The Economic Costs of Trade Sanctions: Evidence from North Korea

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Abstract

This paper investigates the economic costs of the recent United Nations sanctions on North Korea. Exploiting a novel data set on North Korean firms, we construct measures of regional exposure to export and intermediate input sanctions and show that trade sanctions cause sharp declines in local nighttime luminosity. Additional analysis of newly available product-level price data reveals that import sanctions led to significant increases in market prices. We then estimate a quantitative spatial equilibrium model using cross-region variations. The model implies that the sanctions reduced the country's manufacturing output by 12.9% and real income by 15.3%. We further quantify the potential impact of alternative sanction scenarios.

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1 Introduction

Since World War II, sanctions have become a standard non-military instrument in coercive foreign diplomacy. Various types of sanctions have been placed, ranging from travel bans to economic and trade sanctions. Despite their importance in global diplomacy, we know little about the economic consequences of sanctions giving rise to questions about their efficacy (Pape, 1997). In this paper, we study this question in the context of the 2016-2017 UN trade sanctions on North Korea and quantify their aggregate impact, combining regional variation in exposures to the sanctions and a spatial equilibrium model.

From March 2, 2016 to December 22, 2017, the United Nations Security Council adopted five sanction resolutions in response to North Korea's nuclear or ballistic missile tests. Figure A-1 shows that North Korea has been actively conducting nuclear and missile tests since 2013. It also shows that the share of (pre-sanctions) exports and imports exposed to UN sanctions increases from zero to 20 percent after the first UN sanction on trade in 2016 Q1 and gradually rises to almost 60 percent by 2017 Q4. The 2016/17 UN resolutions were the most severe sanctions in the history of the country, advocated as a policy to apply "maximum pressure" on the North Korean economy. Depicted in the same figure, the cease in nuclear testing and drop in the number of missile tests immediately after the last sanction may suggest that sanctions have worked. However, there is little quantitative evidence on the economic impact of the sanctions, which is central to understanding the pressure that these sanctions have on the country and their effectiveness in achieving their stated goals.

A key challenge is the lack of data on North Korea. We overcome the data challenge by collecting and utilizing novel data sets. First, we use new data on North Korean firms to calculate the share of each manufacturing industry in every county in North Korea. This data is provided by a national research institute in South Korea and contains information on firms mentioned in two major state-run North Korean newspapers since 2000. Then we combine the county-level industry shares with trade data from the UN Comtrade Database and the sanctioned product list, to develop a measure of county-level exposure to export and intermediate input sanctions. Second, we use nighttime luminosity data, collected from the Visible Infrared Imaging Radiometer Suite (VIIRS), as a proxy for regional manufacturing activity. To provide an economic interpretation we conduct an auxiliary analysis using Chinese county-level data on Gross Domestic Product (GDP) and nightlight, and apply the estimated GDP-nighttime luminosity elasticity to our findings. Finally, we utilize a novel data set on product prices in local markets of North Korea to infer the impact of trade sanctions on market prices. We purchased the price data from a private company that collects information on products sold at markets in North Korea.

We first provide reduced-form evidence by estimating the impact of county-level exposures to export and intermediate input sanctions. Using a long-difference specification (2013-2019), we find that a 10 percentage point exposure to export sanctions reduces nighttime luminosity by approximately 2.9 log points. We do not find evidence on the effect of input sanction exposure, however. To interpret this estimate in economic terms, we estimate the elasticity of GDP on nighttime luminosity. Using a sample of Chinese counties with characteristics similar to counties in North Korea, we find a GDP-nightlight elasticity of 0.419. Applying this elasticity to our estimates implies that moving a county from the 25th percentile to the 75th percentile of export sanction exposure reduces its manufacturing GDP by 4.1 ($= 34 \times 0.288 \times 0.419$) percent.[1] We conduct extensive tests to show that our results are robust to alternative specifications. Furthermore, we follow the suggestions in Goldsmith-Pinkham, Sorkin and Swift (2020) and perform several checks to validate identification assumptions associated with shift-share research designs.

Our identification strategy assumes that pre-sanction region-industry shares are exogenous to changes in regional nightlight had they not been exposed to export and input sanctions. The presence of pre-trends would indicate that our estimates may be potentially biased. While we find no evidence of a pre-trend with export sanction exposure we find a positive pre-sanction trend in nighttime luminosity among counties more exposed to intermediate input sanctions and a significant drop after the sanctions. The pre-sanction positive trend is consistent with North Korea's ten-year strategic economic development plan (2011-2020), prioritizing heavy industries that later face stronger input sanctions. This implies that our estimate from the 2013-2019 long difference model may be an overestimate (in case of reversal of the pre-sanction trend) or underestimate (in case the government is continuing its investments) of the effect of intermediate input sanctions on nighttime luminosity. While it is difficult to distinguish between the two cases, we also run our long-difference specification with 2014 as the base year. We find an economically significant impact of the intermediate input sanctions on nighttime lights, which suggests that the reduced access to intermediate inputs hinders production under the assumption that the government did not withdraw its pre-sanction strategic investments.

Price information on products sold in North Korean markets provides additional insights into how the effects of trade sanctions permeate local economies. Using a novel dataset that provides a quarterly price at the product level for more than 70 products, we find a 32.2 log points (38%) increase in the average price of products that are import sanctioned. Export sanctioned products are shown to have a moderate fall (4.0 log points) in the average price, but the estimate is not statistically significant. Interestingly, a heterogeneity analysis with

[1] We limit our analysis to manufacturing for two reasons. First, as we discuss in Section 3.1, our night light data likely capture manufacturing activities in North Korea, and we lack measures of agriculture or services output. Second, the company data we use do not cover agriculture or services, so we cannot construct sanctions exposure measures for these sectors.

respect to cities reveals that the price increase from import sanctions is not observed in the country's capital, Pyongyang, and only observed in other major cities, which suggests that the ruling elites may have reallocated resources to smooth the price surge in favored regions (Lee, 2018).

Next, we construct a quantitative spatial equilibrium model of North Korea and use the model to estimate key parameters of the pre-sanction economy as well as to infer the aggregate impact of the trade sanctions. Our model features multiple regions in North Korea that trade with each other and the rest of the world. Regions specialize in different sectors because of differences in region-sector-specific productivities. Though the evidence on the effect of input sanctions is suggestive and depends on how we treat the pre-trends, we allow for realistic input-output linkages between sectors to capture the propagation of import sanctions to downstream sectors. Our model deviates from standard spatial equilibrium models (Adão, Arkolakis and Esposito, 2022; Redding and Rossi-Hansberg, 2017) along two dimensions to better describe the North Korean economy. First, we allow inter-regional trade but shut down labor mobility across regions. In addition, we allow imperfect labor mobility across sectors within a region.[2] Second, we treat North Korea as a small open economy that takes foreign demand and prices as exogenous. The export and import sanctions can be modeled as sector-specific reductions in foreign demand and increases in foreign prices, respectively. Knowing the base period model primitives, we can simply change these variables according to the sanctions and predict county-level output changes.

We estimate the model primitives in the base period using manufacturing industry shares in each region based on the number of company mentions, each industry's share in aggregate imports and each county's share in aggregate output based on the pre-sanction nightlight intensities. In addition, we calibrate three parameters, including the Armington elasticity between domestic and foreign goods, to jointly match North Korea's export-to-GDP ratio, the response of county-level output to export sanctions, and the response of county-industry level prices to import sanctions. Intuitively, export sanctions reduce foreign demand and lower domestic wages and prices, and domestic consumers will buy more domestic goods as they become cheaper. This mechanism boosts domestic demand and increases output, but is weaker when the elasticity of substitution is low. We find an elasticity of 1.4, which suggests that the goods produced in North Korea and foreign countries are not easily substitutable within two-digit ISIC industries. This elasticity is lower than typical Armington elasticities used in the trade literature, such as a value of six in Costinot and Rodríguez-Clare (2014), but falls in the range of the industry-level elasticities estimated in Feenstra, Luck, Obstfeld and Russ (2017) and is slightly lower than the macro elasticity used by Backus, Kehoe and

[2]Our model accommodates any degree of cross-sector mobility. We set it to zero in the baseline and conduct robustness checks with higher mobility, as our interviews with North Korean defectors reveal that changing jobs is generally difficult.

Kydland (1992).

The estimated model implies that the aggregate real output of the industrial sector in North Korea drops by 6.4% due to the export sanctions and by 12.9% due to both export and import sanctions. Welfare, measured by changes in real income, drops by 7.7% and 15.9%, respectively. With the calibrated model, we perform counterfactual analysis by changing the exogenous trade deficits or imposing a full sanctions regime on North Korea. North Korea's trade deficit increases dramatically after 2017. We model the increases in trade deficits as increases in exogenous transfers but expect that such high trade deficits cannot be sustained in the long run, since the country lacks sources of foreign currency income other than from exports and remittances – 88% of the pre-sanction exports are prohibited while the sanctions also require member countries to repatriate all North Korean overseas workers by the end of 2019. We find that forcing North Korea to close its trade deficit will further reduce the aggregate output by 9.1%. In addition, the imposition of a full sanctions regime on all exports and imports will drastically reduce its manufacturing output by 43.7%.

We examine the robustness of the model calibration and aggregate predictions by altering model assumptions, such as introducing industry subsidies, allowing favorable subsidies or transfers to Pyeongyang and using different trade costs and parameter values. Our baseline results are in general robust. One exception is when we introduce subsidies to intermediate inputs that are subject to import sanctions. Such subsidies can mitigate the impact of the exposure to input sanctions on county-level output in the cross-sectional regressions, bringing our model closer to the reduced-form estimates based on nightlight changes from 2013 to 2019. In this setup, we find a much smaller impact on aggregate real output under both export and import sanctions (-9.6%). However, the change in aggregate real income is even larger than our baseline since the government has to tax households to finance the industry subsidies.

Our quantitative model captures several general equilibrium mechanisms that generate "level effects" and are absent from the cross-sectional reduced-form estimates. First, trade in intermediate inputs and final goods between domestic regions leads to "negative spillovers" and creates a negative level effect: regions that are hit harder by the sanctions buy fewer goods from other regions, so regions not directly affected by the sanctions also reduce output. Such spatial linkages are also emphasized by Adão et al. (2022). Second, though workers cannot move across regions, intermediate inputs are reallocated from regions that are more exposed to the sanctions to the others, and will increase the output in the latter group of regions and create a positive level effect. Finally, North Korea experienced a dramatic increase in trade deficits after the sanctions, which are modeled as an increase in exogenous transfers. The additional transfer increases the overall domestic demand and increases the aggregate output, but it is common to all counties and not reflected in the cross-sectional regression coefficients (a positive level effect). Ignoring the level effects, a back-of-envelope calculation based on the reduced-form estimates of the export sanction exposure predicts a decline in aggregate output by 6.9% due to export sanctions alone. The model-predicted effect of export sanctions, -6.4% in real output, suggests that the positive level effects are slightly larger than the negative level effect. The magnitudes of these level effects certainly depend on the structure of the model. However, the robustness of our model to alternative assumptions gives us confidence in its aggregate predictions.

Our paper contributes to three strands of literature. First, it contributes to the recent empirical literature that studies the impact of economic sanctions.[3] To estimate the economic costs of sanctions, in addition to obtaining reliable data, one needs to provide credible identification since the targeted country may have implemented policies that triggered the sanctions and affected national outcomes at the same time. Earlier studies use country-level over-time variations to estimate the impact of sanctions. Neuenkirch and Neumeier (2015), for instance, use country-level panel data. Effectively using non-sanctioned country-year combinations as the control group, they show that the imposition of UN sanctions decreases the target state's real GDP per capita growth by more than two percentage points. Using aggregate bilateral trade data and structural gravity models, Felbermayr, Syropoulos, Yalcin and Yotov (2019) estimate the impact of various sanctions on trade and quantify their impact on real GDP. They find heterogeneous effects of sanctions across countries, with the largest effect on real per capita income being - 4.0% (Iran). Etkes and Zimring (2015) study the impact of the 2007-2010 Gaza blockade using detailed consumption data, but their main identification uses the West Bank as a counterfactual economy.[4]

Other papers address the identification challenge using sub-national variations. For example, Ahn and Ludema (2020) use firm-level data from Russia and find negative impacts of U.S. and EU sanctions against Russia on sanctioned firms relative to non-sanctioned firms. Lee (2018) studies the heterogeneous responses of nightlight intensities to earlier sanctions across different regions in North Korea according to their characteristics: being the capital city, manufacturing cities, or trading hubs near China. We also analyze the sanctions on North Korea at the sub-national level, which helps to address the identification challenge. Compared to Lee (2018), we study the most recent sanctions that target the broader manufacturing sector, and our exposure measures based on region-industry shares provide strong priors on which regions might be affected the most. We find that regions that were more

[3] There are also studies on earlier sanctions such as Hufbauer, Schott, Elliott and Oegg (2009) and Morgan, Bapat and Kobayashi (2014) that constructed sanctions databases, including costs of sanctions. Their cost estimates are computed or collected considering apparent primary costs such as declines in trade volume, reductions in aid, increases in military spending, etc.

[4] When studying the impact of the blockade on firm production, Etkes and Zimring (2015) do use sub-national variations by comparing industries that rely more on international trade than those that rely less. We summarize other papers that use sub-national variations in the next paragraph.

exposed to the export and input sanctions had larger drops in night light intensities. In addition, our structural model provides a framework to evaluate or predict the general equilibrium effects of sanctions that are missing from the cross-region, reduced-form regressions and isolates the causal aggregate effect of the trade sanctions on the North Korean economy.

