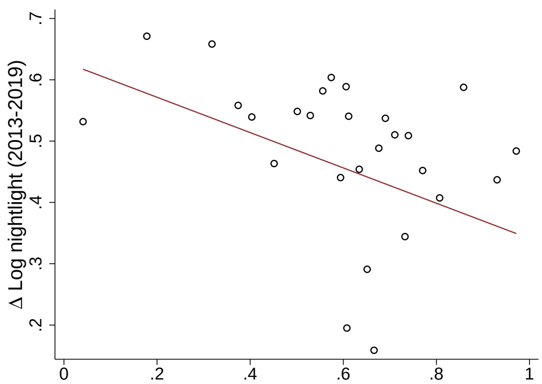
In a press release, the Bank of Korea (2021) explains officially how North Korea's GDP is estimated as follows.

- The Bank of Korea has been estimating the gross domestic product of North Korea annually since 1991 to evaluate the North Korean economy from South Korea's perspective and to use the results in policy-making.
- Their estimation of North Korean GDP follows the System of National Accounts (SNA), the same as how they estimate the GDP of South Korea. Specifically, the Bank of Korea uses data on how much in quantity North Korea produces in each industry, provided by relevant government institutions. However, South Korean prices and value-added rates are applied to the North Korean production quantities in computing the final values of production. That is, the estimated North Korean GDP can be interpreted as how much North Korean productions would be worth if the same quantities were to be produced in South Korea.
- The Bank of Korea's North Korean GDP and its growth rate estimates are then confirmed through a verification process by South Korean experts.

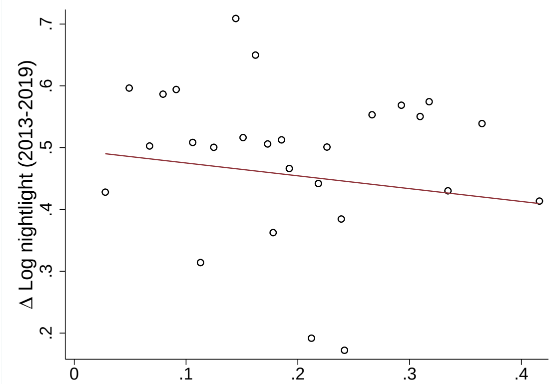
B Additional Reduced-form Results

B.1 Impact of Trade Sanctions on Regional Economies

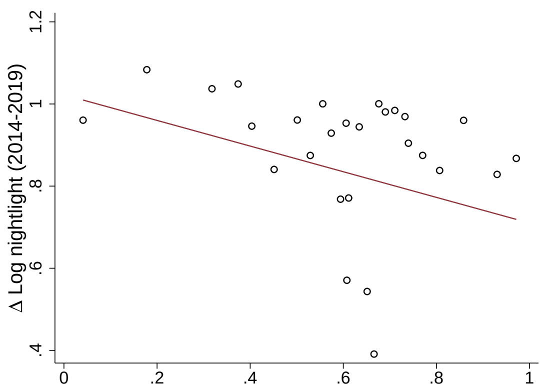
Figure B-1: Long-difference relationship between night light and sanction exposures



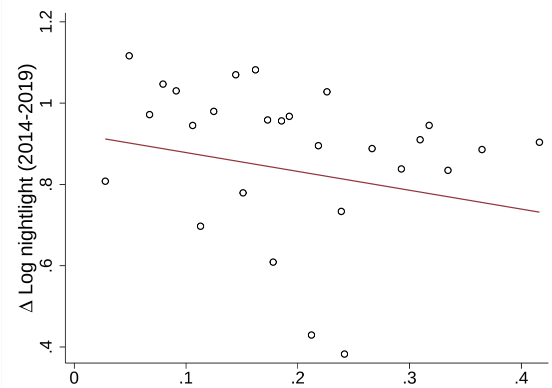
(a) Export sanction exposure



(b) Intermediate input sanction exposure



(c) Export sanction exposure



(d) Intermediate input sanction exposure

Notes: The vertical axis indicates the long-difference in log of annual average nighttime luminosity. Panels (a) and (b) use 2013-2019 and panels (c) and (d) use 2014-2019. County observations are grouped into 30 bins based on sanction exposure. The solid red line depicts the linear fit with population share in 2008 as weights.

Table B-1: Long Difference Estimates of Sanction Indices (2012-2019)

	Δ Log(Night light intensity)		
	(1)	(2)	(3)
Export Sanction Exposure	-0.510***		-0.509***
	(0.148)		(0.149)
Intermediate Input Sanction Exposure		-0.285	-0.276
		(0.263)	(0.261)
R-squared	0.09	0.01	0.10
Observations	174	174	174

Notes: Dependent variable is the difference in log of annual mean night light intensity, obtained by averaging VIIRS data at the county level, between 2012 and 2019. Since 2012 data starts at April we drop first quarter (January-March) data from all years. Observations are weighted by share of population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table B-2: Long Difference Estimates of Sanction Indices (2013-2019)

	Δ Log(Night light intensity)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Export Sanction Exposure	-0.288***		-0.287***		-0.227**		0.030
	(0.093)		(0.093)		(0.090)		(0.143)
Intermediate Input Sanction Exposure		-0.204	-0.200			1.182***	1.288**
		(0.181)	(0.177)			(0.343)	(0.541)
Import Sanction Exposure				-0.280**	-0.173	-0.853***	-0.919***
				(0.117)	(0.113)	(0.223)	(0.352)
R-squared	0.07	0.01	0.08	0.05	0.09	0.11	0.11
Observations	174	174	174	174	174	174	174

Notes: Observations are weighted by share of population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table B-3: Long Difference Estimates of Sanction Indices (2014-2019)

	Δ Log(Night light intensity)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Export Sanction Exposure	-0.312**		-0.311**		-0.196		0.018
	(0.130)		(0.130)		(0.127)		(0.183)
Intermediate Input Sanction Exposure		-0.475**	-0.470**			1.007**	1.071
		(0.223)	(0.226)			(0.496)	(0.695)
Import Sanction Exposure				-0.424***	-0.332**	-0.912***	-0.952**
				(0.153)	(0.147)	(0.322)	(0.461)
R-squared	0.05	0.02	0.07	0.06	0.08	0.08	0.08
Observations	174	174	174	174	174	174	174

Notes: Observations are weighted by share of population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table B-4: Quarterly Difference Estimates of Sanction Indices (2013Q1-2019Q4)

	Δ Log(Night light intensity)		
	(1)	(2)	(3)
Δ Export Sanction Exposure	-0.197*		-0.187*
	(0.111)		(0.099)
Δ Intermediate Input Sanction Exposure		-0.272	-0.082
		(0.348)	(0.304)
R-squared	0.55	0.55	0.55
Observations	4465	4465	4465

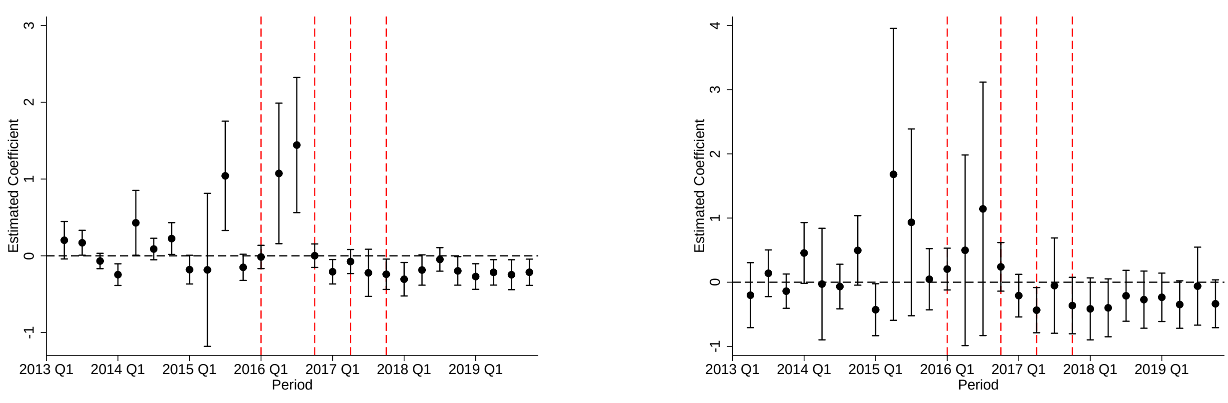
Notes: Dependent variable is the quarterly difference in log of nighttime light intensity between 2013 Q1 and 2019 Q4. Δ Sanction Exposure is the quarterly differential changes in exposure to export and input sanctions. Observations are weighted by share of population in 2008. All specifications include province fixed effects. Standard errors are clustered at the county level and reported in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table B-5: Regional Sanction Exposure and Kim Jong-un visits

	Log(Visits by Kim Jong-un)		
	(1)	(2)	(3)
Export Sanction Exposure	0.686	-0.218	-0.249
	(0.520)	(0.160)	(0.174)
Intermediate Input Sanction Exposure	1.106	-0.315	0.093
	(0.766)	(0.490)	(0.413)
ln(size of population in 2008)		0.066	0.158
		(0.170)	(0.151)
ln(sum of building area in 2014)		-0.003	0.018
		(0.163)	(0.161)
ln(distance to Pyeongyang)		-0.373***	-0.472***
		(0.044)	(0.054)
ln(road length in 2017)		0.307***	0.022
		(0.111)	(0.110)
ln(distance to border)		-0.117**	-0.101*
		(0.051)	(0.054)
ln(distance to major port)		-0.027	0.010
		(0.039)	(0.021)
Nuclear site		0.042	0.002
		(0.122)	(0.131)
Special industrial zone		0.360	0.356**
		(0.284)	(0.152)
Province FE			Yes
R-squared	0.03	0.82	0.88
Observations	174	174	174

Notes: Dependent variable is the log transformed total number of visits made by Kim Jong-un to each county in 2017, 2018 and 2019. Standard errors are reported in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Figure B-2: Quarterly coefficient estimates of sanction exposures on nightlight



(a) Export sanction exposure (b) Intermediate input sanction exposure

Notes: This figure presents quarter-specific coefficient estimates of (a) export sanction and (b) input sanction exposures on nighttime light intensity. Dashed vertical lines indicate each wave of UN sanctions (from left to right): UN 2270 - Export ban of coal and iron ore except for people's livelihood. UN 2321 - Upper limit on coal and iron exports. UN 2371 - Total ban on coal exports. UN 2375, 2397 - Ban on textiles and apparels exports. Freeze on supply of crude oil. Upper limit of supply of refined petroleum products to 500,000 barrels. Import ban on machines, vehicles, and metals.

B.2 Robustness Checks and Bartik Decomposition Analysis

Table B-6: Robustness Check - Long Difference Estimates (2014-2019)

	Δ Log of annual average nighttime luminosity						
	Province	Drop counties from sample				Additional controls	
	Fixed	top and bottom		Pyongyang	NK-China	Pre-trend	Nightlight
	Effects	1 perc.	3 perc.	(Capital)	border	(2014-2015)	+ regional
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Export Sanction Exposure	-0.231**	-0.331**	-0.211***	-0.201**	-0.281**	-0.294***	-0.136***
	(0.096)	(0.130)	(0.061)	(0.083)	(0.135)	(0.108)	(0.052)
Intermediate Input Sanction Exposure	-0.266	-0.412*	-0.389***	-0.370**	-0.439*	-0.411**	-0.051
	(0.186)	(0.220)	(0.149)	(0.183)	(0.225)	(0.199)	(0.137)
Province FE	Yes	No	No	No	No	No	No
R-squared	0.51	0.07	0.10	0.06	0.06	0.27	0.80
Observations	174	170	162	169	158	174	174

Notes: VIIRS nighttime light data is aggregated by county and quarter from 2014 to 2019. Column (7) controls nighttime luminosity in 2015 and quartiles of country characteristics. Observations are weighted by share of population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table B-7 tests robustness with respect to the company weights used to build county-level sanction exposures. In Columns 1-3, we report OLS estimates of equation (4) where county-level industry shares are constructed by weighing all companies equally regardless of whether they were mentioned once or, for instance, 10 times between 2000 and 2015. The estimate on export sanctions is similar to our baseline estimate, shown in Columns 7-9. Columns 4-6 present results by weighing company using the number of mentions instead of the logarithm of the number of mentions that we use in our baseline specification. Compared to the baseline, the coefficient estimate of export sanction is smaller in size (-0.193) but still statistically significant at the one percent level. We also test robustness to company weights using 2014 as the base year. The results, reported in Table B-8, suggest that export and input sanction effects are robust to alternative company weights.