Second, our paper connects to a growing literature that uses quantitative spatial equilibrium models to evaluate the impact of domestic and external shocks (Caliendo, Parro, Rossi-Hansberg and Sarte, 2018; Redding and Rossi-Hansberg, 2017). We focus on the unprecedented UN sanctions on North Korea, which provide a rare opportunity to study large trade shocks. In terms of methodology, our paper is close to several recent papers that use shift-share research designs through the lens of structural models, including Kovak (2013) and Adão, Kolesár and Morales (2019).[5] Adão et al. (2022) argues that it is crucial for quantitative spatial models to capture the cross-region responses to external shocks. Though we do not adopt the optimal instrumental variable approach in their paper, we discipline our model by matching the relationship between regional outcomes and exposures to external shocks. By matching the observed output response to export sanctions, we obtain an independent estimate of the Armington elasticity between domestic and foreign goods for North Korea (1.4), which is at the lower end of the Armington elasticities in the literature (Costinot and Rodríguez-Clare, 2014; Feenstra et al., 2017).

Finally, our paper joins the line of research exploiting data from nighttime satellite imagery. Since the pioneering work by Chen and Nordhaus (2011) and Henderson, Storeygard and Weil (2012), night light luminosity data have been widely applied to a multitude of economics research (for a review, see Michalopoulos and Papaioannou 2018). Previous studies document a robust relationship between nighttime luminosity and economic output statistics at both the national and sub-national levels (Chen and Nordhaus, 2011; Gibson, Olivia, Boe-Gibson and Li, 2021; Henderson et al., 2012; Pinkovskiy and Sala-i-Martin, 2016).[6] We contribute to this literature by using sub-national night light data to study the impact of external shocks, in the same spirit as Chor and Li (2021). Beyond the reduced-form estimate of how night light responds to regional exposure to external shocks, we further estimate the general equilibrium effects of shocks using a spatial equilibrium model.

The rest of the paper is organized as follows. Section 2 describes trade sanctions against North Korea and shows their impact on the country's trade. Section 3 describes the nighttime

[5] This literature is closely connected to reduced-form studies using similar empirical strategies, such as Autor, Dorn and Hanson (2013). It is also worth mentioning that our research question is related to several papers that examine the aggregate impact of the US-China trade war, including Fajgelbaum, Goldberg, Kennedy and Khandelwal (2019).

[6] Other studies have also utilized night light data to study epidemic fluctuations (Bharti, Tatem, Ferrari, Grais, Djibo and Grenfell, 2011), regional favoritism (Hodler and Raschky, 2014; Lee, 2018), and urban growth in developing countries (Dingel, Miscio and Davis, 2019; Michalopoulos and Papaioannou, 2013; Storeygard, 2016).

luminosity data from satellite imagery, the North Korean company data that we utilize, and how we construct the regional sanction exposure measures. Using these data sets, Section 4 presents the results of our reduced-form empirical analysis, and Section 5 presents additional analysis using product price data. Section 6 estimates the spatial equilibrium model, infers the aggregate impact of the current sanctions and predicts the impacts of counterfactual sanctions. Section 7 concludes.

2 Background of the Trade Sanctions

North Korea has long been under unilateral and multilateral sanctions to deter and suspend the country's nuclear development. Sanctions against North Korea go back to as early as 1950, when the US imposed sanctions during the Korean War. While the US further tightened its sanctions in the 1980s and relaxed some in the 1990s, more systematic and internationally coordinated sanctions against North Korea began in 2006 when the UN Security Council passed Resolution 1718 and organized the Sanctions Committee on North Korea in response to the country's first nuclear test.[7] A series of UN sanctions resolutions have been adopted since then, each resolution following a North Korean nuclear test or missile launch. Figure 1 presents the timeline of the UN sanctions against North Korea.

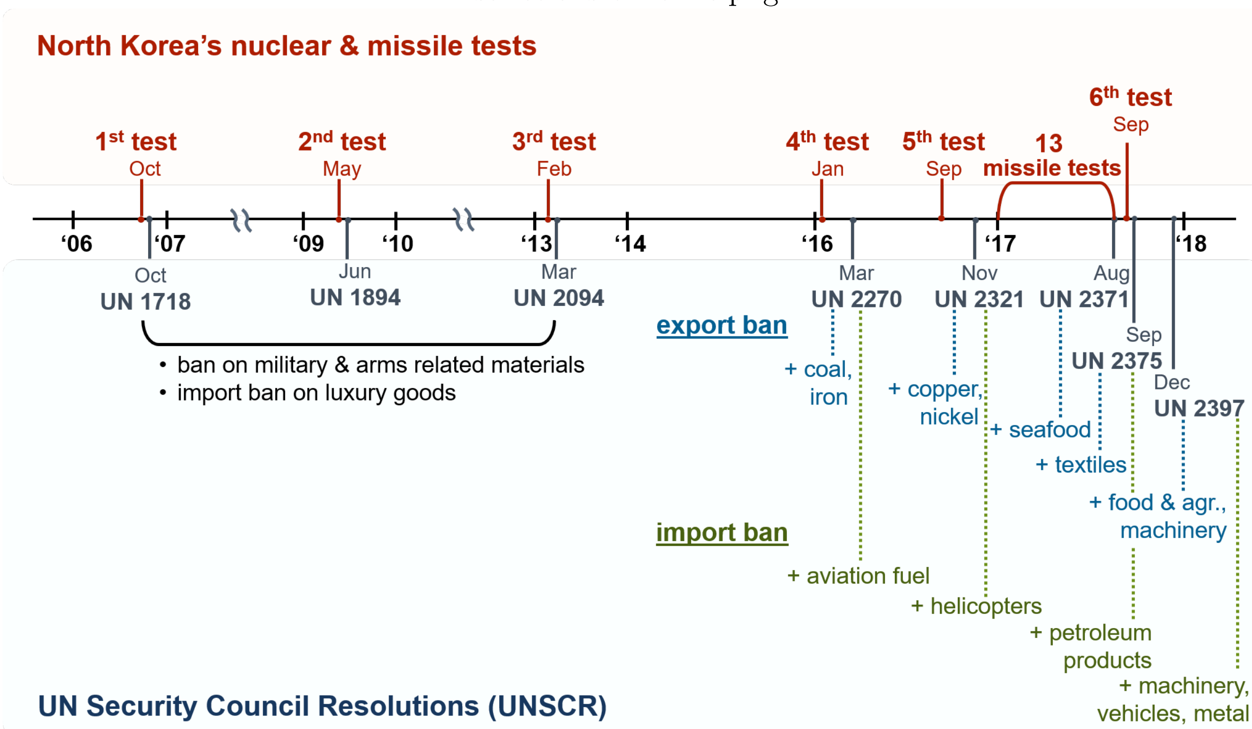
While the UN sanctions against North Korea have been strengthened over time, the UN Sanctions Committee made a notable change in its approach starting from 2016. Prior to 2016, the sanctions against North Korea mainly targeted North Korean military and nuclear operations and imposed restrictions on the elite's financial resources. This targeted approach did not prove successful because North Korea adapted fairly well, finding loopholes and alternative sources of foreign capital (Kwon, 2016).

In contrast, the series of sanctions in 2016-2017 was more comprehensive, designed to pose a direct threat to the North Korean economy. We list the sanctioned trade items by each UN resolution in Table A-1. Most notably, trade sanctions were extensively strengthened, banning the import and export of products crucial to the North Korean economy. Table A-2 shows North Korea's top 10 export and import products from 2011 to 2015 and its sanction status by the UN. The top panel shows that all export products on the list, which accounted for 65.7% of total exports, were sanctioned. The rationale behind targeting top export products was to dry up the hard currency and restrict weapons development. However, unlike export sanctions, sanctions on imports targeted products specifically related to machinery and petroleum products. As shown in the bottom panel of Table A-2: major import products in food or textile industries, such as woven fabrics, soybean oil, or wheat flour, were not

[7]The UN member countries are expected to implement domestic laws and regulations to comply with the Committee's resolutions. Some countries, such as the EU countries and the US, have often introduced sanctions measures against North Korea that are stronger than the UN resolutions.

Figure 1: The Timeline of UN Sanctions against North Korea

sanctions timeline.png



Notes: This figure shows the timeline of North Korea's nuclear and missile tests and the ensuing UN sanctions against the country. See Table A-1 for the complete list of sanctioned items by the UN resolutions.

sanctioned. The choice of products reflects the main purpose of import sanctions which was to prevent further development of weapons and missiles. In addition to trade sanctions, another major sanction measure is that UN member countries are obliged to repatriate all North Korean overseas workers by the end of 2019 (UN Resolution 2397).

In Online Appendix A.1.2, we show that trade in sanctioned products declined dramatically to almost zero after 2018, according to the trade statistics reported by North Korea's trading partners in the UN Comtrade database. While the drastic decline in the reported trade statistics motivates us to study the impact of the 2016/17 trade sanctions, we emphasize that neither our reduced-form analysis in Sections 4 and 5, nor the quantification of our spatial equilibrium model, relies on post-sanction trade data.[8]

[8] The only exception is that, when solving the post-sanction equilibrium, we set the exogenous trade deficit to the value observed in the post-sanction trade data. However, the key model parameters are identified using base-period shares and the cross-region relationship between the change in night light intensities and sanction exposures, which may not be systematically biased due to mismeasured trade deficits. Our counterfactual analysis of reducing deficits suggests that if the post-sanction trade deficits were over-estimated due to illegal exports, the aggregate impact of the sanctions would be larger.

3 Data sources and measures

We now introduce the nighttime light data, the company list database, and how we construct the regional sanction exposure measures. We then present summary statistics for 174 North Korean counties that we use as our main sample.

3.1 Nighttime lights

We utilize nighttime luminosity data from satellite images as a proxy for local economic activities in North Korea. There are two publicly available night light datasets: the United States Air Force Defense Meteorological Satellite Program (DMSP), which spans the years from 1992 to 2013, and the Visible Infrared Imaging Radiometer Suite (VIIRS) from 2012 to 2020. We utilize VIIRS data for two main reasons. First, VIIRS covers the period before and after trade sanctions, while DMSP is available only up to 2013. Second, VIIRS deploys various technical adjustments to measure nighttime luminosity more precisely, overcoming the known limitations of DMSP such as blurring and incomparability over time (Abrahams, Oram and Lozano-Gracia, 2018). Accordingly, as shown in Gibson et al. (2021), VIIRS provides better predictions of GDP than DMSP, especially at sub-national levels, which is crucial for our county-level analysis. We construct quarterly nighttime luminosity by averaging monthly, stray-light corrected VIIRS data, obtained from the Earth Observations Group (EOG) (`https://eogdata.mines.edu`). By working with quarterly data, we are able to mitigate concerns on missing data caused by cloud cover and solar illumination (Beyer, Hu and Yao, 2022).

An important question is *what* economic activities the nighttime light data capture. For all locations in North Korea, the VIIRS data measure the nighttime luminosity of each grid at around 1:30 a.m. (Elvidge, Baugh, Zhizhin and Hsu, 2013). Therefore, the night light data we use most likely capture manufacturing activities at night.[9] In our analysis, we also include the electric power industry because power plants are an important category in the company list database (see Section 3.2) and they generate night light as manufacturing facilities. Therefore, we interpret the night light intensity as a better proxy for the output of the "extended" manufacturing sector (including the electric power industry) than for the total local output, which includes agriculture and services. Henceforth, we refer to the

[9] Night-shift work at factories was reported to be common in North Korea. For example, three-shift work covering 24 hours was a prevalent practice during the peak season in the Kaesong Industrial District (Paek, Jung and Hong (2020) also introduced in a news article `http://nowon.newsk.com/front/news/view.do?articleId=526` (in Korean)). In addition, a North Korean economic official boasted for the country's cheap nighttime labor to attract foreign investment (`https://www.khan.co.kr/politics/north-korea/article/201811270600085` (in Korean)). Our interviews with North Korean defectors also confirmed that some manufacturing factories operate 24 hours in North Korea.

extended manufacturing sector as the "manufacturing" sector.[10]

To provide empirical evidence that the nighttime light represents manufacturing production we examine the correlation between night light intensity in 2015 and regional manufacturing size, which we proxy with a measure obtained from the North Korean Company data (we discuss about this data in the next subsection), controlling for population and other regional economic variables. Table A-6 presents the results. Our proxy for regional manufacturing size is a positive and statistically significant predictor of nighttime luminosity, even after controlling for population and various regional variables, such as road length, building area, and market area. The empirical result is consistent with anecdotal evidence provided by news reports and interviews, and supports the interpretation of nighttime luminosity capturing manufacturing production.

3.2 North Korean Company Data

The Korea Institute for Industrial Economics and Trade (KIET), a national research institute, tracked articles from two major state-run North Korean newspapers (*Rodong Sinmun* and *Minju Chosun*) between 2000 and 2019 to record the lists of all companies and factories mentioned in these newspapers. Overall, there are 2,960 North Korean companies on the list. The list provides information about the location (county) and industry classification of each company. For constructing regional sanctions exposure measures, which we discuss below in detail, we limit our sample to manufacturing firms and power plants that appear in the two newspapers by the year 2015, prior to the first wave of the latest UN sanction resolutions. We discuss the data for North Korean companies in more detail and provide summary statistics in Online Appendix A.2.