Table B-7: Robustness Check: Company weights

	Δ Log of annual average nighttime luminosity (2013-2019)								
Company weights:	None			Num. of mentions			Log(num. of mentions)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Export Sanction Exposure	-0.291***		-0.299***	-0.197***		-0.193***	-0.288***		-0.287***
	(0.096)		(0.099)	(0.073)		(0.073)	(0.093)		(0.093)
Input Sanction Exposure		-0.289	-0.337		-0.113	-0.085		-0.204	-0.200
		(0.252)	(0.249)		(0.116)	(0.119)		(0.181)	(0.177)
R-squared	0.07	0.01	0.08	0.06	0.01	0.06	0.07	0.01	0.08
Observations	174	174	174	174	174	174	174	174	174

Notes: This table reports estimates using alternative weights on company mentions. Number of company mentions is sourced from KIET data from 2000 to 2015. Observations are weighted by share of population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table B-8: Robustness Check: Company weights

	Δ Log of annual average nighttime luminosity (2014-2019)								
Company weights:	None			Num. of mentions			Log(num. of mentions)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Export Sanction Exposure	-0.344**		-0.362**	-0.192*		-0.182*	-0.312**		-0.311**
	(0.135)		(0.139)	(0.100)		(0.102)	(0.130)		(0.130)
Input Sanction Exposure		-0.680**	-0.738**		-0.261*	-0.235		-0.475**	-0.470**
		(0.334)	(0.338)		(0.134)	(0.146)		(0.223)	(0.226)
R-squared	0.05	0.03	0.08	0.03	0.01	0.04	0.05	0.02	0.07
Observations	174	174	174	174	174	174	174	174	174

Notes: This table reports estimates using alternative weights on company mentions. Number of company mentions is sourced from KIET data from 2000 to 2015. Observations are weighted by share of population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table B-9 tests robustness with respect to the input-output table used to construct the intermediate input sanction exposure index. Instead of China's 2002 input-output table, we adopt China's input-output table from 1987 and 1997 to create alternative intermediate input sanction exposure indices. Columns 1-4 suggest that using China's 1987 or 1997 input-output table does not change our estimates of input sanction exposure. An alternative way of constructing input sanction exposure is to first aggregate import sanctions across products at the level of 122 Chinese industry input-output table and then aggregate at the ISIC 2-digit level.[39] We report the estimates in Columns 5-6. Next, following Acemoglu, Autor, Dorn, Hanson and Price (2016), we calculate the input sanction exposure using each industry's total requirements of upstream industries, taking into account direct and indirect usages of intermediate inputs (estimates reported in Columns 7-8). We also check robustness of the intermdiate input sanction measure with the 2014-2019 sample. As shown in Table B-10, both export and input sanction estimates are qualitatively unchanged. In sum, we explore various alternative approaches to construct input sanction exposure and find that our results are robust.

Table B-9: Robustness Check: Alternative Construction of Input Sanction Exposure

	Δ Log of annual average nighttime luminosity (2013-2019)									
	1987 China IO		1997 China IO		Aggregate inputs at 122 China IO		Leontief inverse terms		Exclude industries in strategic plan	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Export Sanction Exposure		-0.291***		-0.289***		-0.280***		-0.293***		-0.222***
		(0.094)		(0.093)		(0.091)		(0.096)		(0.078)
Input Sanction Exposure	-0.076	-0.108	-0.123	-0.129	-0.268	-0.224	-0.081	-0.176	-0.579**	-0.422
	(0.153)	(0.153)	(0.164)	(0.162)	(0.190)	(0.183)	(0.277)	(0.281)	(0.281)	(0.266)
R-squared	0.00	0.08	0.00	0.08	0.01	0.08	0.00	0.07	0.06	0.10
Observations	174	174	174	174	174	174	174	174	174	174

Notes: This table reports estimates using alternative indices of intermediate input sanction exposures. Observations are weighted by share of population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table B-10: Robustness Check: Alternative Construction of Input Sanction Exposure

	Δ Log of annual average nighttime luminosity (2014-2019)									
	1987 China IO		1997 China IO		Aggregate inputs at 122 China IO		Leontief inverse terms		Exclude industries in strategic plan	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Export Sanction Exposure		-0.323**		-0.314**		-0.295**		-0.328**		-0.196*
		(0.132)		(0.131)		(0.129)		(0.134)		(0.107)
Input Sanction Exposure	-0.305*	-0.340*	-0.371*	-0.377*	-0.554**	-0.507**	-0.463	-0.569*	-0.882**	-0.744*
	(0.179)	(0.186)	(0.197)	(0.202)	(0.241)	(0.237)	(0.327)	(0.344)	(0.408)	(0.390)
R-squared	0.01	0.06	0.02	0.06	0.03	0.07	0.01	0.06	0.08	0.10
Observations	174	174	174	174	174	174	174	174	174	174

Notes: This table reports estimates using alternative indices of intermediate input sanction exposures. Observations are weighted by share of population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

[39] We thank an anonymous referee for this suggestion.

Table B-11: Elasticity of Industry Value Added to Overall Manufacturing Value Added

ISIC Code	Short Description	Elasticity	Standard Error	# of Obs.	# of Countries	# of Years
15	Food	0.619	0.105	5516	161	59
16	Tobacco	0.736	0.098	4124	135	59
17	Textiles	0.664	0.104	5453	159	59
18	Apparel	0.693	0.104	5121	152	59
19	Leather	0.130	0.137	2410	117	33
20	Wood	0.741	0.106	5399	156	59
21	Paper	0.754	0.110	5300	152	59
22	Publishing	0.735	0.106	5188	156	59
23	Refined Petro.	0.707	0.112	4152	131	59
24	Chemicals	0.709	0.099	5337	160	59
25	Rubber and Plastic	0.739	0.101	5021	147	59
26	Other non-Metal	0.686	0.107	5463	158	59
27	Basic Metals	0.706	0.107	4917	144	59
28	Fabricated Metals	0.749	0.097	5257	157	59
29	Machinery NEC	0.724	0.113	4911	142	59
31	Elec. Equip.	0.767	0.105	4888	145	59
33	Medical Equip.	0.853	0.122	3076	112	59
34	Motor Vehicles	0.756	0.107	4834	142	59
35	Trans Equip. NEC	0.101	0.065	2163	106	33
36	Furniture	0.727	0.101	5308	157	59

Notes: We estimate each industry's elasticity of value added with respect to overall manufacturing value added using all countries and all years (1963-2021) in the UNIDO INDSTAT 2 database. The set of countries does not include North Korea. The standard errors are two-way clustered at country and year levels.

Table B-12: Robustness Check: Heterogeneous Exposure to Aggregate Shocks

	Δ 2013-2019			Δ 2014-2019		
	(1)	(2)	(3)	(4)	(5)	(6)
Export Sanction Exposure	-0.287***	-0.287***	-0.283***	-0.311**	-0.313**	-0.315**
	(0.093)	(0.093)	(0.092)	(0.130)	(0.132)	(0.130)
Intermediate Input Sanction Exposure	-0.200	-0.199	-0.177	-0.470**	-0.498**	-0.497**
	(0.177)	(0.179)	(0.180)	(0.226)	(0.227)	(0.227)
Weighted Value Added Elasticity		-0.011			0.560	
		(0.371)			(0.475)	
Weighted Output Elasticity			-0.294			0.351
			(0.479)			(0.647)
R-squared	0.08	0.08	0.08	0.07	0.07	0.07
Observations	174	174	174	174	174	174

Notes: This table reports estimates controlling for each county's exposure to aggregate shocks, based on the industry shares in each county and the industry-specific value-added or output elasticities to aggregate trends (see Table B-11 for details). Observations are weighted by share of population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

B.2.1 Bartik Decomposition Analysis

Our key regressors, the regional sanction exposure measures, are constructed as Bartik instruments, i.e., inner products of region-industry shares and the sanction exposures at the industry level.[40] We follow Goldsmith-Pinkham et al. (2020) and make an identification assumption that the pre-sanction region-industry shares are orthogonal to other determinants of the changes in the county-level night light intensity. To provide credibility for our empirical strategy, we perform several diagnostic exercises following the suggestions in Goldsmith-Pinkham et al. (2020). More specifically, the authors show that the Bartik estimator can be decomposed into a weighted sum of the just-identified IV estimators that use each industry share as a separate instrument, where the weights (Rotemberg weights) reflect which industry's exposure receives more weight in the overall estimate. We perform the Rotemberg decomposition in our bivariate, long-difference specification in Columns (1) and (2) of Panel A, Table 3. In our context, we obtain the just-identified estimators using IV regressions in which we instrument the sanction exposure measures, $S_{EX,n}$ and $S_{IN,n}$, by the region-industry shares $\frac{\sum_{f\in n,j} H(M_f)}{\sum_{f\in n} H(M_f)}$ of each industry j.[41] (see equation (3) for the notations)

Table B-13 reports computed Rotemberg weights (α_j), just-identified coefficient estimates ($\hat{\beta}_j$), and their 95 percent confidence intervals.[42] Panel A shows the top five industries with the largest Rotemberg weights for the Bartik coefficients for export sanction exposure. Among the 20 industries that are included in our data set, 10 industries have a positive weight adding up to 1.033. The top five industries account for 90 percent (0.929/1.033) of the positive weight on export sanctions: the food industry has the largest weight (0.45), followed by machinery (0.18), apparel (0.15), electrical equipment (0.08), and textiles (0.07). Surprisingly, the food industry has a positive $\hat{\beta}_j$ while the other four industries have negative coefficients.[43] For input sanction, 13 out of 20 industries have a positive Rotemberg weight which adds to 1.09. Panel B shows the top five industries with the largest weights on input sanctions. Similarly, the top five account for 89.2 percent of the positive weights (0.972/1.09): machinery (0.45), basic metals (0.18), electric equipment (0.16), fabricated metals (0.09), and transportation equipment (0.09). Importantly, all five industries with the largest weights on input sanction show negative coefficient estimates ($\hat{\beta}_j$).

Table B-15 shows the relationship between county characteristics and the 2015 share of the top five industries in Table B-13 as well as the export and input sanction exposures. The

[40] Unlike classic cases such as Bartik (1991) and Autor et al. (2013), we are not interested in estimating the effect of an endogenous variable. Our main specification can be seen as "reduced-form" estimators in IV regressions, or instrumenting the Bartik measures by themselves.

[41] Since the industry shares sum to one, the separate instruments are linearly dependent. We dropped one industry that was never sanctioned, Manufacturing of Tobacco Products (ISIC code 16), from the list of instruments. Goldsmith-Pinkham et al. (2020) provide more discussion on this normalization.

[42] We report the decomposition results for 2014-2019 in Table B-14.

[43] We offer more discussion about the heterogeneous coefficients in Section B.3.

population density in 2008 is a positive predictor for industry share of electrical equipment, basic metals, and transportation equipment, and negatively correlated with the export sanction index. Building area density in 2014 is negatively correlated with the share of food and basic metal industries. Night light intensity in 2015 is shown to have no significant correlation with exposure to either sanction after controlling for county characteristics. It is possible that spurious correlations associated with county characteristics and industry shares are confounding the relationship between regional sanction exposures and night light intensity. As shown in Column 7 of Table 4, our estimates are robust to controlling for night light intensity in 2015 and county characteristics.

Finally, we examine the parallel pre-trend assumption for industries with the top five Rotemberg weights. Appendix Figure B-3 presents pre-trend figures by regressing equation (5) with county-level industry shares of the top five Rotemberg weight industries instead of the sanction exposures. Specifically, Panels (a) and (b) report the estimated coefficient of the total share of mentions that belong to the top five Rotemberg weights for export sanction and input sanction, respectively. In both panels, the coefficients decline in 2017 and remain below zero afterwards.

Table B-13: Industries with the largest Rotemberg weights, 2013 - 2019

Industry j	α_j	Sanction index g_j	$Z_j'B$	$\hat{\beta}_j$	95% CI	
Panel A. Export sanction						
Food	0.447	0.944	3.212	0.182	-0.227	0.591
Machinery NEC	0.183	0.994	1.249	-0.043	-0.482	0.395
Apparel	0.148	0.997	1.009	-0.965	-1.890	-0.040
Elec. Equip.	0.078	0.997	0.529	-1.251	-2.907	0.405
Textiles	0.074	0.999	0.506	-1.075	-2.005	-0.145
Panel B. Intermediate input sanction						
Machinery NEC	0.431	0.644	1.014	-0.054	-0.595	0.488
Basic Metals	0.184	0.501	0.558	-0.236	-1.139	0.667
Elec. Equip.	0.150	0.543	0.419	-1.578	-3.928	0.772
Trans Equip. NEC	0.089	0.712	0.190	-0.708	-1.961	0.546
Fabricated Metals	0.085	0.622	0.208	-1.855	-4.911	1.201

Notes: We perform the Rotemberg decomposition of the long-difference regressions in Columns 1 and 2 of Panel A, Table 3, following the method described in Goldsmith-Pinkham et al. (2020). We leave out one sector, Manufacturing of Tobaccos, to avoid the colinearity issue. The industry-level shocks, g_j, are simply the export and input sanction indices, $S_{EX,j}$ and $S_{IN,j}$. The estimated coefficients, $\hat{\beta}_j$, and the corresponding confidence intervals, are obtained in an IV regression where we regress the change in the night light of region n on the regional export and input exposures, $S_{EX,n}$ and $S_{IN,n}$, instrumented by the share of industry j in region n constructed from the company list database. Our baseline estimates in Table 3 equals the weighted average of all the coefficients from the IV regressions, i.e., $\sum_j \alpha_j \beta_j$.

Table B-14: Industries with the largest Rotemberg weights, 2014 - 2019

Industry j	α_j	Sanction index g_j	$Z_j'B$	$\hat{\beta}_j$	95% CI	
Panel A. Export sanction						
Food	0.447	0.944	3.212	0.337	-0.231	0.905
Machinery NEC	0.183	0.994	1.249	-0.049	-0.669	0.570
Apparel	0.148	0.997	1.009	-1.006	-2.342	0.330
Elec. Equip.	0.078	0.997	0.529	-1.734	-4.250	0.783
Textiles	0.074	0.999	0.506	-0.904	-2.197	0.389
Panel B. Intermediate input sanction						
Machinery NEC	0.431	0.644	1.014	-0.061	-0.825	0.704
Basic Metals	0.184	0.501	0.558	-0.317	-1.192	0.559
Elec. Equip.	0.150	0.543	0.419	-2.186	-5.620	1.248
Trans Equip. NEC	0.089	0.712	0.190	-1.787	-3.491	-0.082
Fabricated Metals	0.085	0.622	0.208	-2.494	-6.661	1.674

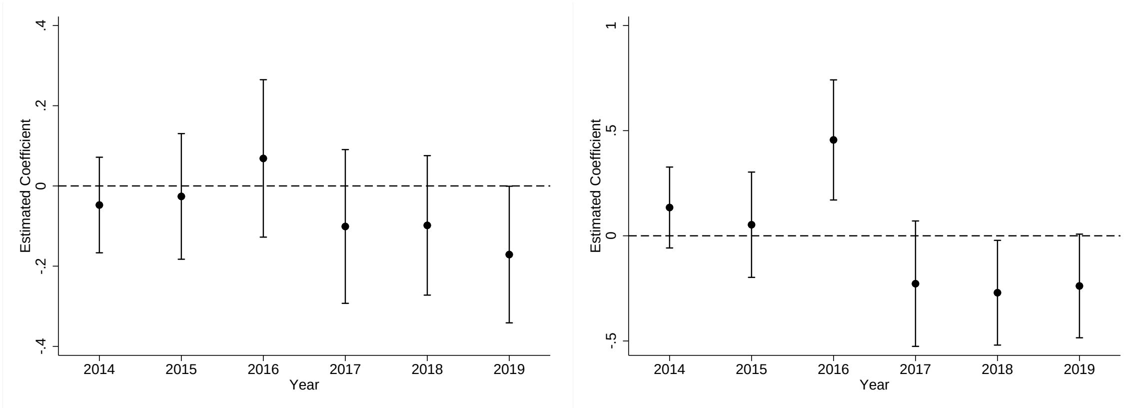
Notes: We perform the Rotemberg decomposition of the long-difference regressions in Columns 1 and 2 of Panel A, Table 3, following the method described in Goldsmith-Pinkham et al. (2020). We leave out one sector, Manufacturing of Tobaccos, to avoid the colinearity issue. The industry-level shocks, g_j, are simply the export and input sanction indices, $S_{EX,j}$ and $S_{IN,j}$. The estimated coefficients, $\hat{\beta}_j$, and the corresponding confidence intervals, are obtained in an IV regression where we regress the change in the night light of region n on the regional export and input exposures, $S_{EX,n}$ and $S_{IN,n}$, instrumented by the share of industry j in region n constructed from the company list database. Our baseline estimates in Table 3 equals the weighted average of all the coefficients from the IV regressions, i.e., $\sum_j \alpha_j \beta_j$.

Table B-15: Relationship Between Sanction Indices, Industry Share and County Characteristics

	Sanction Exposure		Industry share of firms constructed as sum of log-weighted company mentions							
	Export	Intermed. input	Food	Apparel	Machinery	Textile	Electrical Equip.	Basic metal	Transport Equip.	Fabricated metal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ln(mean night light intensity in 2015)	0.032	-0.014	0.034	0.009	0.018	-0.001	-0.029**	-0.011	0.002	0.011
	(0.037)	(0.018)	(0.045)	(0.026)	(0.023)	(0.014)	(0.014)	(0.012)	(0.007)	(0.011)
ln(size of population in 2008)	0.124**	0.059*	-0.050	-0.002	0.025	0.022	0.037**	0.044**	0.020**	0.015
	(0.052)	(0.031)	(0.059)	(0.029)	(0.037)	(0.037)	(0.016)	(0.018)	(0.009)	(0.014)
ln(sum of building area in 2014)	-0.041	0.006	-0.094	0.032	0.067	0.031	-0.021	-0.039*	-0.002	-0.010
	(0.068)	(0.038)	(0.077)	(0.041)	(0.051)	(0.044)	(0.019)	(0.020)	(0.009)	(0.018)
ln(road length in 2017)	-0.070**	-0.017	0.063	-0.027	-0.054**	-0.047***	-0.003	0.010	-0.005	-0.007
	(0.035)	(0.017)	(0.038)	(0.019)	(0.022)	(0.015)	(0.010)	(0.012)	(0.004)	(0.008)
ln(distance to border)	0.016	-0.012*	0.036**	0.003	-0.004	0.001	-0.003	-0.012	0.002	-0.001
	(0.013)	(0.007)	(0.016)	(0.008)	(0.006)	(0.004)	(0.004)	(0.008)	(0.003)	(0.002)
ln(distance to Pyeongyang)	0.012	0.019**	-0.021	-0.008	0.029***	-0.001	-0.013	0.013*	0.007**	-0.002
	(0.015)	(0.008)	(0.013)	(0.009)	(0.008)	(0.007)	(0.010)	(0.007)	(0.004)	(0.003)
ln(distance to major port)	-0.001	-0.010**	0.010	0.003	0.006*	0.006**	-0.002	-0.022***	-0.003	-0.002
	(0.005)	(0.004)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.003)	(0.002)
Nuclear site	0.023	-0.002	-0.066	-0.050***	0.022	0.123	-0.017	-0.011	-0.006	-0.006
	(0.064)	(0.033)	(0.055)	(0.017)	(0.057)	(0.083)	(0.014)	(0.010)	(0.004)	(0.008)
Special industrial zone	-0.063	-0.039	0.006	0.003	-0.034	0.038*	0.003	-0.046*	0.010	-0.016
	(0.052)	(0.025)	(0.055)	(0.030)	(0.024)	(0.021)	(0.019)	(0.027)	(0.012)	(0.011)
Mean	0.55	0.17	0.28	0.07	0.06	0.04	0.02	0.02	0.01	0.01
R-squared	0.10	0.20	0.12	0.10	0.12	0.17	0.15	0.36	0.29	0.11
Observations	174	174	174	174	174	174	174	174	174	174

Notes: Columns 3-10 report results from separate regressions of industry share on county-level characteristics. Regressions are weighted by population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Figure B-3: Annual Coefficient Estimates of Top 5 Rotemberg Weight Industries



(a) Export Sanction (b) Input Sanction

Notes: This figure presents year-specific coefficient estimates of the top five Rotemberg weight industry shares for (a) export sanction and (b) input sanction exposures on nighttime light intensity. The dashed horizontal line indicates the base year, 2013. Vertical capped bars represent 95% confidence intervals.

B.3 Heterogeneous Sectoral Effects

In this section, we discuss the implications of the potential heterogeneous effects of sanctions on each sector. We consider the following statistical model

$$y_n = \sum_j r_{nj} S_{EX,j} \beta_j + \nu_n, \tag{B-1}$$

where y_n is the outcome variable (change in nightlight intensities) in region n, r_{nj} is the share of industry j, region n, $S_{EX,j}$ is the export sanction index and β_j is the impact of a complete export sanction on sector j. If the treatment effects are heterogeneous across sectors, i.e., $\beta_j = \beta, \forall j$, we derive our main specification (see equation 4)

$$y_n = \beta \sum_j r_{nj} S_{EX,j} + \nu_n.$$

In Table B-13, we estimate $\hat{\beta}_j$ by instrumenting the Bartik export sanction exposure $\sum_j r_{nj} S_{EX,j}$ by the share of each sector r_{nj}. However, the estimate $\hat{\beta}_j$ may not converge to the true sectoral effects β_j. To see this, we can write

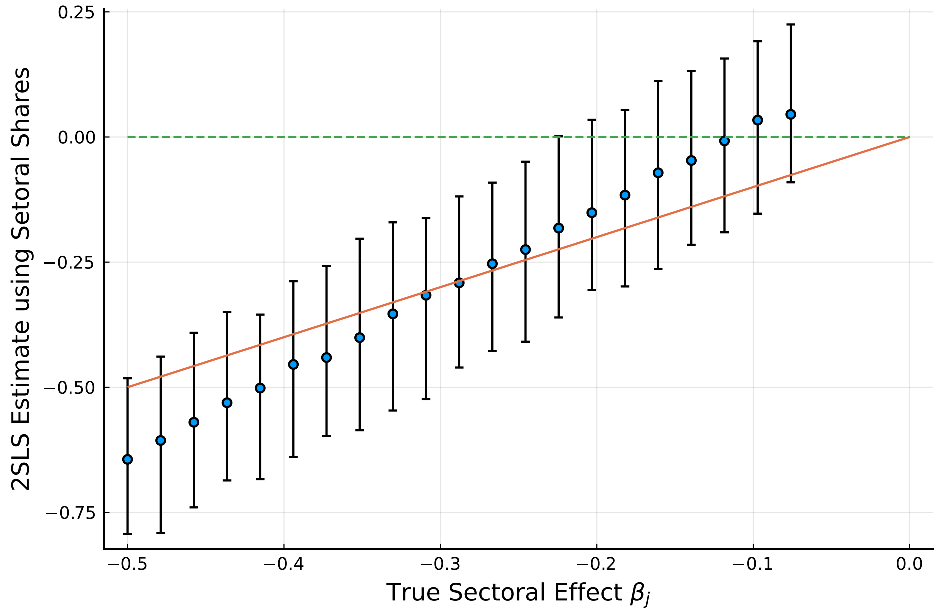
$$\text{plim}_{N\to\infty} \hat{\beta}_j = \frac{Cov(\sum_j \beta_j r_{nj} S_{EX,j}, r_{nj})}{Cov(\sum_k r_{nk} S_{EX,k}, r_{nk})} = \sum_j \beta_j \frac{Cov(r_{nj} S_{EX,j}, r_{nj})}{\sum_k Cov(r_{nk} S_{EX,k}, r_{nk})}. \tag{B-2}$$

Therefore, as long as $r_{nj}S_{EX,j}$ and r_{nj} are not independent, $\hat{\beta}_j$ may not converge to the true sectoral effect β_j.

We offer some insights about the potential biases using simulations. In particular, we consider $N = 174$ North Korean counties and $J = 21$ sectors and use the output shares r_{nj} approximated by the number of company mentions as in our empirical analysis. Export sanction indices are calculated as equation (1). We assume that β_j ranges from -0.500 to -0.076 across 21 sectors with equal distance so that the median is -0.288, the reduced-form estimate in Column 1 of Table 3. We randomly assign these β_j to different sectors and calculate the predicted effect y_n in equation B-1. The error term is assumed to have a normal distribution with a mean of 0 and a standard deviation of 0.205, consistent with the mean squared error based on the regression reported in Column 1 of Table 3. We focus on the true value of β_j for Manufacturing of Food (ISIC code = 15), and plot the median and the confidence interval (5th to 95th percentiles) of the 2SLS estimates of $\hat{\beta}_j$ in Figure B-4.

As can be seen from Figure B-4, the 2SLS estimate $\hat{\beta}_j$ is positively associated with the true effect β_j. However, the median $\hat{\beta}_j$ overestimates β_j when β_j is large and underestimates β_j vice versa. Though we have restricted the true sectoral effect to be smaller than or equal to -0.076, the estimated $\hat{\beta}_j$ can potentially be positive. This is possible if some of the weights in equation $\hat{\beta}_j$ are negative. Therefore, though large $\hat{\beta}_j$ is indicative of large β_j, positive values of $\hat{\beta}_j$ do not necessarily mean that the true sectoral effect is positive.

Figure B-4: Simulated 2SLS Estimates and True Sectoral Effects, Manufacturing of Food (ISIC = 15)



Notes: This figure plots the 2SLS estimate $\hat{\beta}_j$ for the Food Manufacturing Industry against the true effect β_j. We simulate 5000 times in total. The blue dot indicates the median of the estimates across all simulations in which the true β_j is set at the particular value indicated by the horizontal axis. The vertical interval indicates the range of estimates between the 5th to the 95th percentiles. We also plot the 45° line in red.