The data also contain information on the number of times each company is reported each year and the type of report (e.g., whether related to production or investment). The data do not provide information on the size of the company (e.g., revenue or number of employees). Therefore, we employ the frequency of economic reporting as a proxy for the size of the company. Jung, Lim, Jung, Lee and Kim (2019) found that the more frequently a company is mentioned in *Rodong Sinmun*, the higher the company's utilization rate and the amount of rations provided to workers. Based on this observation, the frequency of economic-related news reports was used as a proxy for the importance of the company to the local economy. This is based on the idea that, in North Korea, larger and more important companies are more likely to be mentioned in official news media, especially on issues related to production or facility investment than small companies. Although we cannot verify such

[10] There is also a possibility that the data capture street lights. While we cannot exclude this possibility, our interviews with North Korean defectors suggest that our results are unlikely to be driven by street lights. Street lights are installed in major North Korean cities, but the government turns them off before midnight except in Pyeongyang. Our main results are robust to excluding Pyeongyang from the analysis.

a correlation at the company or the region-industry levels due to the lack of data, we show that, when aggregated at the county level, they are highly correlated with proxies of output such as population and night light. When aggregated at the industry level, they are highly correlated with a model-based measure of output. These validation exercises are presented in Online Appendix A.2.3.

3.3 Regional Sanctions Exposure Measures

We develop regional sanctions exposure measures to capture the potential impact of sanctions on regional economies in North Korea. We first construct sanction indices at the ISIC Rev.3 2-digit industry level, and then calculate sanctions exposure for each North Korean county based on the number of firms in each manufacturing industry. Using a concordance map provided by UN Comtrade, we map each HS 6-digit product, p, to a 2-digit ISIC industry, j. The industry-level export sanction index is simply

$$S_{EX,j} \equiv \frac{\sum_{p \in j} EX_p^0 \times \mathbf{1}(p \in P_{EX})}{\sum_{p \in j} EX_p^0}, \tag{1}$$

where the summation is over products that belong to a particular industry j. We use P_{EX} to indicate the set of products on the export sanctions list. EX_p^0 represents the values of exports of product p by North Korea before the sanctions. We use the average value between 2011 and 2015 to smooth out short-run fluctuations in trade.

To capture the impact of losing access to imported intermediate inputs, we create an "input sanction index" for each industry j:

$$S_{IN,j} \equiv \sum_k a_{kj} S_{IM,k}, \quad S_{IM,j} \equiv \frac{\sum_{p \in j} IM_p^0 \times \mathbf{1}(p \in P_{IM})}{\sum_{p \in j} IM_p^0}, \tag{2}$$

where a_{kj} is the share of inputs from industry k among all intermediate inputs used by industry j, and the input sanction index is a weighted average of the upstream import sanction indices $S_{IM,j}$. The import sanction index is constructed similarly to the export sanction index (1) and captures the share of imports that are banned among all imported goods belonging to a particular industry. In terms of notations, IM_p^0 is the average imports from 2011 to 2015 of product p and P_{IM} is the set of products that are on the import sanction list. Since North Korea's input-output table is not available, we use the 122-sector input-output table of China in 2002 and aggregate these sectors to ISIC 2-digit industries and obtain a_{jk}. As is discussed in Section 4, our results are robust when we use the input-output tables of China in 1987 and 1997, when China's technology was less advanced, and its trade with foreign countries was limited.[11] In sum, the input sanction index captures the share of imported inputs that are affected by the sanctions for each downstream industry j.

In Table 1, we report the export, import and intermediate input sanction indices for industries that we can find in the company list database, which include 20 manufacturing industries and the electricity & gas supply industry (ISIC Code = 40). The average export, import, and input sanction indices are 0.438, 0.335, and 0.261, respectively. There is rich variation across industries: industries such as Manufacturing of Food, Textiles, and Apparel have high export sanction indices but low input sanction indices, while Manufacturing of Refined Petroleum and Motor Vehicles have high input and low export sanction indices. Some other industries such as Manufacturing of Leather Products and Rubber and Plastic have both low export and low input sanction indices. There is no significant correlation between the two indices at the industry level.

Table 1: List of Industries and Sanction Indices

ISIC Code	Short description	$S_{EX,j}$	$S_{IM,j}$	$S_{IN,j}$
15	Food	0.944	0.000	0.028
16	Tobacco	0.000	0.000	0.025
17	Textiles	0.999	0.000	0.039
18	Apparel	0.997	0.000	0.024
19	Leather	0.000	0.000	0.027
20	Wood	0.960	0.000	0.066
21	Paper	0.003	0.000	0.059
22	Publishing	0.015	0.067	0.069
23	Refined Petro.	0.001	0.995	0.127
24	Chemicals	0.116	0.001	0.114
25	Rubber and Plastic	0.007	0.000	0.064
26	Other non-Metal	0.610	0.054	0.195
27	Basic Metals	0.939	0.965	0.498
28	Fabricated Metals	0.765	0.938	0.631
29	Machinery NEC	0.994	0.999	0.619
31	Elec. Equip.	0.997	0.951	0.560
33	Medical Equip.	0.043	0.014	0.484
34	Motor Vehicles	0.029	1.000	0.704
35	Trans Equip. NEC	0.781	1.000	0.706
36	Furniture	0.000	0.054	0.186
40	Elec. and Gas	0.000	0.000	0.250
Average		0.438	0.335	0.261

Notes: The industry-level export sanction index, $S_{EX,j}$, is calculated according to equation (1). The import and input sanction indices are defined in equation (2).

We next construct the regional exposure measures to export and input sanctions.[12] For each county n, we know the set of companies in each county n and industry j, $\{f \in n, j\}$, and

[11] In addition to assuming that China's past input-output tables approximate the current technology in North Korea well, we also make an implicit assumption that imported inputs will be used by downstream industries in the same proportion as domestic inputs. This is a typical assumption used when constructing international input-output tables (Dietzenbacher, Los, Stehrer, Timmer and Vries, 2013).

[12] In principle, we can also examine the impact of the import sanctions by constructing a similar regional

the total number of times that each firm was mentioned from 2000 to 2015, M_f. The county-level export and input sanction exposure measures are the weighted averages of industry-level sanction indices, where the weights are a function of the number of firm mentions in the corresponding industries. In particular,

$$S_{EX,n} \equiv \sum_j \frac{\sum_{f\in n,j} H(M_f)}{\sum_{f\in n} H(M_f)} S_{EX,j}, \quad S_{IN,n} \equiv \sum_j \frac{\sum_{f\in n,j} H(M_f)}{\sum_{f\in n} H(M_f)} S_{IN,j}, \tag{3}$$

where $H(M_f)$ is a transformation of each firm's number of mentions. Ideally, we want $H(M_f)$ to increase with M_f and to be highly correlated with firm size. In our main specification, we assume $H(\cdot)$ takes the format of $H(x) \equiv \log(1+x)$, since the number of mentions at the firm level is highly right-skewed, as is illustrated in Online Appendix Figure A-6. Our results are largely robust when using alternative $H(\cdot)$, such as $H(x) = x$ (effectively using total number of mentions across all firms in a county-industry as weights) and $H(x) = \mathbf{1}(x > 0)$ (effectively using the number of firms that have ever been mentioned in a county-industry as weights).

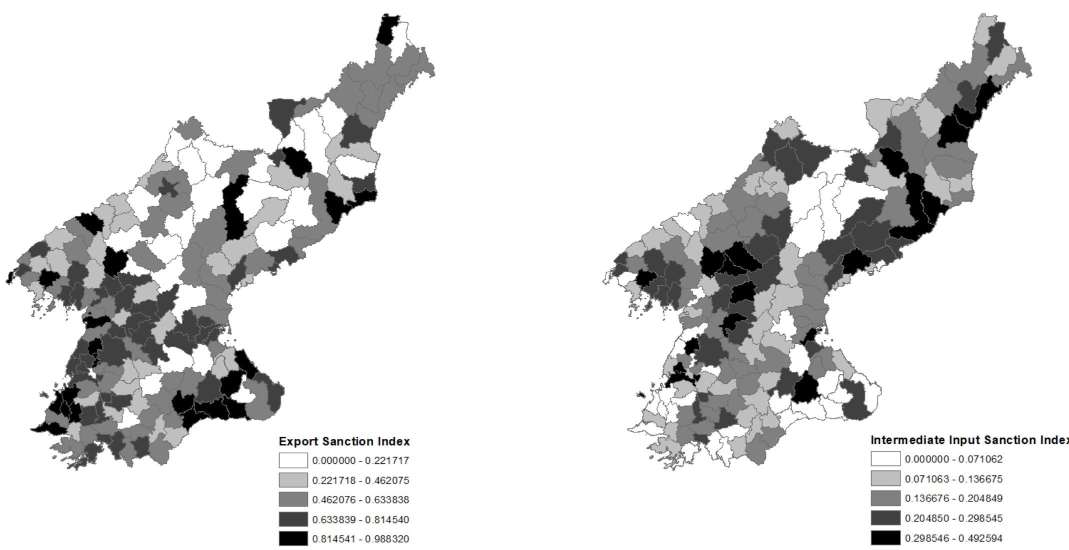
It is worth discussing the potential bias caused by approximating firm size using the number of mentions in national newspapers. The fundamental challenge we face is the lack of measures of industry output or employment at the county level. The number of mentions is used to construct county-specific industry weights that are further used to calculate the exposure measures. Though we provide additional evidence in Online Appendix A.2.3 that a county's total number of firm mentions is highly correlated with the county's night-light intensity and population before the sanctions, there is no doubt that this procedure introduces measurement errors in key our explanatory variables. If the errors are classical, the estimated effects will be biased towards zero. It is also possible that we overestimate the impact of the sanctions if the measurement errors are *negatively* correlated with the change in night light intensities. However, it is not straightforward what data-generating processes we need for such negative correlations.[13] Overall, we find it confirming that our results are robust to using alternative transformation functions $H(\cdot)$ to construct the weights.

import sanction exposure measure. Theoretically, import sanctions will have an expansionary effect on the focal industry, since there is less foreign competition. However, we do not see this as the right way of thinking about imports in North Korea since the country's imports are tightly controlled by permits issued by the government (Yang, 2008). The government can easily protect industries that they want to develop from foreign competition by reducing the number of import permits.

[13]One potential source of bias is that the North Korean newspapers may only report firms in "critical industries", and our data systematically miss firms in other industries. Suppose only such critical industries are sanctioned. The measured exposure will be weakly upward biased in all counties, which does not necessarily imply a negative correlation between the measurement errors and the change in night light intensities, e.g., caused by the true sanction exposure. For example, for counties with all firms in the critical industries, their exposure is correctly measured, which suggests that the correlation between the measurement errors and the true exposure (the change in night light intensities) may be negative (positive).

Figure 2 shows the spatial distribution of our constructed regional sanctions exposure measures. Two notable points arise from this figure. First, the exposures to export and input sanctions are to some extent spread out across the country. The regions closer to the border with China or along the western coastline in which some major trading ports are located do not necessarily display the highest exposure levels. Second, export and input sanction exposure measures do not seem to be highly correlated at the regional level (the correlation coefficient is -0.10 with a p-value of 0.17), which is partly due to the weak correlation of export and input sanction indices at the industry level. The independent variations in the two sanction exposure measures are helpful for separately identifying the impact of different types of sanctions.

Figure 2: Spatial Distribution of Sanction Exposures



(a) Export Sanction Exposure (b) Intermediate Input Sanction Exposure

Notes: This figure shows the distribution of export and intermediate input sanction exposures across North Korean counties.

In Table 2, we report summary statistics on export and intermediate input sanction exposures along with county-level characteristics. The average county's export sanction exposure, $S_{EX,n}$, is 0.55, meaning that 55% of local manufacturing exports are sanctioned, if exports by industries are proportional to the total weights of firms, $\sum_{f \in n,j} H(M_f)$, in each industry j. Notably, export sanction exposure significantly varies across counties, ranging from 0.39 at the 25th percentile to 0.73 at the 75th percentile. For intermediate input sanction exposure, the mean is 0.17, and the standard deviation is 0.1. We collect county-level characteristics from various publicly available data sources. For example, population is reported in the 2008 Population Census conducted by the Central Bureau of Statistics of North Korea and the United Nations (Central Bureau of Statistics of the DPR Korea, 2009). We calculate building area, a proxy for urban area, by utilizing a building footprint map of North Korea released by the National Geographic Information Institute in South Korea (National Spatial Data Infrastructure Portal, 2018). We also measure road length and distances using road network data available at `OpenStreetMap.org`.

Table 2: County Level Summary Statistics

				Percentile				
	Obs.	Mean	S.D.	1st	25th	50th	75th	99th
Export sanction exposure	174	0.55	0.26	0.00	0.39	0.59	0.73	0.98
Intermediate input sanction exposure	174	0.17	0.10	0.03	0.09	0.16	0.23	0.45
Population in year 2008 (unit = 1,000)	174	133.23	223.32	26.58	61.28	96.67	141.41	668.56
Building area in 2014 (km^2)	174	3.48	3.54	0.89	2.05	2.94	4.01	11.37
Road length (km)	174	325.44	300.40	67.94	190.60	262.74	371.79	1120.29
Distance to North Korea-China border (km)	174	229.22	135.00	1.60	117.02	220.74	347.22	458.03
Distance to major seaport (km)	174	129.36	89.42	0.40	56.12	106.79	198.49	338.27
Distance to Pyeongyang (km)	174	254.80	178.41	18.37	138.24	207.53	324.21	789.97
Nuclear facility site	174	0.05	0.21	0.00	0.00	0.00	0.00	1.00
Special industrial zone	174	0.08	0.27	0.00	0.00	0.00	0.00	1.00
Mean nighttime luminosity (2015)	174	0.11	0.09	0.05	0.08	0.09	0.12	0.73

Notes: This table provides summary statistics on county-level characteristics. Mean nighttime luminosity is the annual average of quarterly VIIRS nightlights.

3.4 Market Price Data

We use quarterly product-level price data spanning the period from 2013 to 2019 across six major cities (Pyeongyang, Shineuijoo, Kwaksan, Wonsan, Hweiryoung, Hamheung). The data is purchased from a company based in South Korea that collects information on the prices of products sold at markets (so-called 'Jang-ma-dang' in North Korea[14]). According to interviews with the company owner, price data is collected through contacts in North Korea who visit markets on a weekly basis and record price information for a pre-specified

[14] Jang-ma-dang, the North Korean local markets, have played a crucial role in the North Korean economy, especially after the country's public distribution system failed in the 1990s. While these markets were initially unofficial and illegal, the country started institutionalizing them in 2010 so that tax collection from the markets became one of the main sources of government revenue. It is estimated that, as of 2018, there were more than 400 markets across the country. In these markets, home-produced goods, goods produced in excess of the government's target production quantity, and foreign goods mostly from China or some smuggled from South Korea are traded. A wide range of goods is available, such as agricultural products, food, and manufacturing goods including daily necessities, clothing, household appliances, electronic devices, etc.

list of products.[15] To ensure accuracy, the company separately hires at least two contacts for each market to record the prices. The market price data provides information on each product's price, origin, unit, and, in some cases, specific brand names (e.g., the brand name of a cigarette or beer). For each product, we assign a sanction category – export sanctioned, import sanctioned, and not sanctioned – by matching the product name to the HS 2-digit code associated with the five UN sanctions enacted over the period 2016-2017. Overall, our price data covers prices of 20 export-sanctioned, 8 import-sanctioned, and 42 non-sanctioned products.

4 The Impact of Trade Sanctions on Regional Economies

4.1 Empirical Strategy

In this section, we present our empirical strategy for estimating the impact of trade sanctions on North Korea's regional economies. Using a Bartik-like measure of regional sanction exposures as treatments we estimate a long-run difference specification by taking the difference in the annual average nighttime luminosity between 2013 and 2019 and regressing the difference on regional sanction exposures. This leads to estimating the following equation,

$$\Delta Y_n = \alpha_0 + \alpha_1 \text{Export Sanction}_n + \alpha_2 \text{Input Sanction}_n + \nu_n \tag{4}$$

where ΔY_n is the six-year difference in the natural log of annual nighttime luminosity of county n and Export Sanction$_n$ and Input Sanction$_n$ are export and intermediate input sanction exposures of county n, respectively. We use the county as the unit of analysis because our main treatment variables, export and intermediate input sanction exposures, can only be constructed at the county level given the limited information on firms in North Korea. In the estimation, we weigh each observation by the population share of the county in the year 2008 (the most recent year with official population census data) and report hetroskedasticity-robust standard errors.

Our identification assumption behind specification (4) is that, the two key regressors, export and input sanction exposure measures, are orthogonal to the error term ν_n. Drawing on the conditions for identification with Bartik estimators (Goldsmith-Pinkham et al., 2020), this can be interpreted as an orthogonality condition between the pre-sanction region-industry shares and the *changes* in the outcome variable after the sanctions. This condition would be violated if, for instance, regions more exposed to trade sanctions were experiencing specific economic shocks.[16] To mitigate such concern, later we present results from testing the

[15] Because of confidentiality issues, we have an agreement with the company not to disclose the list of products that we use for our analysis.

[16] Another possible violation of the orthogonality condition is if the UN's product sanction list was specifi-

relationship between sanction exposures and pre-trends in nighttime luminosity. Moreover, we present results from implementing robustness checks as suggested by Goldsmith-Pinkham et al. (2020). Alternatively, the identification assumption would also hold if the error term is uncorrelated with industry-specific sanction shocks at the national level (Borusyak, Hull and Jaravel, 2018). As described in Section 2, the UN sanctions against North Korea were designed to target top export products and specific import products, such as machinery and petroleum products, that are crucial for industrial production. Therefore, we believe it is unlikely for national-level industry shocks to be exogenous.

In addition to our baseline specification, we estimate an annual difference-in-differences specification that allows us to estimate the relationship between trade sanctions and night light intensity for each year:

$$Y_{nt} = \sum_{t=2013}^{2019} \left(\delta_t \text{Exp Sanc}_n \times 1\{\text{Year} = t\} + \gamma_t \text{Inp Sanc}_n \times 1\{\text{Year} = t\}\right) + \eta_n + \tau_t + \epsilon_{nt}, \quad (5)$$

where Y_{nt} denotes the natural log of night light intensity of county n in year t, η_n and τ_t denote county fixed effect and year fixed effect, respectively. δ_t and γ_t estimate year-specific parameters of interest, how night light varies with export and input sanction exposures in year t relative to 2013.

4.2 Main Results

Table 3 reports coefficient estimates of export and intermediate input sanction exposures.[17] Panel A shows long-difference estimates of sanction exposure indices from equation (4). The first two columns separately report estimates on export and intermediate input sanction exposures. Estimates suggest that an increase in export and intermediate input sanction exposures by 10 percentage points is associated with declines in night light intensity by 2.9 and 2.0 log points, respectively. The estimate for export sanction is statistically significant at the one percent level; the input sanction estimate is statistically insignificant. The third column reports estimates on both sanction exposures which are fairly similar to those when estimated separately (Columns 1 and 2). This is not surprising since export sanction and

cally designed to target certain regional economies in North Korea (e.g., ban export or import of items more crucial to the elites in Pyongyang). While this might have been the case with earlier sanctions, we do not see an obvious geographical concentration of exposure to trade sanctions imposed after 2016 (refer to Figure 2).

[17] In Table B-2, we also report estimates including import sanction exposure in specification (4). The export sanction estimate is qualitatively similar to that in Table 3. Without export or input sanction exposures, import sanction is estimated at -0.280 (s.e. $= 0.117$) but, when estimated together with export sanction, the estimate is -0.173 (s.e. $= 0.113$). The correlation between export and import sanction exposures is 0.38. However, in equations with both input and import sanctions the estimates are difficult to interpret since regional exposure to input and import sanctions are highly correlated (coefficient $= 0.83$).

Table 3: Long Difference Estimates of Sanction Indices

Panel A. Long-difference in log of annual average nighttime luminosity						
	Δ 2013-2019			Δ 2014-2019		
	(1)	(2)	(3)	(4)	(5)	(6)
Export Sanction Exposure	-0.288***		-0.287***	-0.312**		-0.311**
	(0.093)		(0.093)	(0.130)		(0.130)
Intermediate Input Sanction Exposure		-0.204	-0.200		-0.475**	-0.470**
		(0.181)	(0.177)		(0.223)	(0.226)
R-squared	0.07	0.01	0.08	0.05	0.02	0.07
Observations	174	174	174	174	174	174
Panel B. Pre-sanction difference in log of annual average in nighttime luminosity						
	Δ 2013-2015			Δ 2014-2015		
	(1)	(2)	(3)	(4)	(5)	(6)
Export Sanction Exposure	-0.006		-0.007	-0.030		-0.030
	(0.077)		(0.077)	(0.085)		(0.086)
Intermediate Input Sanction Exposure		0.165	0.166		-0.105	-0.105
		(0.209)	(0.209)		(0.225)	(0.226)
R-squared	0.00	0.01	0.01	0.00	0.00	0.00
Observations	174	174	174	174	174	174

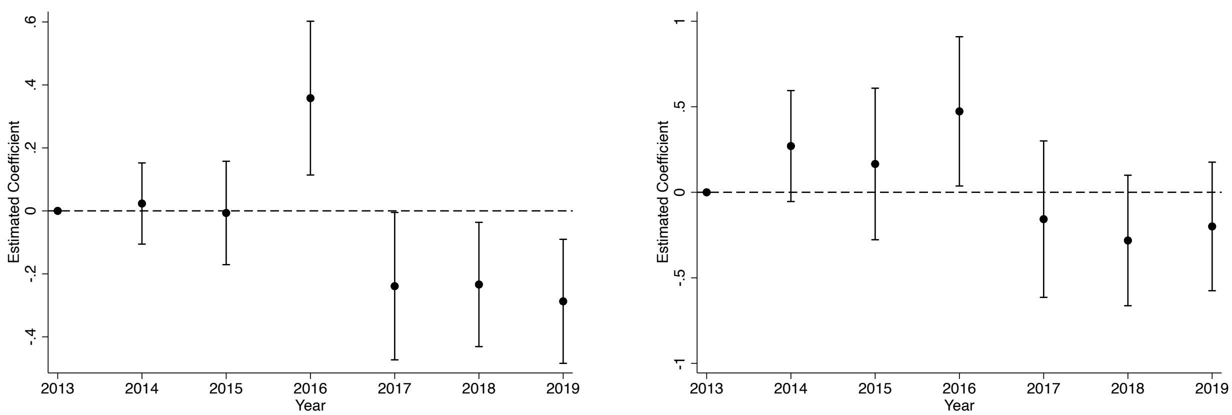
Notes: Dependent variable is the difference in log of annual mean nighttime luminosity, obtained by averaging VIIRS data at the county level. Observations are weighted by share of population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

intermediate input sanction exposures are not highly correlated (the correlation coefficient is -0.10). In Section 4.3, we convert these numbers into sensible economic measures by estimating the GDP-nightlight elasticity using Chinese county-level data.

In Panel B, we report estimates of pre-trends from regressing equation (4) with the difference in annual night light intensity between 2013 and 2015 as the outcome variable. The results suggest that export and input sanction exposure are not associated with pre-sanction trends in night light intensity: the estimate of export sanction exposure in columns 1 and 3 are close to zero while input sanction has a coefficient of 0.17 with a standard error of 0.21. Of course, failure to reject parallel trends with pre-sanction period data is not equivalent to confirming parallel counterfactual trends (Kahn-Lang and Lang, 2020). However, the test results on pre-trends do provide some suggestive evidence to validate our identification assumption. As a robustness check, we adopt the approach of Dix-Carneiro and Kovak (2017) and show that our estimates are robust to controlling for the pre-sanction change in night light intensity (in section 4.4).

Figure 3 shows year-specific estimated coefficients on export (Panel (a)) and intermediate input sanctions (Panel (b)) from estimating equation (5). Panel (a) suggests that counties subject to larger export sanction exposure experienced increases in night light intensity in 2016, the first year when UN trade sanctions were imposed, but their night light intensity declined and remained negative afterwards. (We offer a potential explanation for the positive effects in 2016 next) In Panel (b) the estimated coefficient for intermediate input sanction exposure is also positive from 2014 to 2016, suggestive of a positive pre-trend with input sanction exposure. Similar to export sanctions, annual estimates of input sanctions drop immediately after 2017 and remain negative and stable.[18] We discuss the implications and potential explanations of the positive pre-trend in details below.

Figure 3: Annual Coefficient Estimates of Sanction Exposures



(a) Export sanction

(b) Input sanction

Notes: This figure presents year-specific coefficient estimates of (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.

A potential explanation for the positive coefficient of export sanction exposure in 2016 is that, in anticipation of new sanctions on export products, firms were ramping up their production for exports. Specifically, UN Resolution 2270 (March 2016) permitted exports of coal and iron ore under the condition of exporting for people's livelihood. If North Korean exporters were anticipating additional bans on export products, such as apparel and iron ores, they could have increased production leading to an increase in night light intensity in counties with larger anticipated exposure to export sanctions. Subsequently, when the export ban was strengthened through UN Resolution 2321 (November 2016), which included iron ore exports, production in these sectors declined. In Online Appendix A.1.4, we analyze monthly trade data between China and North Korea. We find temporary growth in exports

[18]It is possible that in the longer term, the import sanctions will have an even larger effect on output due to the depreciation of capital stocks. In this case, our estimates can be seen as a lower bound of the overall effects of the sanctions.

of sanctioned products in the months immediately before the sanctions. However, the 2016 surge in exports and output among regions that are exposed to the export sanctions has no impact on our main reduced-form estimates using the long-difference specification.

The pre-trends in counties with high exposure to intermediate input sanctions from 2013 to 2015 deserve more discussion. Counties with high exposure to intermediate input sanctions specialize in heavy industries such as metals and chemicals, which could be prioritized by North Korea's strategic development plan (2011-2020). It is possible that the positive pre-trends are caused by extra resources allocated to these counties. At the same time, we see a significant decline in night light in these counties after the 2016-17 sanctions if we use 2014 (or later years) as the benchmark year. The results are presented in columns 4-6 of Table 3. In column 6, while the export sanction coefficient is close to that in column 3 the input sanction coefficient is -0.470 and now statistically significant at the 5% level. Such a decline can be explained by either a reversal of the strategic development plan (resources are allocated away from these counties) or a negative impact of the intermediate input sanctions.[19] Though it is hard to know to which extent each sector is supported by the strategic development plan during this entire period, we obtain a list of strategic sectors in the 2016-2020 Five-Year Economic Strategy and create an alternative input exposure measure excluding these sectors.[20] Compared to the baseline estimates using the 2013-2019 long difference, using this alternative measure suggests a more negative impact of the input sanctions (-0.422 instead of -0.200, see column 10 of Table B-9). Therefore, we believe that some of the negative effects may well be driven by the sanctions.