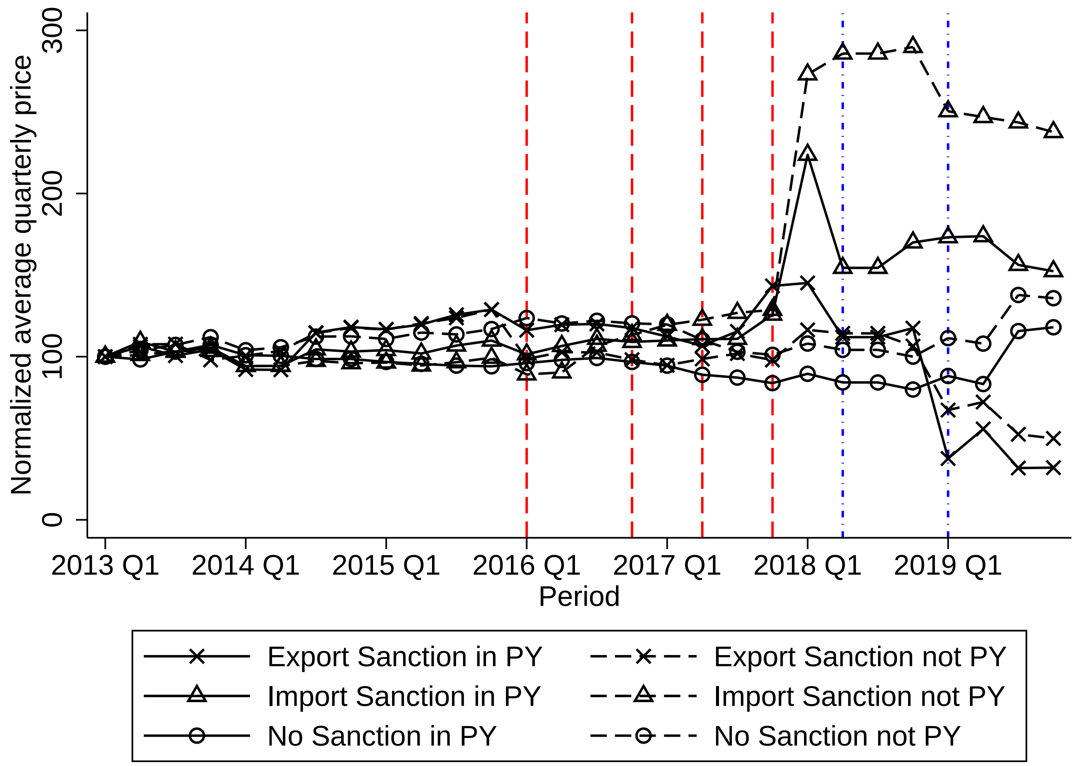
B.4 Impact of Trade Sanctions on Market Price

Table B-16: Estimated Impacts of Sanctions on Market Price

	Log(Quarterly Mean Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Export Sanction $\times \mathbf{1}$(Post Sanction)	-0.032			-0.040	-0.052	-0.042
	(0.066)			(0.063)	(0.064)	(0.064)
Import Sanction $\times \mathbf{1}$(Post Sanction)		0.319***		0.322***		0.303*
		(0.055)		(0.050)		(0.158)
Input Sanction $\times \mathbf{1}$(Post Sanction)			0.358***		0.374***	0.030
			(0.094)		(0.089)	(0.238)
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.76	0.77	0.77	0.77	0.77	0.77
Number of products	72	72	70	72	70	70
Observations	6825	6825	6675	6825	6675	6675

Notes: This table reports estimates of sanctions on market prices. Each product's price is normalized with respect to price in first quarter of 2013 (Price in 2013 Q1 is set at 100). All specifications include product, quarter, and city fixed effects. Standard errors are clustered at product level and reported in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Figure B-5: Price Trends by Product's Sanction Status: City Heterogeneity



Notes: This figure plots normalized average quarterly price trends of products grouped by sanction type. Solid lines indicate price in Pyeongyang and dashed lines indicate the average price across five cities excluding Pyeongyang. Red dashed horizontal lines indicate periods in which sanctions were imposed. Blue short-dashed horizontal lines mark periods at which the two NK-US summits took place: Singapore summit in June 12, 2018 and Hanoi summit in February 27, 2019.

Table B-17: Placebo test of sanction impacts on market price

	Log(Quarterly Mean Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Placebo Sanction Quarter = T-4						
Export Sanction $\times\mathbf{1}$(Post Placebo Sanction)	0.123			0.126	0.121	0.123
	(0.081)			(0.079)	(0.080)	(0.082)
Import Sanction $\times\mathbf{1}$(Post Placebo Sanction)		0.151		0.156*		0.033
		(0.094)		(0.080)		(0.234)
Input Sanction $\times\mathbf{1}$(Post Placebo Sanction)			0.259*		0.246*	0.204
			(0.138)		(0.127)	(0.351)
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.67	0.67	0.67	0.67	0.68	0.68
Number of products	71	71	69	71	69	69
Observations	6923	6923	6749	6923	6749	6749
Panel B. Placebo Sanction Quarter = T-8						
Export Sanction $\times\mathbf{1}$(Post Placebo Sanction)	0.196*			0.192*	0.198*	0.183*
	(0.105)			(0.103)	(0.105)	(0.102)
Import Sanction $\times\mathbf{1}$(Post Placebo Sanction)		-0.094		-0.067		-0.260
		(0.124)		(0.104)		(0.263)
Input Sanction $\times\mathbf{1}$(Post Placebo Sanction)			-0.032		-0.025	0.313
			(0.188)		(0.166)	(0.388)
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.56	0.55	0.56	0.56	0.57	0.57
Number of products	72	72	70	72	70	70
Observations	6715	6715	6559	6715	6559	6559

Notes: This table reports estimates of sanctions on market prices using placebo sanction quarters. Placebo sanction quarters are four quarters earlier than actual sanctions in Panel A and eight quarters earlier in Panel B. Each product's price is normalized with respect to price in first quarter of 2013 (Price in 2013 Q1 is set at 100). All specifications include product, period, and city fixed effects. Standard errors are clustered at product level and reported in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table B-18: City Heterogeneity: Estimates of Sanction Indices on Price

	Log(Quarterly Mean Price)		
	(1)	(2)	(3)
Export Sanction $\times \mathbf{1}$(Post Sanction)	-0.029		-0.040
	(0.070)		(0.066)
Export Sanction $\times \mathbf{1}$(Post Sanction) $\times$ Pyongyang	-0.023		-0.005
	(0.042)		(0.028)
Import Sanction $\times \mathbf{1}$(Post Sanction)		0.353***	0.356***
		(0.061)	(0.059)
Import Sanction $\times \mathbf{1}$(Post Sanction) $\times$ Pyongyang		-0.204	-0.202
		(0.157)	(0.152)
Product FE	Yes	Yes	Yes
Quarter $\times$ Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
R-squared	0.81	0.81	0.81
Number of products	72	72	72
Observations	6825	6825	6825

Notes: This table reports estimates of sanctions on market prices. Each product's price is normalized with respect to price in first quarter of 2013 (Price in 2013 Q1 is set at 100). All specifications include product, quarter, and city fixed effects. Standard errors are clustered at product level and reported in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

C GDP-Nightlight Elasticity

In this section, we discuss the GDP-nightlight elasticity that we use for interpreting our reduced-form results and for disciplining the spatial equilibrium model. We estimate county-level GDP-nightlight elasticities based on panel data of Chinese counties that are similar to North Korean counties in terms of nightlight intensity and population density, using an instrumental variable approach developed by Chor and Li (2021).

We briefly discuss the statistical framework in Chor and Li (2021). They allow both measurement errors in GDP and nightlight intensity. In particular, denoting y_{nt} as the log of true GDP in location n and period t, z_{nt} as the log of measured GDP, and x_{nt} as the observed nightlight intensity, we have the following statistical model:

$$z_{nt} = y_{nt} + \varepsilon_{z,nt},$$
$$x_{nt} = \beta y_{nt} + \varepsilon_{x,nt},$$

where $\varepsilon_{z,nt}$ and $\varepsilon_{x,nt}$ are the measurement errors in GDP and nightlight, respectively. Under the assumption that the contemporaneous measurement errors are uncorrelated, i.e., $Corr(\varepsilon_{z,nt}, \varepsilon_{x,nt}) = 0$, and the assumption that the auto-correlation in the measurement error of nightlight intensity is zero, i.e., $Corr(\varepsilon_{x,nt}, \varepsilon_{x,n,t-1}) = 0$, the coefficient from an IV regression of z_{nt} on x_{nt} using the lagged nightlight intensity $x_{n,t-1}$ provides a consistent estimate of the GDP-nightlight elasticity $1/\beta$, while the OLS estimate contains an attenuation bias due to $\varepsilon_{x,nt}$.[44]

We first obtain the VIIRS data for China and aggregate them to county-year levels. We drop the year 2012 since VIIRS does not cover the first quarter of that year. County-level GDP data are available for more than 2000 counties from statistical yearbooks between 2013 and 2018. We dropped observations with abnormal growth in nightlight intensity (top/bottom 2% of $\Delta \log(light_{nt})$) in all our regressions since the strength of the first stage depends crucially on how well the previous year's nightlight intensity predicts current nightlight intensity.

In Table C-1, we report the IV estimates in the upper panel and the first-stage results in the lower panel. In the cross-sectional regression (Column 1, without county fixed effects), past nightlight strongly predicts current nightlight and the estimate of the GDP-nightlight elasticity is 0.776. However, since our focus in the paper is on the change in output, we prefer estimates from specifications with county fixed effects. Adding county fixed effects

[44] Though Henderson et al. (2012) are the first to propose this statistical model, they do not use an IV approach in their paper. Instead, they impose parametric assumptions on the signal-to-noise ratio in the measured GDP, z_{nt}. For example, they assume that $\varepsilon_{z,nt} = 0$ for a set of "good data countries", estimate β directly and estimate the variance of $\varepsilon_{z,nt}$ for the remaining "bad data" countries. We do not adopt such an approach since it is unclear which Chinese counties have zero measurement error in the GDP data.

Table C-1: IV regressions: $\log(GDP_{nt})$ on $\log(light_{nt})$, instrumented by $\log(light_{j,t-1})$

IV Estimates	All Counties		Similar Nightlight	Similar Nightlight & Population Density	Northeast
	(1)	(2)	(3)	(4)	(5)
$\log(light_{nt})$	0.776***	0.417**	0.494**	0.419**	0.425
	(0.080)	(0.158)	(0.196)	(0.169)	(0.308)
county FE		Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
First Stage	(1)	(2)	(3)	(4)	(5)
$\log(light_{n,t-1})$	0.970***	0.262***	0.265***	0.294***	0.168**
	(0.004)	(0.038)	(0.043)	(0.046)	(0.024)
county FE		Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
Observations	9351	9351	7720	6548	731
# of Counties	2020	2020	1692	1396	149
F-stat	46755.36	47.46	37.23	41.54	48.42
R-squared	0.965	0.980	0.962	0.960	0.975

Notes: Standard errors are clustered at the province level. Significance levels: 0.1 *, 0.05 **, 0.01 ***.

(Column 2) greatly reduces the first-stage coefficient and the IV estimate, suggesting that nightlight intensity is less powerful in predicting the change in GDP than in predicting the cross-sectional differences in the level of GDP. In Column 3, we restrict our sample to Chinese counties with nightlight intensity falling in the range found among North Korean counties in 2014-2015. The brightest county in North Korea is Sinuiju with a nightlight intensity of 0.825 $W/(cm^2 - sr)$, which is at the 84th percentile of nightlight intensity of Chinese counties in our sample. The IV estimate from this subsample of counties is 0.494, slightly larger than that in Column 2. In Column 4, we further restrict the sample to Chinese counties with population density within the range of that of North Korean counties. Finally, in Column 5, we restrict our sample to counties in three provinces in Northeastern China (Heilongjiang, Liaoning, and Jilin), that we believe are the most comparable to North Korea.[45] We obtain a GDP-nightlight elasticity of 0.425, though it has a larger standard error due to the much smaller sample size.

Our preferred estimate of the elasticity is the one in Column 4 of Table C-1. It is also a relatively conservative value compared to those used in other studies. Henderson et al. (2012) find a value of 0.3 with OLS and a value between 0.58 and 0.97 after correcting for the attenuation bias, depending on the imposed signal-to-noise ratio in measured GDP of the "good-data" countries. Our preferred coefficient is close to the value estimated from similar regressions using the Chinese prefecture-level data in Chor and Li (2021).

[45] These three provinces have the shortest geographic distance to North Korea, and two of them share borders with the country. The majority of ethnic Koreans in China live in these provinces. Finally, this region is China's traditional industrial base, which makes it more comparable to North Korea than other regions.

C.1 Robustness to Oil Shocks

One might be concerned that a negative supply shock in petroleum products, such as the one experienced by North Korea, will change the relationship between GDP and night light intensity. For example, petroleum-fired power plants might have reduced their production, and a shortage of electricity made it difficult to produce at night. This might result in less production at night and more production during the day. We use the Chinese county level data to show that the GDP-nightlight elasticity does not vary with international oil prices and province-level consumption prices of electricity.

Table C-2: IV regressions: GDP-nightlight elasticity and oil/electricity prices

	(1)	(2)	(3)	(4)	(5)
$\log(light_{nt})$	0.428**	0.434**	0.416**	0.414**	0.422**
	(0.168)	(0.167)	(0.165)	(0.168)	(0.182)
$\log(light_{nt}) \times \mathbf{1}(t \leq 2014)$	-0.042				
	(0.029)				
$\log(light_{nt}) \times OilPrice_t$		0.008			
		(0.008)			
$\log(light_{nt}) \times ElecPrice_{prov,t}$			0.014		
			(0.014)		
$\log(light_{nt}) \times ElecPrice_{prov,2013}$				0.001	
				(0.020)	
$\log(light_{nt}) \times \mathbf{1}(ElecPrice_{prov,2013} > Median)$					-0.019
					(0.065)
county FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
Observations	6548	6548	6526	6526	6526
# of Counties	1396	1396	1391	1391	1391
F-stat	23.27	22.23	21.72	20.14	20.16

Notes: In all columns, the dependent variable is $\log(GDP_{nt})$, the log of GDP in county n, year t. We instrument current nightlight intensity, $\log(light_{nt})$ and its interaction with variable X, with $\log(light_{n,t-1})$ and the corresponding interaction terms. $OilPrice_t$ is the average daily crude oil price (dollar per barrel) in year t, obtained from Federal Reserve Economic Data. $ElecPrice_{prov,t}$ is the average consumer price of electricity in province $prov$, year t, obtained from the National Energy Administration of China. All prices are standardized to mean zero and standard deviation of one to facilitate interpretation of the magnitude.