4.3 From Changes in Night Light Intensity to Changes in GDP

A remaining question is how we interpret the changes in night light intensity as changes in economic outcomes, such as output or value added. Estimating GDP-nightlight elasticity has been discussed extensively since the seminal work of Henderson et al. (2012), and various approaches have been proposed (Chor and Li, 2021; Hu and Yao, 2019). Instead of borrowing an elasticity from the literature, we estimate our preferred elasticity using data from a subset of Chinese counties with night light intensities and population densities that fall in the range of those observed in North Korea. We resort to Chinese data because we do not have measures of county-level GDP in North Korea. We believe that the elasticity estimated from the subset of Chinese counties provides a reasonable approximation for the GDP-nightlight elasticity

[19] The North Korean leader attributes the decline post 2017 to the sanctions. In a rare move, Kim Jong-un admitted the failure of the national economic development plans due to "external factors" during his opening speech of the 8th Congress of the Worker's Party on January 6, 2021.

[20] According to Ward and Han (2021), the North Korean government focused on the following products in the 2016-2020 Five-Year Economic Strategy: electricity, coal, steel, fertilizer, cement, textile, rail freight, and food. We map them to the following ISIC 2-digit manufacturing industries: 15, 17, 23, 24, 26, 27, 40.

among North Korean counties.

We discuss our data and methodology in detail in Online Appendix C and provide a brief summary here. We follow the panel-IV approach developed by Chor and Li (2021) and use lagged night light intensity as an instrumental variable to correct for the measurement errors in contemporary night light intensity (as a measure of true GDP). We use panel data of Chinese counties from 2013 to 2018 with both GDP and VIIRS night light data. In the IV regressions, we control for county and year fixed effects so that our elasticity better describes the relationship between *changes* in output and *changes* in nightlight intensity. In our preferred specification, we limit our sample to Chinese counties that are in the same range of night light intensity and population density as the North Korean counties in our sample, which means that we have to drop the most developed Chinese counties. This gives us a GDP-nightlight elasticity of 0.419. The estimates based on the full sample, a sub-sample selected only based on night light intensities and a sub-sample only including the three Northeastern provinces in China, are all similar to our preferred estimates. Our preferred estimate is also similar to Chinese prefecture-level estimates from Chor and Li (2021). [21]

Applying our estimated GDP-nightlight elasticity to the long-difference estimates in Column 3, Panel A of Table 3 implies that a 10 percent increase, which corresponds to a 0.45 standard deviation, in export sanction exposure reduces GDP by 1.2 percent (0.287*0.419*10). In addition, converting the estimate for input sanction in Column 6 implies that a 10 percent increase in input sanction, commensurate with an increase by 1.25 standard deviation, reduces GDP by 2.0 percent (0.470*0.419*10). To infer the aggregate impact of trade sanctions on North Korea's GDP, we conduct a back-of-the-envelope exercise as follows. First we calculate each county's response in night light intensity to trade sanctions by multiplying the county's export sanction exposures by the long-difference coefficient in Column 3 of Table 3. Second, we obtain the population-weighted sum of the change in nightlight over all counties and then multiply that term by our estimated GDP-nightlight elasticity. Our back-of-the-envelope calculation implies that export sanctions alone caused North Korea's GDP to fall by 6.9%. An important caveat to this exercise is that it does not take into account general equilibrium level effects. In Section 6, we discuss and quantify these effects using a spatial equilibrium model disciplined by the reduced-form coefficients.

[21] Our estimate is at the lower end of the range of estimates in Henderson et al. (2012), which use a different approach (imposing parametric assumptions on the size of the measurement errors in a subset of geographic units) and focus on the cross-section relationship between GDP and nightlight luminosity. We provide more discussions in Online Appendix C.

4.4 Robustness Checks

A plausible threat to the identification of trade sanction effects is that government response to sanctions may vary across regions. In a centrally planned economy, such as North Korea, the central government may have tight control over the allocation of resources and use its power to maximize its interest. For instance, the government can mitigate the negative effect of sanctions by deploying additional resources to regions with industries more severely affected by export sanctions at the cost of providing fewer resources to regions unaffected by trade sanctions. In this case, we expect that our estimates would be biased towards zero. To address this concern, we measure government response to sanctions using North Korean newspaper reports on visits by Kim Jong-un, the supreme leader of North Korea, to counties between 2017 and 2019. In North Korea, reports on Kim's visit to a specific region often represent the government's support for recent or future policy interventions (e.g., inspecting manufacturing factories or visiting construction sites). Accordingly, we check whether the number of visits by Kim Jong-un is systematically related to our export and input sanction exposures. Table B-5 presents the results. The estimates on export and input sanction coefficients indicate that reports on Kim's visits are not significantly correlated with regional sanction exposures.

We next present results from conducting a battery of robustness checks in Table 4. Column 1 shows that our results are robust to including province fixed effects that control for province-specific shocks. Columns 2 and 3 show that dropping the top and bottom one percentile and three percentile of counties, respectively, does not qualitatively change our results. In Columns 4 and 5 we show estimates from dropping counties in Pyongyang and counties proximate to the NK-Chinese border. Column 6 controls for the pre-sanction trend (2013-2015) in night light intensity. Column 7 controls for night light in 2015 and regional characteristics, and reports an export sanction coefficient estimate of -0.105 which is still statistically significant at the five percent level although the magnitude drops to about a third of the baseline estimate. Overall, the coefficient estimate for the export sanction is robust across all specifications.

In all columns other than Column (7), though statistically insignificant, the input sanction coefficient remains negative with similar magnitudes as the regressions reported in Table 3. It becomes close to zero once we control for pre-sanction nightlight intensities and other county characteristics. In Table B-6, we report robustness check results using 2014 as the base year. We find similar patterns: the export and input sanction coefficients are robust to alternative specifications, except for the latter coefficient when we control for county-level characteristics. These results are consistent with our discussion of the pre-trends in counties with higher exposure to input sanctions. As we discuss in Online Appendix B.2.1 and Table B-15, input sanction exposure is correlated with pre-sanction county characteristics such as population. Therefore, controlling for county characteristics is similar to controlling for the pre-trends, which are correlated with the post-sanction decline in nightlight intensities, rendering the input sanction coefficients to become insignificant.

Table 4: Robustness Check - Long Difference Estimates (2013-2019)

	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.	(Captial)	border	(2013-2015)	+ regional
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Export Sanction Exposure	-0.204***	-0.295***	-0.257***	-0.220***	-0.286***	-0.286***	-0.105**
	(0.074)	(0.090)	(0.043)	(0.068)	(0.097)	(0.092)	(0.040)
Intermediate Input Sanction Exposure	-0.230	-0.254	-0.231	-0.142	-0.147	-0.225	-0.011
	(0.145)	(0.166)	(0.146)	(0.166)	(0.176)	(0.171)	(0.110)
Province FE	Yes	No	No	No	No	No	No
R-squared	0.54	0.09	0.16	0.07	0.07	0.10	0.79
Observations	174	170	162	169	158	174	174

Notes: VIIRS nighttime light data is aggregated by county and quarter from 2013 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.

Our key regressors, the regional sanction exposure measures, are constructed as Bartik shocks, i.e., inner products of region-industry shares and the sanction exposures at the industry level.[22] 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). We provide a detailed discussion on the Bartik instruments and diagnostic results in Online Appendix Section B.2.1. The Rotemberg decomposition exercise reveals potential heterogeneity in each industry's treatment effects. We offer more detailed discussions about the implications of the industry-specific 2SLS coefficients in Online Appendix B.3.

We provide a battery of other robustness checks in Online Appendix B.2. First, our results (both 2013-2019 and 2014-2019 long-difference regressions) are robust to alternative weights for each company when constructing the industry shares in a county. Second, our results are similar when using alternative IO tables (China 1987 and 1997) or when using total instead of direct requirement to construct industry-level input sanction indices. Finally, we construct a measure of each county's responsiveness to aggregate output trends and show

[22] 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.

that our results are not driven by counties' heterogeneous exposure to other aggregate shocks during this period.

5 The Impact of Trade Sanctions on Market Prices

5.1 Empirical Strategy

We next investigate the impact of sanctions on market prices using quarterly market price data covering a period of seven years (2013-2019) across six major cities. We normalize each product's quarterly price to the level of the first quarter of 2013 (price = 100 in 2013 Q1). Figure 4 plots price trends of products averaged by sanction category. The red dashed horizontal lines indicate the timing of UN sanction resolutions and blue short-dashed lines mark the two North Korea-United States summits that took place on June 12, 2018 in Singapore and February 27, 2019 in Hanoi, Vietnam. There are three points to take away from this figure. First, the average import-sanctioned product shows a drastic price increase (the average price doubles from 2017 Q4 to 2018 Q1) after sanctions in 2017 Q4 and remains high throughout the post-sanction period of our data. Second, the average price of export-sanctioned products remains relatively stable until the first quarter of 2019 but falls by almost half afterwards. Third, there is not much change in the average price of non-sanctioned products during the entire seven-year period. Putting these findings together suggests that trade sanctions were associated with considerable changes in market prices for products affected by those sanctions but not for products that were not subject to trade sanctions.

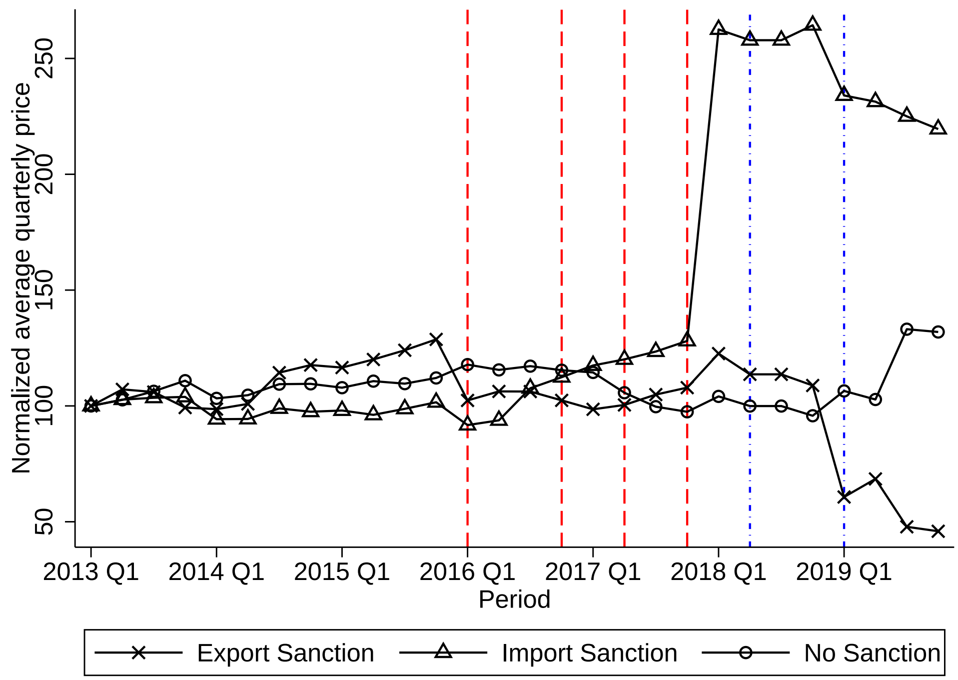
In our empirical investigation of the effect of trade sanctions on market price we compare price changes before and after the sanction shock across 72 products. Specifically, we restrict each product's sample period to eight quarters before and eight quarters after the quarter the product was sanctioned and estimate the following difference-in-differences specification:

$$Y_{pct} \quad = \quad \beta_1 \mathbf{1}(p \in P_{EX}) \times \text{Post}_{pt} + \beta_2 \mathbf{1}(p \in P_{IM}) \times \text{Post}_{pt} + \delta_p + \delta_c + \delta_t + \epsilon_{pct} \tag{6}$$

where Y_{pct} is normalized price of product p in city c at time t, P_{EX} is the set of export-sanctioned products, P_{IM} is the set of import-sanctioned products.[23] Each sanction indicator is interacted with Post_{pt}, which is equal to one if product p is sanctioned before or in period t and zero, otherwise. We include product (δ_p), city (δ_c), and quarter (δ_t) fixed effects along with the idiosyncratic error term (ϵ_{pct}). Standard errors are clustered at the product level.

[23] We can also include the share of sanctioned inputs for each product p, which takes a common value for all products belonging to the same industry j. We leave out the input sanction coefficient from our baseline price regression since input and import sanctions would be highly correlated. The table results with input sanction is shown in a separate table in the Appendix.

Figure 4: Price Trend by Product's Sanction Status



Notes: This figure plots normalized average quarterly price trends of products grouped by sanction type. Average quarterly price is obtained by averaging across six cities in North Korea (Pyeongyang, Shineuijoo, Kwaksan, Wonsan, Hweiryoung, Hamheung) and normalized with respect to first quarter of 2013. 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.

5.2 Estimation Results

Table 5 reports OLS estimates on the product sanction coefficients. Column 1 shows a negative estimate of -0.032 for export sanction but is not statistically significant at conventional levels. Column 2 shows that the average price of import-sanctioned products increased by 31.9 log points after the sanction relative to before. Column 3 also suggests a rise of 32.2 log points in the average price of import sanctioned products even when export sanction is estimated together. The results in Columns 2 and 3 are economically and statistically significant. In Table B-16, we report estimates from regressions including input sanctioned products. Input sanction coefficient estimate has a similar magnitude (increase by 35.8 log points) and statistical significance to that of import sanction. However, since import sanctions and input sanctions are highly correlated due to each industry's high usage of its own output as input, we do not have sufficient power to identify their effects on prices separately. For completeness, we report regressions including both terms in Table B-16 and find that the impact of import sanctions remains significant.