Within the period with which we estimate the elasticity for Chinese counties, the annual crude oil prices had a drastic drop after 2014. The price was 99.0 USD per barrel in 2014, while the average between 2015 and 2018 was 55.4 USD per barrel. This drop was known as "the great oil collapse", one of the largest oil-price shocks in modern history. According to World Bank (2018), this shock was triggered by supply-side shocks: surging U.S. shale oil production, the decline in geopolitical risks for certain key producers, and shifts in policies among the Organization of Petroleum Exporting Countries (OPEC). In Column 1 of Table C-2, we interact the night light intensity with a dummy variable indicating whether the year is before 2014, instrumented with previous night light intensity and the corresponding dummy variable. Though the global oil price has been cut in half after 2014, and China is a large net importer of crude oil, we do not see this shock induce a large and significant change in the GDP-nightlight elasticity. In Column 2, we do not attempt to use the supply shock around 2014 but simply interact the night light intensity with the annual oil prices. We again do not find a significant interaction term, suggesting that international oil prices do not affect the GDP-nightlight elasticities in our sample of Chinese counties.

A key mechanism for the oil shock to affect the GDP-nightlight elasticity is its impact on the electricity price. We further examine whether variation in electricity prices will affect the elasticity. We obtain the average consumer price of electricity in each Chinese province and year (the finest level we can get) from the National Energy Administration. In Column 3, we interact the night light intensity with the electricity prices but do not find a significant coefficient of the interaction term. Most of the variation in the electricity price is across provinces – for instance, province fixed effects explain 94% of the variation in $ElecPrice_{prov,t}$. In our base year 2013, provinces that are endowed with rich hydro, solar and wind powers, such as Qinghai, Ningxia and Inner Mongolia, have lower electricity prices than heavy user provinces such as Guangdong. Given this source of variation, Column 4 uses the electricity price in 2013 instead of the current year to reduce endogeneity concerns. Column 5 uses a dummy indicating whether the province's electricity price in 2013 is above the median. In both columns, we do not find significant effects of the interaction terms. In all columns, the point estimates of the interaction terms are small relative to the coefficients of $\log(light_{nt})$.

C.2 Re-weighting Based on Industry Shares

In this section, we first compare the distribution of industry shares between the North Korean and Chinese counties in our data. For North Korea, we follow our main specification in the paper and assume that firms' sales are proportional to $\log(\#mentions + 1)$. For Chinese counties, we obtain the firm-level data of the 2013 Annual Survey of Industrial Firms conducted by the National Bureau of Statistics (NBS). We aggregate the total sales by county-industry cells, and then compute the share of each industry within a county. We focus on the sample of Chinese counties in our preferred specification in Column 4 of Table C-1. We lose about 40 counties (out of 1391) because they cannot be matched to the administrative area codes in the NBS firm-level data. We also combine some industries together, following the industry definitions in the World Input-Output Table, to improve the readability of the table and avoid industries that are very sparsely distributed, such as Manufacturing of Tobacco Products.

Table C-3 presents the comparison of average and median share of each industry in the North Korean and Chinese counties. The first row shows that the average (median) output share of Food and Tobacco manufacturers among North Korean counties is 0.229

(0.215), while the average (median) among Chinese counties is 0.280 (0.164). A T-test rejects the hypothesis that the two samples have equal mean, while a nonparametric two-sample test rejects the hypothesis that the two samples have equal median. In the last column, we test whether the two samples are from populations with the same distribution using the Wilcoxon rank-sum test. Again, the null hypothesis is rejected at conventional significance levels. For majority of the industries, we reject the two samples have the same mean/median/distribution.

Table C-3: Compare Industry Output Shares: Original Data

Share of Industry		Equal Mean?			Equal Median?			Rank-sum Test
Code	Short Description	NK	CN	P-value	NK	CN	P-value	P-value
15t16	Food and Tobacco	0.280	0.229	0.006	0.215	0.164	0.037	0.021
17t18	Textiles and Apparel	0.101	0.051	0.000	0.064	0.009	0.054	0.000
19	Leather	0.010	0.010	0.891	0.000	0.000	0.000	0.001
20	Wood	0.011	0.042	0.000	0.000	0.004	0.000	0.000
21t22	Paper and Publishing	0.052	0.020	0.000	0.000	0.002	0.171	0.060
23	Refined Petro.	0.004	0.022	0.020	0.000	0.000	0.000	0.000
24	Chemicals	0.138	0.120	0.168	0.099	0.070	0.108	0.752
25	Rubber and Plastic	0.003	0.023	0.000	0.000	0.004	0.000	0.000
26	Other non-Metal	0.073	0.111	0.001	0.000	0.063	0.001	0.000
27t28	Metals	0.032	0.135	0.000	0.000	0.047	0.000	0.000
29	Machinery NEC	0.062	0.039	0.000	0.000	0.010	0.000	0.088
30t33	Elec. and Optical Equip.	0.028	0.038	0.149	0.000	0.003	0.000	0.000
34t35	Trans Equip.	0.008	0.020	0.005	0.000	0.000	0.000	0.000
36t37	Manufacturing NEC	0.042	0.023	0.000	0.000	0.000	0.000	0.245
40	Elec. and Gas	0.156	0.117	0.013	0.000	0.045	0.171	0.001
	# of Counties	174	1353					

Notes: We combine some ISIC two-digit industries together, following the industry definitions in the World Input-Output Table, to improve the readability of the table and avoid industries that are very sparsely distributed. We perform T-tests to test whether the two samples have equal means, non-parametric tests to test whether the two samples have equal medians (Stata command `median`) and Wilcoxon rank-sum test (Stata command `ranksum`) to test whether the two samples are drawn from the same distribution.

To address the possible biases caused by different industry distributions in the two countries, we design a strategy to re-weight the Chinese counties so that the distribution of industry shares mimics that of North Korea. Generating a similar joint distribution of all 15 industries' shares is challenging. For example, if we divide the share of every industry into two bins, this implies that we will have $2^{15-1} = 16384$ cells in the 14-dimensional space (one fewer dimension because industry shares add up to one), and the chance that at least some North Korean or Chinese counties fall into a single cell is small. We therefore focus on mimicking the distribution of each particular industry's share in North Korea. Specifically, we first pull Chinese and North Korean counties together and divide the range of one industry's shares into six bins. The first bin is zero, while the other five bins are generated based on the quintiles among counties with strictly positive shares of that industry. We then count the number of Chinese and North Korean counties in each bin. We use the ratio of the number of North Korean counties to that of the Chinese counties as the weight for each Chinese county in its corresponding bin. Using this weight, our sample of Chinese firms can mimic the distribution of industry shares in the North Korean sample. To confirm this, we re-run the T-test, non-parametric median test and the Wilcoxon rank-sum test with the weights. Table C-4 shows that we cannot reject the null hypothesis that the two samples have equal mean/median/distribution for any of the 15 industries.

Table C-4: Compare Industry Output Shares: After Re-weighting

Share of Industry		Equal Mean?			Equal Median?			Rank-sum Test
Code	Short Description	NK	CN	P-value	NK	CN	P-value	P-value
15t16	Food and Tobacco	0.280	0.262	0.305	0.215	0.204	0.650	0.693
17t18	Textiles and Apparel	0.101	0.100	0.894	0.064	0.056	0.650	0.893
19	Leather	0.010	0.012	0.618	0.000	0.000	1.000	0.997
20	Wood	0.011	0.013	0.625	0.000	0.000	1.000	0.986
21t22	Paper and Publishing	0.052	0.053	0.862	0.000	0.000	1.000	0.999
23	Refined Petro.	0.004	0.005	0.871	0.000	0.000	1.000	0.991
24	Chemicals	0.138	0.141	0.864	0.099	0.092	0.545	0.981
25	Rubber and Plastic	0.003	0.002	0.722	0.000	0.000	1.000	0.997
26	Other non-Metal	0.073	0.075	0.835	0.000	0.000	1.000	0.886
27t28	Metals	0.032	0.033	0.840	0.000	0.000	1.000	0.990
29	Machinery NEC	0.062	0.057	0.509	0.000	0.000	1.000	0.861
30t33	Elec. and Optical Equip.	0.028	0.025	0.571	0.000	0.000	1.000	0.984
34t35	Trans Equip.	0.008	0.008	0.767	0.000	0.000	1.000	0.991
36t37	Manufacturing NEC	0.042	0.039	0.654	0.000	0.000	1.000	0.963
40	Elec. and Gas	0.156	0.160	0.831	0.000	0.000	1.000	0.990
	# of Counties	174	1353					

Notes: We divide counties into six bins according to the share of one industry at a time. We then count the numbers of North Korean and Chinese counties in each bin and use the ratio of the two as new weights. We combine some ISIC two-digit industries together, following the industry definitions in the World Input-Output Table, to improve the readability of the table and avoid industries that are very sparsely distributed. We perform T-tests to test whether the two samples have equal means, non-parametric tests to test whether the two samples have equal medians (Stata command `median`) and Wilcoxon rank-sum test (Stata command `ranksum`) to test whether the two samples are drawn from the same distribution.

We next re-run the regression in Column 4 of Table C-1 using the weights that are generated based on each industry's shares. In Table C-5, we present the corresponding second- and first-stage coefficients, standard errors and the first-stage F-stat. We find the estimates to be largely robust across different re-weighting schemes. The IV estimates of the GDP-nightlight elasticity range from 0.32 to 0.46, except for the case in which we re-weight based on the share of electricity and heat supply firms (0.25). We conclude that the different industry share distributions between North Korean and Chinese counties observed in Table C-3 may not introduce large biases into our estimate of the GDP-nightlight elasticity.

Table C-5: Re-run the Preferred Specification in Column 4 of Table C-1: Re-weighted

Reweight by Industry		Second Stage		First Stage		
Code	Short Description	Coef.	Std. Err.	Coef.	Std. Err.	F-stat
15t16	Food and Tobacco	0.451	(0.196)	0.300	(0.051)	34.471
17t18	Textiles and Apparel	0.389	(0.161)	0.305	(0.048)	41.300
19	Leather	0.411	(0.175)	0.315	(0.046)	45.952
20	Wood	0.339	(0.211)	0.300	(0.053)	31.718
21t22	Paper and Publishing	0.343	(0.152)	0.314	(0.046)	45.717
23	Refined Petro.	0.458	(0.161)	0.294	(0.041)	50.272
24	Chemicals	0.384	(0.198)	0.306	(0.055)	30.451
25	Rubber and Plastic	0.322	(0.198)	0.361	(0.050)	51.932
26	Other non-Metal	0.327	(0.210)	0.314	(0.055)	32.056
27t28	Metals	0.378	(0.176)	0.340	(0.050)	45.415
29	Machinery NEC	0.456	(0.209)	0.307	(0.047)	42.143
30t33	Elec. and Optical Equip.	0.333	(0.197)	0.330	(0.053)	38.143
34t35	Trans Equip.	0.369	(0.180)	0.331	(0.049)	44.759
36t37	Manufacturing NEC	0.350	(0.180)	0.304	(0.054)	32.326
40	Elec. and Gas	0.251	(0.180)	0.364	(0.054)	44.560

Notes: Each row presents the IV regression result of Column 4 in Table C-1 after applying the weights constructed based the share of each particular industry. The weights are obtained as follows: we first divide counties into six bins according to the share of one industry at a time; we then count the numbers of North Korean and Chinese counties in each bin and use the ratio of the two as weights.

D Additional Theoretical and Quantitative Results

D.1 General Equilibrium Effects of Input Prices

In this section, we discuss the general equilibrium effects of input prices in a special case of our model. Adão et al. (2022) has highlighted that direct trade shocks can reinforce each other through trade between domestic regions. In our context, for example, a county hit harder by the export sanctions will have a larger drop in income and will buy fewer final goods and intermediate inputs from other domestic regions. This mechanism suggests that the back-of-envelope calculation from the reduced-form coefficients may underestimate the overall impact of the shocks. However, we want to highlight another general equilibrium force that works through the price of intermediate inputs. In particular, lower foreign demand will lower the marginal product of intermediate inputs and lower the overall demand for these products. With an inelastic labor supply, the prices of intermediate inputs will decline, and it will increase the nominal wage and real output in all regions.

To see this effect clearly, we now consider a special case of our more general model. We assume that all foreign imports are used for final consumption. North Korea has N normal regions. In each region, competitive firms produce final goods combining intermediate inputs and labor. We do not allow domestic trade in final goods. This implies that all final goods produced in a location will be either consumed by local residents or sold to the foreign country.

We assume that there is Region 0, which specializes in producing one intermediate input good. The intermediate input is used by the other final goods production regions, $n = 1, \ldots, N$. Consistent with our main model, we assume that labor is inelastically supplied at L_0 in Region 0. Without loss of generality, we assume unit productivity, and the total output of intermediate inputs is $Q_0 = L_0$. The price of the intermediate inputs, p_0, will be determined in general equilibrium.

It is worth discussing the role of our assumption that there is no trade in final goods between regions. The goal of this assumption is to shut down the "reinforcing" mechanism caused by the final goods trade highlighted in Adão et al. (2022). However, because of the trade between other regions and region 0, the reinforcing mechanism still exists for intermediate inputs. For example, lower foreign demand will cause a decline in revenue in final goods production regions, and they buy fewer inputs from Region 0. This, in turn, lowers the price of inputs p_0 and the wage in Region 0, w_0. As we show later, this reinforcing mechanism will cause some subtleties when the outcome of interest is aggregate nominal wage. However, we can show that there is a strict positive general equilibrium level effect due to changes in input prices when the outcome of interest is aggregate real output, despite the existence of the reinforcing mechanism.

We make some additional assumptions/parameter restrictions to obtain sharper analytical characterization. First, we assume that each final goods production region faces separate iso-elastic foreign demand. That is, instead of assuming that foreign demand has a nested CES structure as in the main model, we assume that there is no direct competition between varieties produced in different regions in North Korea to attract foreign consumers. Therefore, exports in region n, industry j can be written as $B_j \left(P_{n,j}^{dom}\right)^{1-\eta}$. Second, we assume that within each region, labor is perfectly mobile across sectors, corresponding to the case with $\alpha_m = 1$. Third, we assume that the labor share of each sector is the same, i.e., $a_{Lj} \equiv a_L, \forall j$. We denote the share of intermediate inputs in production by $a_0 = 1 - a_L$. Finally, we assume away taxes and subsidies before and after the sanctions, so $t_{nj}^{u\prime} = t_{nj}^{u} = 0, \forall n, j$ and $u \in \{fin, int\}$.

We only illustrate the general equilibrium effects of inputs under export demand shocks B_j and assume that foreign prices $p_{F,j}$ are fixed. In addition, we consider small shocks and use log-linearization to obtain an approximate solution. The equilibrium change of domestic prices P_{nj}^{dom} can be written as

$$\hat{P}_{n,j}^{dom} = a_L \hat{w}_n + a_0 \hat{p}_0.$$

According to the formula of domestic consumption shares $s_{n,j}^{dom}$ (see equation 7), we have

$$\hat{s}_{n,j}^{dom} = (1-\sigma)(1-s_{n,j}^{dom})\hat{P}_{n,j}^{dom} = (1-\sigma)(1-s_{n,j}^{dom})\left(a_L \hat{w}_n + a_0 \hat{p}_0\right).$$

Note that we have omitted the superscript for final goods "fin", as all intermediate inputs are purchased from domestic region 0.

The labor market clearing condition can be simplified as

$$w_n L_n = a_L \sum_j s_{n,j}^{dom} \xi_{nj} E_n + a_L \sum_j B_j \left(P_{nj}^{dom}\right)^{1-\eta}.$$

In this expression, we have allowed consumption shares, ξ_{nj}, to differ by region, a more general case than our baseline model. This extension will be helpful later when we remove sectoral heterogeneity and obtain a sharper analytical expression for the aggregate effects. We denote the share of domestic sales and foreign sales in total regional sales as

$$b_{D,nj} = \frac{s_{n,j}^{dom} \xi_{nj} E_n}{R_n}, \quad b_{F,nj} = \frac{B_j \left(P_{nj}^{dom}\right)^{1-\eta}}{R_n},$$

where $R_n \equiv \sum_j R_{nj}$ is the total sales in region n. Log-linearizing the labor market clearing condition, we obtain

$$\hat{w}_n = \sum_j b_{D,nj}\left(\hat{s}_{nj}^{dom} + \hat{w}_n\right) + \sum_j b_{F,nj}\left(\hat{B}_j + (1-\eta)\hat{P}_{nj}^{dom}\right).$$

Substitute in the expression for $\hat{P}_{nj}^{dom}$ and $\hat{s}_{nj}^{dom}$, we can solve $\hat{w}_n$ as

$$\hat{w}_n = \frac{\sum_j \frac{b_{F,nj}}{\sum_k b_{F,nk}} \hat{B}_j - (\eta-1)a_0\hat{p}_0 - (\sigma-1)a_0\hat{p}_0 \sum_j \frac{b_{D,nj}}{\sum_k b_{F,nk}}(1-s_{nj}^{dom})}{1 + (\eta-1)a_L + (\sigma-1)a_L \sum_j \frac{b_{D,nj}}{\sum_k b_{F,nk}}(1-s_{nj}^{dom})}. \tag{D-1}$$

The goods market clearing condition for intermediate inputs is

$$p_0 Q_0 = a_0 \sum_n R_n.$$

Log-linearizing it, we obtain

$$\hat{p}_0 = \sum_n \frac{R_n}{R}\hat{R}_n = \sum_n \frac{R_n}{R}\hat{w}_n.$$

Substitute in the expression of $\hat{w}_n$ and denote $z_n \equiv \sum_j \frac{b_{D,nj}}{\sum_k b_{F,nk}}(1-s_{nj}^{dom})$, we can solve $\hat{p}_0$ as

$$\hat{p}_0 = \frac{\sum_n \frac{R_n}{R(1+(\eta-1)a_L+(\sigma-1)a_L z_n)} \times \sum_j \frac{b_{F,nj}}{\sum_k b_{F,nk}}\hat{B}_j}{1 + \sum_n \frac{R_n}{R}\frac{(\eta-1)a_0+(\sigma-1)a_0 z_n}{1+(\eta-1)a_L+(\sigma-1)a_L z_n}}.$$

The derivations above have two key implications. First, the impact of foreign demand shocks on the price of inputs, p_0, is proportional to some weighted average of regionspecific direct impact, $\sum_j \frac{b_{F,nj}}{\sum_k b_{F,nk}} \hat{B}_j$. When foreign shocks are negative, i.e., $\hat{B}_j \leq 0, \forall j$ and $\sum_j b_{F,nj} \hat{B}_j < 0$ for at least one region, we must have $\hat{p}_0 < 0$. Second, according to equation (D-1), the change in nominal wage in region n can be decomposed into a direct effect (first term in the numerator) and indirect effects (second and third terms in the numerator). The indirect effects are caused by the changes in the price of the intermediate inputs.

The outcome of interest in our paper is real output instead of nominal wages, as night light intensity better captures production and output instead of nominal income. We define real output after the shocks as the total quantity evaluated by base period prices. That is,

$$\begin{aligned}\widehat{realGO}_n &= \sum_j P_{nj}^{dom} Q'_{nj} = \sum_j \frac{R_{nj}}{R_n} \hat{Q}_{nj} \\ &= \sum_j \frac{R_{nj}}{R_n} (\hat{R}_{nj} - \hat{P}_{nj}^{dom}) = \sum_j \frac{R_{nj}}{R_n} (\hat{w}_n + \hat{L}_{nj} - a_L \hat{w}_n - a_0 \hat{p}_0).\end{aligned}$$

Under our assumption that $a_{Lj} = a_L, \forall j$, the labor market clearing condition implies that

$$\sum_j \frac{R_{nj}}{R_n} \hat{L}_{nj} = \sum_j \frac{L_{nj}}{L_n} \hat{L}_{nj} = 0.$$

Therefore, we have

$$\widehat{realGO}_n = a_0(\hat{w}_n - \hat{p}_0) = \frac{a_0 \sum_j \frac{b_{F,nj}}{\sum_k b_{F,nk}} \hat{B}_j - a_0 \left(\eta - 1 + (\sigma - 1) z_n\right) \hat{p}_0}{1 + (\eta - 1) a_L + (\sigma - 1) a_L z_n}.$$

We summarize the above results in the following proposition:

Proposition D-1. *Suppose we have negative foreign demand shocks such that $\hat{B}_j \leq 0, \forall j$ and in some region the aggregate foreign demand shock is strictly negative, $\sum b_{F,nj} \hat{B}_j < 0$, the price of the intermediate input will drop. The change in real output in region n is proportional to the difference between the change in nominal wage and input price. Formally,*

$$\widehat{realGO}_n = a_0(\hat{w}_n - \hat{p}_0).$$

An immediate implication from the expression of $\widehat{realGO}_n$ is

Corollary D-1. *When the production of final goods does not involve intermediate inputs, i.e., $a_0 = 0$, real output in any region does not respond to export demand shocks.*

Therefore, we need $a_0 > 0$ to make real output respond to export demand shocks. Note that Corollary D-1 holds trivially under the no mobility case ($\alpha_m = 0$) since the allocation of the only input in production (labor) does not change after the sanctions. Intuitively, when labor is fully employed and is the only factor of production, export demand shocks only affects the nominal output but not the real output. When production involves both labor and intermediate inputs, real output responds to export demand shocks because the marginal revenue product of inputs in regions that face larger declines in export demand is lower and these regions use fewer inputs in production.

To further highlight the intuition behind the predicted changes in input prices and real output, we consider a case shares of exports in total sales and shares of imports in total absorption are the same across all sectors. In particular, we assume

$$\frac{b_{F,nj}}{b_{F,nj}+b_{D,nj}} = x, \quad s_{nj}^{dom} = s^{dom}, \forall j. \tag{D-2}$$

Note that under these restrictions, we have

$$1-x = \frac{b_{D,nj}}{b_{D,nj}+b_{F,nj}} = \frac{s^{dom}\xi_{nj}E_n}{r_{nj}R_n} = \frac{s^{dom}\xi_{nj}a_L}{r_{nj}}, \forall j$$

where $r_{nj} \equiv R_{nj}/R_n$ is the output share of sector j in region n. This immediately implies that $r_{nj} = \xi_{nj}, \forall j$. The trade balance condition reveals an implicit restriction

$$\sum_j \frac{b_{F,nj}}{b_{D,nj}+b_{F,nj}} r_{nj}R_n = \sum_j (1-s^{dom})\xi_{nj}E_n \Rightarrow x = (1-s^{dom})a_L.$$

With these relationships between parameters, we have

$$z_n \equiv \sum_j \frac{b_{D,nj}}{\sum_k b_{F,nk}}(1-s_{nj}^{dom}) = \frac{(1-x)(1-s^{dom})}{x} = \frac{1-x}{a_L} \equiv z$$

$$\hat{w}_n = \frac{\sum_j r_{nj}\hat{B}_j - (\eta-1)a_0\hat{p}_0 - (\sigma-1)za_0\hat{p}_0}{1+(\eta-1)a_L+(\sigma-1)za_L} \tag{D-3}$$

$$\widehat{realGO}_n = \frac{a_0\sum_j r_{nj}\hat{B}_j - a_0\left(\eta-1+(\sigma-1)z\right)\hat{p}_0}{1+(\eta-1)a_L+(\sigma-1)a_Lz} \tag{D-4}$$

Proposition D-2. *Under the additional assumption that shares of exports in total sales and shares of import in total absorption are the same across all sectors (equation D-2), we have*

1. *In regions $n = 1, \ldots, N$, changes in nominal wage and real output are linear in the output-weighted export demand shocks $\sum_j r_{nj}\hat{B}_j$, with a positive level effect proportional to $\hat{p}_0$ that is common across all regions.*

2. *In Region 0, the change in nominal wage is the same as the change in input price $\hat{p}_0$. Real output in Region 0 does not change.*

3. *The (population) weighted average of $\widehat{realGO}_n$ can be decomposed into a cross-sectional component that is proportional to the weighted average of $\sum_j r_{nj}\hat{B}_j$ (corresponding to the back-of-envelope calculation from the reduced-form) and a constant term. The constant term is proportional to $\hat{p}_0$ and is strictly positive.*

4. *The nominal-sales weighted average of $\hat{w}_n$ can be decomposed into a cross-sectional component that is proportional to the weighted average of $\sum_j r_{nj}\hat{B}_j$ (corresponding to the back-of-envelope calculation from the reduced-form) and a constant term. The constant term is proportional to $\hat{p}_0$ and is strictly positive if and only if*
$$\eta - 1 + \frac{1}{a_L}(\sigma - 1)(1 - x) < 1.$$

Proof. Part 1 of the proposition is straightforward given the equations D-3 and D-4. Part 2 holds because labor is supplied inelastically in region 0 and it is the only factor for producing the intermediate input.

For parts 3 and 4, note that the weighted averages of the terms involving $\hat{p}_0$ in $\hat{w}_n$ and $\widehat{realGO}_n$ are always positive regardless of the weights used if we do not take into account Region 0. Take real output for example. From regional regressions, we are able to identify the cross-sectional component $\frac{a_0 \sum_j r_{nj}\hat{B}_j}{1+(\eta-1)a_L+(\sigma-1)a_L z}$. The missing constant term is a weighted average of the remaining terms involving $\hat{p}_0$, and the coefficient is negative, so the constant term is strictly positive. The same applies to the change in nominal wage.