Table 5: 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	-0.029		-0.040
	(0.068)		(0.065)	(0.070)		(0.066)
Import Sanction $\times \mathbf{1}$(Post Sanction)		0.319***	0.322***		0.353***	0.356***
		(0.056)	(0.052)		(0.061)	(0.059)
Export Sanction $\times \mathbf{1}$(Post Sanction) $\times$ Pyongyang				-0.023		-0.005
				(0.042)		(0.028)
Import Sanction $\times \mathbf{1}$(Post Sanction) $\times$ Pyongyang					-0.204	-0.202
					(0.157)	(0.152)
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	0.81	0.81	0.81	0.81	0.81	0.81
Number of products	72	72	72	72	72	72
Observations	6825	6825	6825	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.

One plausible concern for a causal interpretation of the price effect of sanctions is the existence of pre-trends for products that happened to be sanctioned. Descriptively, as shown in Figure 4, the average quarterly price trend is relatively stable prior to the year 2018, which may partly assuage such concerns. Empirically, we conduct placebo tests by moving the sanction period earlier by one and two years, respectively. If import-sanctioned products were already experiencing a price increase before the sanctions, then it should be captured by these placebo sanction indicators. The results are presented in Online Appendix Table B-17. Across all columns and panels, we find no evidence of significant increases in the prices of import-sanctioned products in periods preceding the actual imposition of import sanctions.

The above results imply that on average the price of import-sanctioned products significantly increased after trade sanctions were imposed. Yet, the magnitude of the price increase may vary across cities as domestic trade costs also vary from city to city. Online Appendix Figure B-5 separates Pyongyang from the other five cities and plots the average quarterly price of products by sanction category for Pyongyang only and for the other cities. First, before the first quarter of 2018, there was not much difference in prices between Pyongyang and non-Pyongyang cities. Second, there is a notable divergence in the price of import-sanctioned products starting from 2018 Q1, which is right after the last wave of trade sanctions, and does not converge for the next two years that we observe in this data. Note that there is no observable pattern of divergence in export-sanctioned or non-sanctioned products between Pyongyang and the other cities. As the country's capital city, it is possible that prices for import-sanctioned products were held stable by sourcing imported products from other regions or supplying domestic products to appease the country's elites. Columns 4-6, Table 5 reports estimates from regressing an extended model of equation (6) to incorporate heterogeneity with respect to Pyongyang city. The estimation results largely support these findings.

6 Quantifying the General Equilibrium Impact of the Sanctions

In this section, we develop a spatial equilibrium model to characterize the North Korean economy. The model serves two main purposes. First, it helps us estimate key parameters of the North Korean economy, especially a parameter that governs the country's reliance on foreign goods and markets. Second, we use the model to calculate the aggregate impact of the current sanctions regime as well as counterfactual sanction situations.

6.1 Model Setup

In our model, there are $n = 1, \ldots, N$ regions (counties) in North Korea. Each region is endowed with L_n workers, and we assume they are not mobile across regions.[24] In each region, there is potentially production in sector $j = 1, \ldots, J$. We denote the set of domestic regions by the calligraphic $\mathcal{N}$ and the set of sectors by $\mathcal{J}$. North Korea is a small open economy that takes the foreign expenditure on its output in sector j, $E_{F,j}$, and the foreign price of imported goods in sector j, $p_{F,j}$ as exogenous.

In each region n and sector j, a sector-specific composite good is used for both intermediate input and consumption use as in Caliendo and Parro (2015)

$$Q_{n,j} = \left(\alpha_{dom}^{1/\sigma} \left(Q_{n,j}^{dom}\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha_{dom})^{1/\sigma} \left(Q_{n,j}^{for}\right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \quad Q_{n,j}^{dom} = \left[\sum_{i \in \mathcal{N}} (q_{in,j})^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}},$$

where the composite good $Q_{n,j}$ is a nested CES aggregator of goods sourced from different origins. The upper nest is between the domestic composite $Q_{n,j}^{dom}$ and the foreign goods $Q_{n,j}^{for}$, with an Armington elasticity σ. The lower nest is among final goods $q_{in,j}$ sourced from different regions i within North Korea, with an Armington elasticity ϵ. The home bias parameter, α_{dom}, controls the expenditure share of domestic composite goods. Formally,

[24] According to The United Nations Human Rights Council (2014) that disclosed the human rights status in North Korea, North Koreans do not have the freedom to choose where to live. They are not allowed to move from designated residences to other residences without official permission from the authorities. Our interviews with North Korean defectors confirmed that such permission to relocate residences or workplaces is possible only in exceptional circumstances with valid documents of proof. However, we cannot rule out the possibility that the government relocate workers after the sanctions. If this is the case, our model may over-estimate the impact of the sanctions.

denoting the price index of the domestic composite goods as $P^{dom}_{n,j}$, the price of foreign goods as $p_{F,j}$ and the iceberg trade costs between the rest of the world and region n as τ_{Fn}, the final price index faced by consumers and producers (for purchasing intermediate inputs) is

$$P^{u}_{n,j} = (1 + t^{u}_{n,j}) \left(\alpha_{dom} \left(P^{dom}_{n,j} \right)^{1-\sigma} + (1 - \alpha_{dom}) \left(\tau_{Fn} p_{F,j} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} .$$

We use $t^{u}_{n,j}$ to denote the sales tax/subsidy of final/intermediate goods in sector j and region n. The superscript u can be either fin for final goods or int for intermediate inputs. Positive $t^{u}_{n,j}$ can be seen as "taxes", which tend to raise the price of goods j in location n faced by consumers/firms, while negative $t^{u}_{n,j}$ can be seen as "subsidies" having the opposite effects. We set all $t^{u}_{n,j}$ to zero in our baseline calibration but consider the possibilities of various taxes/subsidies that the North Korean government use to offset effects of the sanctions as robustness checks.[25] The expenditure share of domestic composite goods is

$$s^{dom}_{n,j} = \frac{\alpha_{dom} \left(P^{dom}_{n,j} \right)^{1-\sigma}}{\alpha_{dom} \left(P^{dom}_{n,j} \right)^{1-\sigma} + (1 - \alpha_{dom}) \left(\tau_{Fn} p_{F,j} \right)^{1-\sigma}}. \tag{7}$$

This share is closely related to the export-to-GDP ratio of the country.

Competitive firms produce final goods $q_{n,j}$ combining labor and intermediate inputs from all upstream sectors according to the following Cobb-Douglas production function

$$q_{n,j} = A_{n,j} \left(\frac{L_{n,j}}{a_{jL}} \right)^{a_{jL}} \prod_{k \in \mathcal{J}} \left(\frac{Q_{n,kj}}{(1 - a_{Lj}) a_{kj}} \right)^{(1-a_{Lj}) a_{kj}} , \quad L_{n,j} = \left(\frac{L^{m}_{n,j}}{\alpha_m} \right)^{\alpha_m} \left(\frac{L^{s}_{n,j}}{1 - \alpha_m} \right)^{1-\alpha_m} ,$$

where $A_{n,j}$ denotes the productivity of sector j in location n, $Q_{n,kj}$ is the quantity of composite goods of sector k used by j. Composite labor $L_{n,j}$ is a Cobb-Douglas aggregator of labor that is mobile across sectors, $L^{m}_{n,j}$, and labor that is specific to sector j, $L^{s}_{n,j}$. The shares of mobile and specific labor are α_m and $1 - \alpha_m$, respectively. We impose constant returns to scale, i.e., $\sum_k a_{kj} = 1$. Our interviews with North Korean émigré reveal that labor is not freely mobile across sectors even within a region. However, in the very long term, the government may decide to allocate labor according to national or international demand. We allow for both types of labor so that we can experiment with various degrees of cross-sector labor mobility. In our baseline calibration, we assume that labor is perfect mobile in the pre-sanction equilibrium ($\alpha_m = 1$) but cannot move at all after the sanctions ($\alpha_m = 0$). We use perfect mobility $\alpha_m = 1$ for the post-sanction equilibrium as a robustness check. Due to

[25] We know very little about the actual policies that North Korea uses to influence output in different locations and sectors. However, we still think these wedges are useful for understanding the potential effects of post-sanction government responses.

perfect competition, the unit cost of producing $q_{n,j}$ becomes

$$c_{n,j} = (w_n^m)^{a_{jL}\alpha_m} \left(w_{n,j}^s\right)^{a_{jL}(1-\alpha_m)} \prod_{k\in\mathcal{J}} P_{n,k}^{(1-a_{Lj})a_{kj}},$$

where w_n^m is the wage of mobile labor and $w_{n,j}^s$ is the wage of labor that is specific to sector j.[26]

We denote the iceberg trade costs to ship from origin i to n as τ_{in}. Due to perfect competition, the price of goods from i faced by consumers in region n is $\tau_{in}c_{i,j}/A_{i,j}$. The share of location n's domestic expenditure on sector j goods from origin i takes the gravity form

$$x_{in,j} = \frac{(\tau_{in}c_{i,j}/A_{i,j})^{1-\epsilon}}{\sum_{o\in\mathcal{N}}(\tau_{on}c_{o,j}/A_{o,j})^{1-\epsilon}}.$$

The corresponding price index for the domestic composite goods is

$$P_{n,j}^{dom} = \left(\sum_{o\in\mathcal{N}}(\tau_{on}c_{o,j}/A_{o,j})^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}.$$

Note that we have adopted the "Armington setup" to derive trade shares that follow gravity. We can derive similar expressions following the setup in Eaton and Kortum (2002), in which the trade elasticity $\epsilon - 1$ will be interpreted as the concentration of productivity draws of producers in the same sector.

For domestic consumers, we assume that they have Cobb-Douglas preferences for goods in different sectors, and the consumption shares are ξ_j. Final goods are exported to the rest of the world, consumed by domestic consumers, or used by downstream sectors as inputs. Foreign demand (of quantity) in each sector is isoelastic in North Korean aggregate border prices, i.e., $B_j\left(P_{F,j}^{dom}\right)^{-\eta}$ (see Caliendo and Feenstra (2022) for the microfoundations of this functional form in Armington models). The price $P_{F,j}^{dom}$ reflects sourcing from all potential North Korean regions by the foreign country

$$P_{F,j}^{dom} = \left(\sum_{o\in\mathcal{N}}(\tau_{oF}c_{o,j}/A_{o,j})^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}},$$

where τ_{oF} is the trade cost between domestic region o and the foreign country. The demand

[26] Workers in North Korea may not be paid according to their marginal product of labor. Note that the perfect competitive labor market assumption does not affect labor allocation in response to the sanctions in our baseline model, as we assume that all labor is sector-specific and its allocation does not respond to the sanctions. However, the assumption that all of the marginal product of labor is paid to the worker for consumption makes a difference if the government takes a large share of the marginal product and its expenditure patterns are very different from those of households.

elasticity η reflects the substitutability between North Korean goods and goods from other countries, from the perspective of foreign consumers/firms.[27]

Therefore, the goods market clearing condition can be written as

$$R_{n,j} = \sum_{i\in\mathcal{N}} x_{ni,j} s_{i,j}^{dom} \frac{\xi_j E_i}{1+t_{i,j}^{fin}} + \sum_{i\in\mathcal{N},k\in\mathcal{J}} x_{ni,j} s_{i,j}^{dom} \frac{(1-a_{Lk})a_{jk}R_{i,k}}{1+t_{i,j}^{int}} + x_{nF,j} B_j \left(P_{F,j}^{dom}\right)^{1-\eta}, \quad (8)$$

where $R_{n,j}$ denotes the output value of sector j in region n. On the right-hand side of equation (8), the three terms denote the usage of output by domestic consumers and domestic downstream industries, and foreign buyers, respectively. In particular, domestic consumption by a particular destination i depends on the trade shares $x_{ni,j}$, the industry consumption shares ξ_j and total consumer expenditure E_i. The second term captures the usage of the output from sector j, location n by all downstream industries in all locations. Finally, foreign demand depends on foreign total expenditure on sector j goods produced by North Korea $B_j \left(P_{F,j}^{dom}\right)^{1-\eta}$ and the share that foreign buyers source from a particular county n, $x_{nF,j}$. We assume that foreign consumers also have a CES demand for North Korean goods produced in different regions with an elasticity of substitution ϵ. Therefore, the expenditure shares $x_{nF,j}$ can be written as

$$x_{nF,j} = \frac{(\tau_{nF} c_{n,j}/A_{n,j})^{1-\epsilon}}{\left(P_{F,j}^{dom}\right)^{1-\epsilon}} = \frac{(\tau_{nF} c_{n,j}/A_{n,j})^{1-\epsilon}}{\sum_{o\in\mathcal{N}}(\tau_{oF} c_{o,j}/A_{o,j})^{1-\epsilon}},$$

where τ_{nF} is the iceberg trade cost from region n in North Korea to the rest of the world.

The total consumer expenditure, in turn, equals the sum of labor income in region i and a transfer, capturing exogenous trade imbalances and endogenous sales tax revenues. In particular, total sales tax revenue collected from sales of goods j in location n can be written as

$$\frac{t_{n,j}^{fin}}{1+t_{n,j}^{fin}} \xi_j E_n + \frac{t_{n,j}^{int}}{1+t_{n,j}^{int}} \sum_k (1-a_{Lk}) a_{jk} R_{n,k}.$$

We assume that the exogenous trade imbalance, T, is distributed across regions according to weights ω_n^T. We incorporate this feature because North Korea has been running trade deficits, and the deficits increased dramatically after the sanctions and are important for the model's aggregate predictions. In addition, the North Korean government distributes the total sales tax revenue, according to weights ω_n^t across locations. Therefore, the disposable

[27] We do not distinguish whether the exports are for final consumption or for intermediate input usage. Since we assume that North Korea is a small open economy and takes $B_{F,j}$ as exogenous, the exact usage of exports is irrelevant in our model.

income (and total expenditure) E_n equals

$$E_n = w_n^m L_n^m + \sum_j w_{n,j}^s L_{n,j}^s + \omega_n^T T + \omega_n^t \sum_{i,j} \left(\frac{t_{i,j}^{fin}}{1+t_{i,j}^{fin}} \xi_j E_i + \frac{t_{i,j}^{int}}{1+t_{i,j}^{int}} \sum_k (1-a_{Lk}) a_{jk} R_{i,k} \right)$$

It is clear from equation (8) that the final goods are consumed by domestic or foreign consumers, or used as intermediate inputs by downstream sectors. Given all equilibrium prices, we can solve $R_{n,j}$ from the $N \times J$ equations as (8). Finally, we express the labor market clearing conditions

$$\sum_{j \in \mathcal{J}} L_{n,j}^m = L_n^m, \tag{9}$$

where L_n^m is the mobile labor in region n.[28] We have the following definition of the general equilibrium

Definition 1. *A general equilibrium under $\alpha_m = 1$ is a vector of allocations $L_{n,j}^m$ and prices w_n^m such that goods markets clear according to condition (8), and labor markets clear according to condition (9).*

A general equilibrium under $\alpha_m = 0$ is a vector of prices $w_{n,j}^s$ such that goods markets clear according to condition (8).

A general equilibrium under $\alpha_m \in (0,1)$ is a vector of allocations $L_{n,j}^m$ and prices $w_n^m, w_{n,j}^s$ such that goods markets clear according to condition (8), and labor markets clear according to condition (9).

We now discuss how we model "sanctions" in this setup. Recall that we have defined the export and import sanction exposure measures, $S_{EX,j}$ and $S_{IM,j}$, in equations (1) and (2). These measures represent the pre-sanction shares of exports and imports of goods belonging to a particular industry j that were sanctioned by the UN in 2016-2017. Zeros mean no sanction at all and ones mean full sanctions.

For export sanctions, we simply assume that the foreign demand shifters on North Korean goods $B_{F,j}$ drops to $(1 - S_{EX,j})B_{F,j}$. For import sanctions, we connect the share $S_{IM,j}$ to the foreign prices that North Korea faces. In particular, we assume that the foreign imported goods are a continuum of symmetric varieties at the same price $p_{F,j}(\omega)$. They are combined in a CES aggregator with an elasticity of substitution θ. The import sanctions prohibited a fraction of $S_{IM,j}$ of these goods from being traded. The foreign price p_{Fj} that we introduced earlier is the price index of the composite foreign good, and the change in $p_{F,j}$ can be written

[28] We assume that labor is fully employed in each region. However, if regional total employment can adjust endogenously as in other context (see Adão et al. (2022), our model will generate larger cross-sectional responses to sanctions, taking all other model parameters fixed. To match the same cross-region responses, we need to modify other parameters to dampen the responses. It is unclear how the assumption of full employment will bias the aggregate predictions of the model.

as

$$\hat{p}_{F,j} \equiv \frac{p'_{F,j}}{p_{F,j}} = \frac{\left(\int_0^{1-S_{IM,j}} p_{F,j}(\omega)^{1-\theta} d\omega\right)^{1/(1-\theta)}}{\left(\int_0^1 p_{F,j}(\omega)^{1-\theta} d\omega\right)^{1/(1-\theta)}} = (1 - S_{IM,j})^{1/(1-\theta)}. \tag{10}$$

The change in the price index of the final composite good of sector j, region n becomes

$$\hat{P}^u_{n,j} = \frac{P^{u\prime}_{n,j}}{P^u_{n,j}} = \widehat{1+t^u_{n,j}} \left(s^{dom}_{n,j}(\hat{P}^{dom}_{n,j})^{1-\sigma} + (1 - s^{dom}_{n,j})(\hat{p}_{F,j})^{1-\sigma}\right)^{\frac{1}{1-\sigma}}, \tag{11}$$

where $\widehat{1+t^u_{n,j}}$ denotes the effect of changes in taxes and s^{dom}_j is the expenditure share on domestic goods in the base period as defined in equation (7). Under complete import sanctions, we have $\hat{p}_{F,j} = \infty$ and

$$\hat{P}^u_{n,j} = \widehat{1+t^u_{n,j}} \hat{P}^{dom}_{n,j} \left(s^{dom}_{n,j}\right)^{\frac{1}{1-\sigma}}, \tag{12}$$

which resonates with the formula for the welfare gains from trade in Arkolakis, Costinot and Rodríguez-Clare (2012). Under partial import sanctions, the parameter θ governs the relationship between $S_{IM,j}$ and the change in prices (equations 10 and 11). In our calibration, we adjust the value of θ to match the response of prices to import sanctions.[29]

6.2 Parameterization and the Aggregate Impact

We now parameterize our model, and the calibration and estimation results are summarized in Tables 6 and 7. Panel A of Table 6 displays the parameters that are calibrated without solving the model. We choose five sets of parameter values from the literature. First, the domestic Armington elasticity across regions, ϵ, is set to five, implying a domestic trade elasticity of four as in Simonovska and Waugh (2014). Second, for the Foreigner's Armington elasticity between goods from North Korea and other origins, we set the value to two, close to the median value across industries estimated by Feenstra et al. (2017). Third, we calibrate the domestic trade costs τ_{in}. We do not have direct information about the domestic trade costs or trade flows in North Korea. To discipline these parameters, we combine the road network distance between any two counties in North Korea and an estimate of the impact of road distance on trade costs in China. In particular, Fan, Lu and Luo (2021) estimate that an additional 100 km of (regular) road distance increases trade costs by 4.2%. Therefore, we set the trade costs between two North Korean counties i and n at $\tau_{in} = e^{0.042 d_{in}}$, where d_{in} is the

[29]In equation (10), we have made an implicit assumption that the foreign prices of non-sanctioned products do not change after the sanctions. This is a standard assumption in small-open-economy models. In addition, Figure 4 shows that the prices of non-sanctioned products are stable before and after the sanctions, supporting our modeling assumption.

length of the shortest path from i to n based on the map from www.openstreetmap.org.[30] We set the trade costs between county n and the rest of the world at twice the value of the domestic trade costs from n to the China-North Korea border.[31] Fourth, we use China's 2002 Input-Output Table to compute labor and input shares in each sectors' production, consistent with our empirical strategy. We also use China's consumption shares in each industry in 2002 to calculate ξ_j. Finally, we simply set the share of foreign and domestic transfers received by country n to be proportional to its population.

Table 6: Calibrated and Estimated Parameters

Parameters	Description	Value	Source / Targets
Panel A: Calibrated (without solving the model)			
ϵ	Domestic Regional Armington Elasticity	5	Simonovska and Waugh (2014)
η	Foreigners' Armington Elasticity	2	Feenstra et al. (2017)
τ_{in}	Domestic iceberg trade costs	$e^{0.042 d_{in}}$	Fan et al. (2021)
$\tau_{nF} = \tau_{Fn}$	International iceberg trade costs	$2\tau_{n,border}$	Twice the domestic trade costs to the China-NK border
a_{Lj}, a_{jk}	Labor/input shares		China IO Table 2002
ξ_j	Share of j in consumption		China IO Table 2002
$\omega_n^T = \omega_n^t$	Share of transfers received by county n	L_n/L	Population share (2008)
Panel B: Estimated in the inner loop			
p_{Fj}	Foreign prices in the base period		Shares of goods j in imports, 2011-2015
B_j	Foreign demand shifter for goods j		Shares of goods j in exports, 2011-2015
$\tilde{A}_{nj}$	Productivity of sector j in region n		Share of firms weighted by log(# mention + 1) in each county
$\tilde{A}_n$	Region-specific productivity		Shares of country n's output approximated by $(Light_n^{2013})^{0.419}$

Notes: d_{in} denotes the road network distance between counties i and n. L_n is the population of county n according to the 2008 census. We use value-added shares for a_{Lj} and interpret "labor" as labor equipped with capital.

We estimate the remaining parameters by solving the model and matching moments that we observe from the data. We perform the estimation in two loops. In the inner loop, given the "macro" Armington Elasticity σ, the elasticity of substitution between varieties of foreign goods, θ, and the home bias parameter, α_{dom}, we estimate the foreign prices, $p_{F,j}$, the foreign demand shifters B_j, the productivities A_{nj} by matching shares of goods j in pre-sanction imports/exports, output shares of industry j in region n, and shares of each county's output. We parameterize A_{nj} as the product of a region-sector-specific component $\tilde{A}_{nj}$ and a region-specific component $\tilde{A}_n$, i.e., $A_{nj} \equiv \tilde{A}_n \times \tilde{A}_{nj}$. Denoting output in region n, industry j by R_{nj}, and total output in region n by $R_{n\cdot} \equiv \sum_j R_{nj}$, we choose $p_{Fj}, \tilde{A}_{nj}, \tilde{A}_n$ to

[30] It is possible that the domestic trade costs are larger in North Korea than those in China and the semi-elastic functional form may not be a precise description. We later experiment with higher trade costs, as well as a specification with log-log trade costs in Online Appendix D.4.

[31] Our assumption on the level of international trade costs is innocuous since the export-to-GDP ratio will also be affected by the home-bias parameter α_{dom}. Higher international trade costs will have a similar effect as imposing higher α_{dom}, but what matters for the aggregate impact is the base-period export-to-GDP ratio and other elasticities such as σ.

minimize

$$\sum_j \left| \frac{IM_j^{model}}{IM^{model}} - \frac{IM_j^{data}}{IM^{data}} \right| + \sum_{n,j} \left| \frac{R_{nj}^{model}}{R_{n\cdot}^{model}} - \frac{R_{nj}^{data}}{R_{n\cdot}^{data}} \right| + \sum_n \left| \frac{R_{n\cdot}^{model}}{R^{model}} - \frac{R_{n\cdot}^{data}}{R^{data}} \right|.$$

Import shares IM_j^{data}/IM^{data} are obtained from aggregate trade data in 2011-2015. As in our reduced-form analysis, we interpret the share of firms weighted by the log of the number of mentions plus one as a proxy for the local revenue shares of sector j, $R_{nj}^{data}/R_{n\cdot}^{data}$. We use our estimated GDP-nightlight elasticity, 0.419, to infer each county's output. We assume that $R_{n\cdot}^{data}$ is proportional to $(Light_n^{2013})^{0.419}$, which yields the last set of moments $R_{n\cdot}^{data}/R^{data}$. Since we are matching shares, we normalize the geometric mean of $p_{Fj}, \tilde{A}_{nj}, \tilde{A}_n$ all to one. We do not directly search for a vector of foreign demand shifters B_j. Instead, we set the value of $B_j \left(P_{F,j}^{dom}\right)^{1-\eta}$ on the right hand of equation (8) to the observed exports EX_j in the period of 2011-2015 when solving the model. After the model is solved, we back out $B_j = EX_j \left(P_{F,j}^{dom}\right)^{\eta-1}$ using the equilibrium prices.

In the outer loop, we search for the values of North Korea's Armington elasticity between foreign and domestic goods, σ, the elasticity between different foreign varieties θ, and the home bias parameter α_{dom} such that the model can match (1) the response of output to export sanction exposure as estimated in Column 3 of Table 3 (scaled by the GDP-nightlight elasticity 0.419); (2) the response of price to import sanction as estimated in Column 3 of Table 5; (3) an export-to-GDP ratio of 0.25.[32] As described in Section 6.1, to simulate the post-sanction economy, we reduce the foreign demand shifter $B_{F,j}$ to $(1 - S_{EX,j})B_{F,j}$ and change foreign prices according to equation (10), i.e., $\hat{p}_{F,j} = (1 - S_{IM,j})^{1/(1-\theta)}$. We also adjust the trade deficits to match the level in 2018. North Korea's trade deficit increased by 2.2 times after the sanctions. In our calibration, we use the total exports in the base period as the numeraire and normalize it to one. Trade deficits in both the base and post-sanction periods are measured relative to the numeraire, with $T = 0.18$ and $T' = 0.58$. For the price regressions, we select the six counties and eleven industries that correspond to the cities and products in our price data.[33] Since we use a sanction dummy in our city-product level regressions, we consider an industry being "sanctioned" if its export/import sanction indices are above 0.9. Table 1 shows that the export/import sanction indices of the majority of industries are close to either one or zero. We then project the change in consumption prices

[32]We calculate this ratio based on trade data before the sanctions and GDP statistics published by the Bank of Korea (BoK). Online Appendix A.3 provides a summary of the methodology that the BoK uses to estimate GDP for North Korea.

[33]Five "cities" in our price data are actually administrative counties. The only exception is Pyeongyang, which consists of a central district (Pyeongyang City) and four peripheral counties (Kangdong, Junghwa, Kangnam, Sangwon), all seen as administrative counties. We only include the central district in our simulated price regressions because the price data only covers a market there but not in the peripheral counties.