Taking Region 0 into account does not affect the result for the change in real output, since Region 0 has a zero direct effect and a zero indirect effect: its real output does not change. However, adding Region 0 can potentially change the sign of the constant term for nominal wage, since $\hat{w}_0 = \hat{p}_0 < 0$, the opposite of the sign of the constant term for the other regions. The sign of the weighted average depends on the weights and the coefficients before $\hat{p}_0$. We can sign the term if we use nominal sales as the weights, i.e.,
$$\begin{aligned}
&R_0\hat{p}_0 + \sum_{n=1}^{N} R_n \frac{-(\eta-1)a_0\hat{p}_0 - (\sigma-1)z a_0 \hat{p}_0}{1+(\eta-1)a_L+(\sigma-1)z a_L} \\
&= a_0 R\hat{p}_0 - R\frac{-(\eta-1)a_0\hat{p}_0 - (\sigma-1)z a_0 \hat{p}_0}{1+(\eta-1)a_L+(\sigma-1)z a_L} \\
&= a_0 R\hat{p}_0 \frac{1-(\eta-1)-(\sigma-1)\frac{1-x}{a_L}}{1+(\eta-1)a_L+(\sigma-1)z a_L}
\end{aligned}$$
It is positive if and only if
$$\eta - 1 + \frac{1}{a_L}(\sigma - 1)(1 - x) < 1.$$

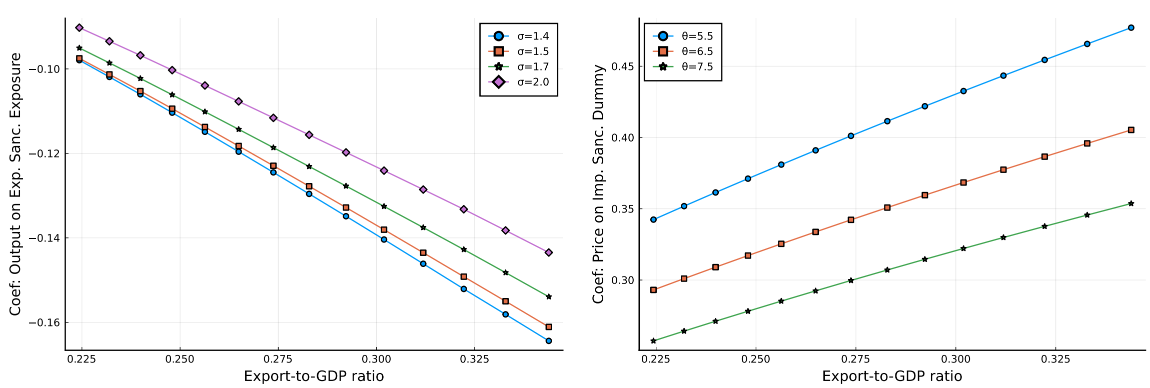
□

D.2 Comparative Statics and Identification

In this section, we perform comparative statics with the outer loop parameters, σ, θ and α_{dom}, to understand how they affect the key moments that we aim to match. This helps us understand the identification behind the calibration procedures.

Panel (a) of Figure D-1 plots how the regression coefficient of real output change on export sanction exposure varies with the export-to-GDP ratio and different values of the Armington elasticity between domestic and foreign goods, σ. A higher home bias, α_{dom}, always implies a lower export-to-GDP ratio. For ease of interpretation, we plot the relationship between the targeted regression coefficient and the export-to-GDP ratio, but it should be understood that different export-to-GDP ratios correspond to different values of α_{dom} We find that, in general, the absolute value of the regression coefficient becomes larger when the export-to-GDP ratio (thus α_{dom}) is higher and when σ is lower. In our calibration, we match both the export-to-GDP ratio and the export sanction coefficient for output. Conditional on a fixed level of the export-to-GDP ratio, it is σ that determines how much output responds to export sanctions across counties. That being said, we find that around the value of the baseline value of σ, 1.4, and the targeted export-to-GDP ratio 0.25, further reducing σ has a limited effect of further increasing the response in output. However, we are confident that a value such as $\sigma = 2.0$ is well rejected. It would not generate enough output response to export sanctions, given an export-to-GDP ratio of 0.25.

Figure D-1: Identification of σ and θ



(a) Identification of σ (b) Identification of θ

Notes: in Panel (a), we plot the regression coefficient of county-level change in real output on export sanction (controlling for intermediate input sanction exposure) exposure in our model under various values of σ and export-to-GDP ratios. Different export-to-GDP ratios are generated by different values of α_{dom}. Panel (b) plots the regression coefficient of county-industry-level change in consumption prices on import sanction dummies (controlling for export sanction dummies) in our model under various values of θ and export-to-GDP ratios.

We examine the identification of θ in Panel (b) of Figure D-1. We plot the regression coefficient of county-industry-level consumption price changes on the import sanction dummies (controlling for export sanction dummies) against export-to-GDP ratios under various values of θ. It is straightforward that a larger θ tends to increase $\hat{p}_{F,j}$ under the same import sanction shares $S_{IM,j}$ according to equation (10). A higher export-to-GDP ratio implies a smaller share of foreign goods in domestic absorption $s_{n,j}^{dom,fin}$, which also increases the response of prices to import sanctions (see equation 11).

D.3 Other Untargeted Moments

In this section, we present untargeted moments other than the pass-through coefficients in Section 6.4.

We first examine other regression coefficients that are not targeted in the calibration and compare them to the data counterparts. In Columns (3) of Table D-1, we report the responses of output to export and intermediate input sanction exposure measures in our baseline model. Since we target the coefficient of the export sanction exposure in Column (1), the coefficient of the export sanction exposure is close to its data counterparts. As an untargeted moment, the cross-sectional impact of intermediate input sanction exposure in the model (-0.196) is much larger than the estimated effect based on the long difference between 2013 and 2019 (-0.084, Column 1), but close to the estimated effect when we use 2014 as the base period (-0.197, Column 2). As discussed earlier, we are unable to identify whether the decline in nightlight intensities in counties more exposed to the input sanctions was due to a reversal in the pre-sanction trends or the actual impact of the sanctions. However, our model predicts a strong effect of the input sanction exposure and suggests that the observed decline in these counties from 2014 to 2019 can be rationalized by the reduced access to intermediate inputs.

In Table D-2, we present the price regressions in our model. In the baseline calibration, prices of import sanctioned industries increase by 32.8 log points, it is targeted and close to what we observe in the data (32.2 log points). We also find an 11-log-point decline in prices among export-sanctioned industries. Intuitively, when foreign demand drops, equilibrium wages and prices also drop. It is larger than what we observe in the data (-4 log points) in Column 3 of Table 5. Though the effect estimated from the data is smaller and insignificant, its confidence interval contains the point estimate that we obtain from the model. In Column 2 of Table D-2, we examine whether the price responses in Pyongyang are different from other cities, as we observe in the data. The last two columns in Table 5 provide suggestive evidence that the consumer prices in Pyongyang respond 20 log points less to import sanctions compared to the other five cities. This is in contrast with the baseline model, which only shows a 1.3-log-point difference.

Table D-1: Output responses in the data and model

	0.419 $\times\Delta$ log(light)		Δ log(real output)		
	Data 2013-2019 (1)	Data 2014-2019 (2)	Baseline Model (3)	Model with Input Subsidies (4)	Model with Cons. Subsidies (PY) (5)
Export sanction exposure	-0.120***	-0.130**	-0.114***	-0.110***	-0.112***
	(0.039)	(0.055)	(0.020)	(0.014)	(0.020)
Intermediate input sanction exposure	-0.084	-0.197**	-0.196***	-0.025	-0.200***
	(0.074)	(0.094)	(0.030)	(0.020)	(0.030)
Observations	174	174	174	174	174
R-squared	0.080	0.068	0.390	0.277	0.393

Notes: columns 1 and 2 replicate the regressions in columns 3 and 6 of Panel A, Table 3, scaling the dependent variable (thus the coefficients and standard errors) by the GDP-nightlight elasticity 0.419. Standard errors are clustered at the county level. Significance levels: * 0.1, ** 0.05, *** 0.01.

Table D-2: Price responses in the model

	Baseline Model		Model with Input Subsidies		Model with Cons. Subsidies (PY)	
	(1)	(2)	(3)	(4)	(5)	(6)
Export sanctioned	-0.108*	-0.109*	-0.119**	-0.120**	-0.111*	-0.112*
	(0.050)	(0.051)	(0.051)	(0.052)	(0.051)	(0.052)
Export sanctioned $\times$ Pyeongyang		0.005		0.005		0.005
		(0.004)		(0.004)		(0.004)
Import sanctioned	0.328***	0.330***	0.320***	0.323***	0.326***	0.362***
	(0.065)	(0.066)	(0.070)	(0.071)	(0.068)	(0.069)
Import sanctioned $\times$ Pyeongyang		-0.013***		-0.014***		-0.214***
		(0.002)		(0.002)		(0.002)
Observations	64	64	64	64	64	64
R-squared	0.802	0.802	0.788	0.788	0.753	0.804

Notes: the price regressions use a sample of six cities and eleven industries (two city-industry combinations are dropped due to missing prices in the data we use for estimating the specifications in Table 5). Export and import sanction dummies are set to one if the industry export/import sanction indices, $S_{EX,j}$ or $S_{IM,j}$, are above 0.9. Standard errors are clustered at the industry level. Significance levels: * 0.1, ** 0.05, *** 0.01.

D.4 Sensitivity Analysis

In this section, we consider the sensitivity of our calibration and the implied aggregate effects under alternative assumptions.

Table D-3: Fit of the Model for Output and Prices

	Δ log(real output$_n$)		Δ log(price$_{nj}$)	
	(1)	(2)	(3)	(4)
Fit Coef. (ρ^Y)	0.178 (0.091)	0.206 (0.142)	0.507 (0.263)	0.507 (0.540)
Observations	174	174	64	64
p-value of $H_0 : \rho^Y = 1$	0.000	0.000	0.065	0.382
R-squared	0.023	0.020	0.042	0.042
Weighted by		Population		
Clustered by				Industry

Notes: Columns 1 and 2 regress the change in log real output in the data (0.419 times the change in log nightlight intensity) on the change in log real output predicted by the model in each of the 174 counties. Column 1 is simple OLS while Column 2 uses county population as weights. Columns 3 and 4 regress the change in prices observed in the data (2013-2019) on the predicted change in consumption prices by the model in six cities and eleven industries. The last row of the table reports at which level the standard errors are clustered. We report the p-value for the null hypothesis that the pass-through coefficient is one below the standard errors.

Table D-4: Calibration and Aggregate Results in All Specifications

Specification	Outer-loop Parameters			Outer-loop Model Moments			Aggregate Percentage Change Δ%		
	σ	θ	α_{dom}	Exp. Sanc.	Imp. Sanc.	Export/GDP	Real Output		Real Income
				on Output	on Prices		weights=pop.	weights=output	weights=pop.
Baseline	1.4	6.0	0.60	-0.114 (0.020)	0.328 (0.065)	0.253	-12.9	-12.5	-15.3
With Input Subsidies	1.5	7.0	0.56	-0.110 (0.014)	0.320 (0.070)	0.256	-9.6	-9.4	-11.0
With Cons. Subsidies (PY)	1.4	5.5	0.60	-0.112 (0.020)	0.326 (0.068)	0.253	-13.3	-12.9	-15.4
$\alpha_m = 1$	1.4	6.0	0.60	-0.079 (0.023)	0.304 (0.046)	0.253	-13.1	-12.7	-14.2
Trade Deficit PY Only	1.4	6.0	0.60	-0.114 (0.020)	0.328 (0.065)	0.252	-12.9	-12.5	-15.3
High Trade Costs	1.5	6.0	0.66	-0.117 (0.016)	0.323 (0.073)	0.247	-11.7	-11.5	-14.1
Log-log Trade Costs	1.4	6.0	0.62	-0.108 (0.019)	0.325 (0.062)	0.251	-12.5	-12.3	-15.0
Border or Ports	1.4	6.0	0.61	-0.111 (0.019)	0.323 (0.065)	0.247	-12.7	-12.3	-15.1
$\epsilon = 9$	1.5	6.0	0.59	-0.106 (0.021)	0.321 (0.057)	0.256	-11.8	-11.3	-14.2
$\eta = 1$	1.5	6.5	0.56	-0.114 (0.017)	0.323 (0.067)	0.256	-12.3	-11.9	-14.2
$\eta = 4$	1.4	6.0	0.60	-0.113 (0.021)	0.322 (0.063)	0.253	-12.8	-12.4	-15.3

Notes: each row presents an alternative calibration and the associated aggregate predictions. See the text of this section for the details of each specification.

First, we consider subsidies to consumption goods that are import sanctioned in Pyongyang, which can generate a weaker response of prices to import sanctions in the capital city as we find in Columns 5 and 6 of Table 5. Consistent with our baseline model calibration, we define industries with an import sanction index above 0.9 as "sanctioned", and set a 20-log-point subsidy for Pyongyang only

$$\log(1 + t_{nj}^{cons}) = -0.2 \times \mathbf{1}\left(n = \text{Pyongyang}, \quad S_{IM,j} \geq 0.9\right).$$

We re-calibrate the model and find a slightly smaller θ (5.5 instead of 6.0), and we find the interaction term between Pyongyang and import sanction dummies to be -0.214 (Column 6 in Table D-2), very close to the data counterpart. However, this alternative calibration predicts very similar aggregate effects of real output and income as the baseline model.

Second, in our baseline model, we have assumed that labor is not mobile across sectors in response to the sanctions. While this may be useful to capture short-run adjustment costs and non-market forces in North Korea's local labor market, one may expect sectoral employment to respond more in the longer run. When we assume perfect mobility across sectors within a county, i.e., $\alpha_m = 1$, we find that, given our previously calibrated values of $\sigma, \theta, \alpha_{dom}$, the response of output to export sanction exposure becomes much weaker. This is because labor mobility can mitigate some of the losses due to the decline in foreign demand. If labor is not mobile, labor is not reallocated to sectors with relatively strong demand after the sanctions, and the local economy will incur a larger loss in real output relative to other regions since the sectoral output prices are low and the use of intermediate inputs is reduced. However, as we discuss in Online Appendix D.2, around our baseline value of σ (1.4), reducing it further does not increase the response of real output much. We therefore cannot find a version of the calibration that generates an output-export-sanction coefficient of -0.119. Row 4 of Table D-4 presents the implications of our baseline calibration under $\alpha_m = 1$. We see an output-export-sanction coefficient of -0.079, much smaller than the data counterpart. The post-sanction aggregate real output is even lower than the baseline without labor mobility, while the post-sanction aggregate real income is 1.1-percentage-point higher. This suggests that labor mobility may not necessarily increase real output given that all North Korean labor is employed before and after the sanctions, while keeping labor in the "wrong sectors" does hurt welfare.

Third, we consider alternative assumptions about the allocation of the exogenous transfer (trade deficits) among counties. In the model, we assume the share of transfer to each county is proportional to their population in 2008, i.e., $\omega_n^T = L_n/L$. We now assume that only Pyeongyang receives the exogenous transfer. Mathematically, we set

$$\omega_n^T = \mathbf{1}\left(n = \text{Pyeongyang}\right).$$

The new assumptions about ω_n^T imply that the county of Pyeongyang will be larger in terms of total expenditure in the base period. More important, residents in the county benefit greatly from the increase in the exogenous transfer from $T = 0.18$ to $T' = 0.58$. However, such reallocation within the country does not alter our aggregate predictions much. We re-calibrate our model under the new assumptions about ω_n^T and find the calibrated parameters and the aggregate real output and income almost identical to the baseline (new results reported in Row 5, "Trade Deficit PY Only" in Table D-4).

Fourth, we examine the robustness of our baseline results to higher trade costs. Using price data, Atkin and Donaldson (2015) estimate how the level of trade costs (in dollars) vary with the log of distance for the United States, Ethiopia and Nigeria and find that the trade costs in the latter two countries are around four to five times of those in the United States. Instead of setting $\tau_{in} = e^{0.042 d_{in}}$ following the estimates in Fan et al. (2021), we multiply these costs by four to mimic the differential domestic trade costs found in Atkin and Donaldson (2015). Higher domestic trade costs effectively reduce the attractiveness of domestic trade. To match the same export-to-GDP ratio, we need a higher home bias and find a value of 0.66 as shown in Row 6 of Table D-4. We find slightly higher σ and the same θ. The aggregate impact on real output is 1.2-percentage-point smaller, likely because less domestic trade reduces the negative spillover and level effects caused by spatial trade linkages within the country.

Fifth, we consider an alternative functional form of trade costs. In our baseline model, we follow Fan et al. (2021) and assume that trade costs between two domestic locations are a semi-elastic function of road-network distance (unit = 100 km), i.e., $\tau_{in} = e^{0.042 d_{in}}$. Here we instead assume that trade costs take the format of $\tau_{in} = d_{in}^{\zeta}$. To find a value for ζ, we assume that the trade costs implied by the semi-elastic function coincide with those implied by the constant-elasticity function at the average road network distance between Chinese cities (1478 km). Setting $e^{0.042*1478/100} = 1478^{\zeta}$, which implies an elasticity ζ of 0.085. Applying this elasticity to the distance between North Korean counties, we obtain the predicted trade costs $\tau_{in} = d_{in}^{0.085}$. Row 5 of Table D-4 shows the calibrated outer loop parameters under this form of trade costs. The calibrated σ and θ are the same and the home bias parameter is slightly higher. The predicted aggregate impacts are similar to the baseline.

Sixth, we change our parametric assumption on the international iceberg costs τ_{Fn} (which equals τ_{nF}). In the baseline model, we assume that $\tau_{Fn} = 2\tau_{n,border}$ and $\tau_{n,border} = e^{0.042 d_{n,border}}$, where $\tau_{n,border}$ is the domestic trade cost between county n and the border, and $d_{n,border}$ is the distance from n to the border. This assumes that there is no waterborne shipping. Online Appendix A.1.5 shows that waterborne shipping accounts for 24% and 37% of North Korea's imports from and exports to China. We now calculate the distance from n to its nearest port, $d_{n,port}$ and assume that[46]

$$\tau_{Fn} = 2 \min\{\tau_{n,border}, \tau_{n,port}\} = 2 \times \exp\left(0.042 \min\{d_{n,border}, d_{n,port}\}\right).$$

Under the alternative international trade costs, we re-calibrate our model and obtain the implied aggregate output change. The results are presented in the Row 8, "Border or Ports" of Table D-4. The results, however, are very close to our baseline model.

Seventh, in our baseline model, we set the domestic Armington elasticity, ϵ, to a value

[46] We calculate the minimum distance from eight ports, Chongjin, Haeju, Hungnam, Nampo, Rajin, Songrim, Sunbong and Wosan.

of five following Simonovska and Waugh (2014). We now perform a robustness check with a higher value, $\epsilon = 9$, which is adopted by Allen and Arkolakis (2014) for US domestic trade. We re-calibrate the model and calculate the corresponding aggregate predictions. We find that the results are very similar. (see Row 9, $\epsilon = 9$, in Table D-4) A higher ϵ makes products produced in different regions more substitutable and boosts demand for goods produced in regions that are hit harder by the sanction shocks and see larger declines in nominal wages. However, we find that the quantitative impact of moving ϵ from 5 to 9 is minimal in our current calibration in terms of changing the regression coefficients. The aggregate effects are slightly smaller than the baseline.

Finally, we consider alternative values of the Armington elasticity of foreign consumers regarding goods from North Korea and other origins (η). In the baseline model, we set η to two, a median value of the industry-specific estimates in Feenstra et al. (2017). We consider η as low as one and as high as four. We re-calibrate the model and present the results in the rows with headings $\eta = 1$ and $\eta = 4$. We find results that are similar to our baseline. A lower η leads to a slightly larger σ (1.5 instead of 1.4) and slightly lower aggregate output and welfare effects.

D.5 Non-linear Effects of Counterfactual Sanctions

Though the recent UN sanctions prohibited more than 80% of North Korea's export, the counterfactual full trade sanction generates almost three times of the current decline in manufacturing output (-43.7% v.s. -16.1%, see Table 8). The effect of the sanctions seems to be highly non-linear. In this section, we perform counterfactual sanctions in our baseline model to understand the source of the non-linearity.

We start from a base-period equilibrium without sanctions and use all model parameters calibrated under the baseline setup (see Table 7). We also force the trade balance to be zero in both the pre- and post-sanction equilibria to better isolate the nonlinear effects, because the trade deficit must be zero in the full sanction case. Since sectors are different from each other, we consider a "symmetric" export sanction by imposing a uniform decline in the foreign demand parameter $B_{F,j}$ as

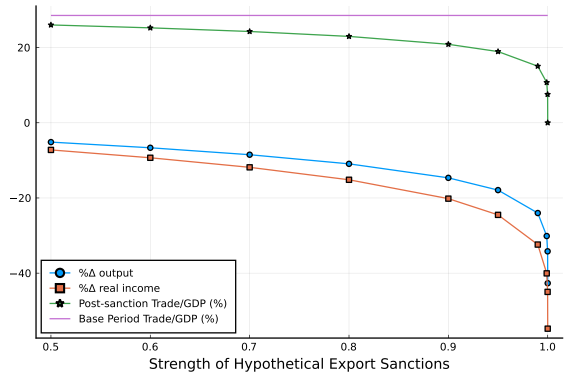
$$B'_{F,j} = (1 - S_{EX})B_{F,j}, \quad \forall\ j.$$

We use S_{EX} to denote the proportional decline in foreign demand. When the foreign demand elasticity $\eta = 1$, S_{EX} coincides with the percentage decline of total exports. We vary the parameter S_{EX} from 0.5 to 1.0. The maximum $S_{EX} = 1.0$ indicates a full sanction. Due to trade balance, imports also have to be zero in this scenario.

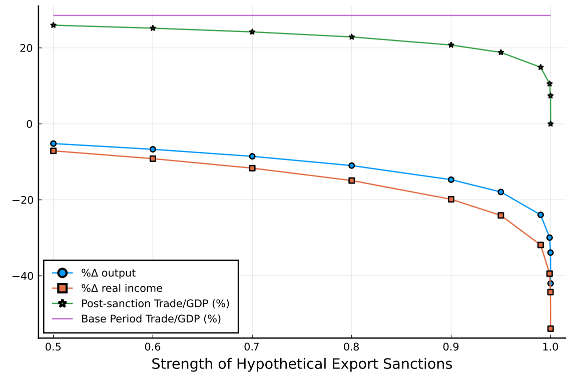
Panel (a) of Figure D-2 shows the effects of the hypothetical export sanctions under the baseline parameters. As expected, the effects on aggregate output and real income are nonlinear – the decline in output is less than 20% even when 95% of the foreign demand has disappeared. However, as the sanction further strengthens, output declines rapidly until it reaches the level of the full sanction effect (-43.7%). The patterns for real income (welfare measure) are similar. It is difficult to isolate the mechanisms of the non-linearity due to the richness of the input-output and domestic trade structure. However, we find a plausible explanation from sanction's non-linear effects on trade-to-GDP ratio. Arkolakis et al. (2012) derive a sufficient statistic for the change in real income from the change in the share of domestic expenditure and the trade elasticity. We do not have such a sufficient statistic, but the trade-to-GDP ratio may still be informative about the aggregate effects of trade shocks. When foreign demand B_j and exports drop, North Korean wages drop, which dampens the decline in the export-to-GDP ratio. As the economy becomes closer to autarky, export becomes less important and further sanctions do not reduce wage much. This accelerates the decline in export-to-GDP ratio, which comoves with aggregate real output and income.

Finally, we show that the nonlinear effects are not driven by model assumptions. In panel (b), we consider the same hypothetical export sanctions under perfect labor mobility, $\alpha_m = 1$. In panel (c), we use a lower foreign demand elasticity, $\eta = 1$. As mentioned above, this case has the advantage that we can interpret the strength of sanction, S_{EX}, as the percentage decline of trade volume. In panel (d), we consider a higher elasticity of substitution between products produced in different North Korean regions, $\epsilon = 9$ instead of 5. The nonlinear effects are all present in these setups.

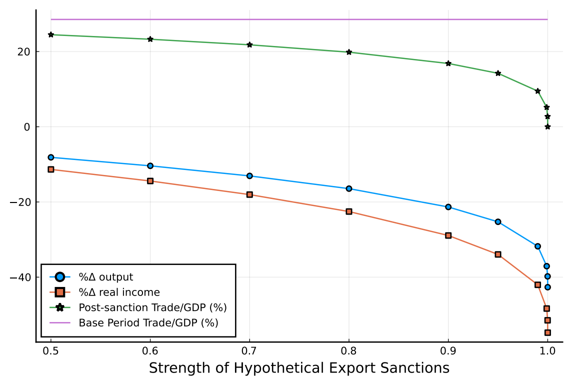
Figure D-2: Nonlinear Effects of Hypothetical Export Sanctions



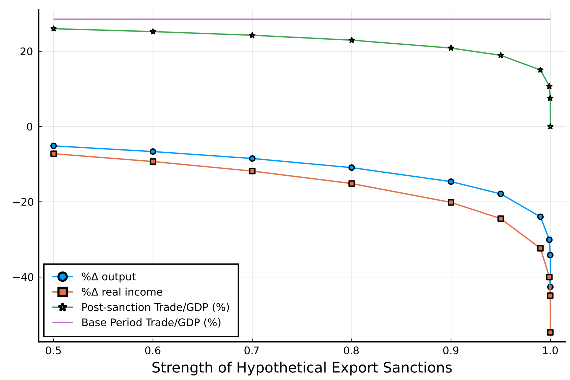
(a) Baseline, $\alpha_m = 0, \eta = 2, \epsilon = 5$



(b) $\alpha_m = 1$



(c) $\eta = 1$



(d) $\epsilon = 9$

Notes: we present the effects of hypothetical export sanctions by reducing all sectors' foreign demand by a fraction of S_{EX}, where S_{EX} ranges from 0.5 to 1.0. Each dot represents a post-sanction equilibrium. Panel (a) uses the parameters obtained from the baseline calibration. Panel (b), (c), and (d) alter one parameter from the baseline: labor mobility across sectors α_m, foreign demand elasticity η and the Armington elasticity of substitution between domestic varieties, ϵ.

References

Adão, Rodrigo, Costas Arkolakis, and Federico Esposito, "General Equilibrium Effects in Space: Theory and Measurement," Working Paper 2022.

Chor, Davin and Bingjing Li, "Illuminating the Effects of the US-China Tariff War on China's Economy," Working Paper 2021.

Fan, Jingting, Yi Lu, and Wenlan Luo, "Valuing Domestic Transport Infrastructure: A View from the Route Choice of Exporters," Working Paper 2021.

Guillaume, Gaulier and Soledad Zignago, "BACI: International Trade Database at the Product-Level. The 1994-2007 Version," Working Papers 2010-23, CEPII Research Center 2010.

Henderson, J V, Adam Storeygard, and David N Weil, "Measuring Economic Growth from Outer Space," *American Economic Review*, 2012, *102* (2), 994–1028.