$\log \hat{P}^{fin}_{n,j}$ on these sanction dummies and use the coefficient of the import sanction dummy as the model counterpart for the reduced-form estimates.

We now discuss the intuition of the identification of the three outer-loop parameters. When σ is higher, domestic and foreign goods are more substitutable to each other. A decline in foreign demand will lower domestic wages and prices, which, in turn, boost consumption of domestic products. Such an effect is larger when σ is higher. Conditional on the export-to-GDP ratio, the output response to export sanctions will help us identify σ. Next, from equation (10), a higher θ implies a smaller direct impact of import sanctions on the prices of foreign goods at the border, p_{Fj}. Therefore, conditional on σ and other base-period shares, higher θ will reduce the response of consumption (and intermediate input) prices to import sanctions (equation 11). Finally, it is straightforward that a higher home bias α_{dom} will lower the export-to-GDP ratio, according to equation (7). It is worth noting that the value of the home bias parameter will depend on the level of inner-loop parameters $p_{Fj}, \tilde{A}_{nj}, \tilde{A}_n$ and the international trade costs. We have normalized the other parameters and used the export-to-GDP ratio to discipline the home bias parameter. In Online Appendix D.2, we provide more comparative statics with respect to the model parameters to understand the identification.

Table 7: Parameters Calibrated in the Outer Loop: Baseline and Alternative Models

Panel A: Calibration								
Data Moments		Baseline Model			Model with Input Subsidies			
Description	Moment	Parameter	Value	Moment	Parameter	Value	Moment	
Coef: Exp. Sanc. on Output	-0.120	σ	1.4	-0.114	σ	1.5	-0.110	
Coef: Imp. Sanc. on Prices	0.322	θ	6.0	0.328	θ	7.0	0.320	
Export-to-GDP ratio	0.250	α_{dom}	0.60	0.253	α_{dom}	0.56	0.256	
Panel B: Implied Aggregate Effects								
			Exp.+Imp.	Exp. Only		Exp.+Imp.	Exp. Only	
Δ% real output			-12.9	-6.4		-9.6	-6.3	
Δ% real pre-tax income			-15.3	-7.7		-11.0	-7.5	
Δ% real income			-15.3	-7.7		-16.5	-7.5	

Notes: in Panel A, we present the parameter values and their corresponding data/model moments for two models: the baseline model and a model with subsidies to intermediate inputs that face import sanctions. Panel B provides the implied aggregate effects under each version of the calibration. For each calibration, we report the impact of the current export and import sanctions, as well as the impact of export sanctions alone.

In Panel A of Table 7, we report the calibration results for the outer loop parameters. To reduce computational burden, we do a grid search for $\sigma, \theta, \alpha_{dom}$ at the precision of 0.1, 0.5 and 0.01, respectively. In our baseline model, we find the elasticity between domestic and foreign goods for North Korea to be 1.4. It is lower than an Armington elasticity of five implied by Simonovska and Waugh (2014), but is in line with the range of industry-level Armington elasticities estimated by Feenstra et al. (2017) (between 0.88 and 3.60 in their two-step GMM estimates). We find the value of the home bias parameter α_{dom} to be 0.60, though the value itself is not informative without taking into account the levels of $p_{Fj}, \tilde{A}_{nj}$ and $\tilde{A}_n$. We estimate the value of θ to be 6.0, suggesting that the substitution between foreign varieties within a sector is much easier than the substitution between foreign and domestic goods.

Panel B presents the implied aggregate effects in our calibration. We first compute the changes in real output, real pre-tax income and real income at the county level and then aggregate them across counties using population as weights.[34] Real output is defined as the value of total output evaluated at base period prices, while real income is the total labor income in a county divided by its aggregate price index (only considering manufacturing labor income and prices). Pre-tax income is the same as labor income in our baseline since we assume zero taxes/subsidies, $t^{u\prime}_{nj} = t^{u}_{nj} = 0$. We find that the export and import sanctions jointly reduce North Korea's real manufacturing output by 12.9% and real labor income by 15.3%. Since the reduced-form evidence for the impact of input sanction exposure is not as robust as that for export sanction exposure, we also report the effects of export sanctions alone. The export sanctions reduce real output and income by 6.4% and 7.7%, respectively.

The model captures several general equilibrium mechanisms that generate "level effects" and are absent from the cross-sectional reduced-form estimates. First, trade in intermediate inputs and final goods between domestic regions leads to "negative spillovers" and creates a negative level effect: regions that are hit harder by the sanctions buy fewer goods from other regions, so regions not directly affected by the sanctions also reduce output. Such spatial linkages are also emphasized by Adão et al. (2022). Second, though workers cannot move across regions, intermediate inputs are reallocated from regions that are more exposed to the sanctions to the others, and will increase the output in the latter group of regions and create a positive level effect. We prove the existence of such an effect in a special case of the general equilibrium model in Online Appendix D.1. Finally, North Korea experienced a dramatic increase in trade deficits after the sanctions, which are modeled as an increase in exogenous transfers. The additional transfer increases the overall domestic demand and increases the aggregate output, but it is common to all counties and not reflected in the cross-sectional regression coefficients (a positive level effect). Ignoring the level effects, a back-of-envelope calculation based on the reduced-form estimates of the export sanction exposure predicts a decline in aggregate output by 6.9%. The model-predicted effects of export sanctions, -6.4% in real output, suggests that the positive level effects are slightly larger than the negative level effect.[35]

[34] We calculate population-weighted real output to be consistent with our empirical specifications. In Online Appendix Table D-4, we also report base-period-output-weighted real output.

[35] Though it is difficult to decompose the level effects caused by the demand spillovers and the reallocation of intermediate inputs, we can quantify the positive level effect due to the increase in trade deficits. In Section 6.5, we show the impact of export sanctions alone on aggregate output almost doubles when we force North Korea to keep the pre-sanction trade deficits (-12.6%). This also implies that the negative level effect

Other than comparing the model's prediction to the back-of-envelope calculation based on reduced-form estimates, it is also useful to compare it to aggregate national trends. According to independent estimates from the Bank of Korea (BoK), the cumulative decline of manufacturing GDP from 2017 to 2019 is 16.3%, larger than our model's prediction for the decline in real output (-12.9%). However, it is important to point out that the national trends may be confounded by factors other than the sanctions. For example, North Korea adopted the "Dual Strategy of Nuclear and Economic Development" in 2013. Resources might be allocated differently to nuclear and economic development at different stages of the plan. Our approach of using sub-national data can avoid such confounding factors and isolate the causal effects of the sanctions.

6.3 Extension with Government Taxes/Subsidies

Given the lack of data on domestic trade and other related information, we have made various assumptions when calibrating the baseline model. Online Appendix D.4 provides a battery of robustness checks by recalibrating the model under different assumptions. In this section, we consider one major deviation from our baseline model – allowing government taxes/subsidies to mitigate the impact of the sanction on intermediate inputs. We use this extension to illustrate the potential impact of government interventions in responses to the sanctions, and to bring our model closer to the weak effect of the intermediate input sanction exposure we find in the long-difference specification from 2013 to 2019. We do not have direct evidence for such subsidies in North Korea, nor do we believe that government interventions necessarily take the form of ad valorem subsidies. However, we use them as a robustness check for the aggregate predictions of our baseline model and to understand the extent to which the government can mitigate the impact of the sanctions.

In particular, we assume zero subsidies in the base period, $t_{nj}^{int} = 0$, but set it to an industry-specific value $t_{nj}^{int\prime} = t_{\cdot j}^{int\prime}$ after the sanctions (negative values as subsidies). We set these subsidies in a way such that the government can remove a fraction of the "partial equilibrium price changes" in intermediate inputs. Based on the equilibrium change in prices described in equation (11), we define the partial-equilibrium changes taking domestic prices as fixed, i.e., $\hat{P}_{n,j}^{dom} = 1$ and

$$\hat{P}_{n,j}^{int,pe} = \left(s_{n,j}^{dom} + (1 - s_{n,j}^{dom}) \left(\hat{p}_{F,j}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} .$$

We take the simple average across counties and obtain partial equilibrium changes at the

due to demand spillovers dominates the positive level effect resulted from the reallocation of intermediate inputs.

industry level $\hat{P}^{int,pe}_{\cdot j}$. We then set the industry-level subsidies as

$$\log\left(1+t^{int\prime}_{n,j}\right) = -0.5\log\left(\hat{P}^{int,pe}_{\cdot,j}\right)\ \forall\, n. \tag{13}$$

Had domestic prices not changed, such post-sanction subsidies will remove exactly 50% of the increase in prices in sanctioned sectors. However, due to lower wages, domestic prices also decline, and these subsidies may remove more than 50% of the price increase. We choose the fraction to be 50% because this is the level of subsidy needed to neutralize the cross-sectional effect of intermediate input sanction exposure in our model. We keep the subsidies to consumption goods at zero since we still want the model to match the observed effect of import sanctions on the prices of consumption goods.

We re-calibrate our model with the input subsidies specified in equation (13), which is reported under the columns with column head "Model with Input Subsidies" in Table 7. We find slightly higher σ (1.5) and θ (7.0) but lower α_{dom} (0.56). As reported in Column 3 of Table D-1, we still observe a large effect of export sanction exposure but an almost zero (and insignificant) effect of intermediate input sanction exposure. From Panel B of Table 7, we see that such input subsidies also mitigate the aggregate impact of the import sanctions. The joint effect of export and import sanctions on real output shrinks from -12.9% to -9.6%. In our model, these input subsidies are financed by lump-sum taxes that are proportional to each county's population and create a discrepancy between pre-tax and post-tax income. The predicted change in real pre-tax income is -11.0%, close to the change of real output. However, the predicted change in real post-tax income is -16.5%, even larger than that in the baseline model. Therefore, though government input subsidies can mitigate some of the impact of the import sanctions on real output, they also come with costs. Taking extra taxes into account, aggregate welfare measured by real income cannot be improved compared to the case of zero subsidies.

6.4 Evaluating the Fit of the Model

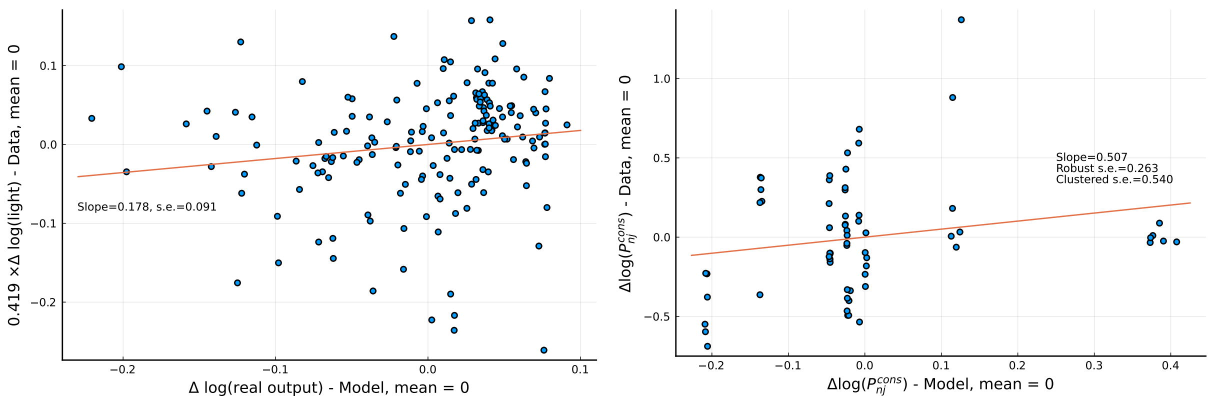
In this section, we evaluate the fit of the model using moments that we do not directly target in our calibration/estimation. In particular, we follow Adão et al. (2022): we regress the changes in output and prices in the data on the corresponding changes predicted by the model and examine whether the slopes are significantly different from one.

Adão et al. (2022) propose a framework for estimating and evaluating the fit of spatial equilibrium models in the context of the "China shock". They adopt the "quasi-random assignment of shocks" assumptions in Adão et al. (2019) and Borusyak et al. (2018) and show that

$$\hat{Y}_i = \alpha^Y + \rho^Y \hat{Y}^M_i + \nu^Y_i, \quad E[\nu^Y_i \hat{Y}^M_i] = 0,$$

where $\hat{Y}_i$ is the observed (log) change in location i, $\hat{Y}_i^M$ is the model-predicted change and ν_i^Y is the residual term. Under the assumption of "quasi-random assignment of shocks" and the log-linear structure of the spatial trade model, they formally derive ν_i^Y as linear combinations of other shocks that are orthogonal to the China shocks that they use to construct the instruments and $\hat{Y}_i^M$. Under the null hypothesis that the model is well specified, they show that the "pass-through coefficient", ρ^Y, has a probability limit of one.[36]

Figure 5: Goodness of Fit, Baseline Calibration



(a) Change in Output (b) Change in Prices

Notes: Panel (a) plots the changes in output in the data (0.419 × changes in night light) against changes in output in the model of each North Korean county. Panel (b) plots the changes in consumption prices in the data against those in the model at the county-industry level. Red lines indicate the linear regression lines. Their coefficients are also reported in Table D-3.

We present the relationship between the changes in the model and data graphically in Figure 5 and report the estimates of the "pass-through" coefficients for output and prices more formally in Table D-3. We find the "pass-through" coefficient to be 0.178 in the simple OLS regression and 0.206 when we use the county population as weights in the regression. Though positive, the null hypothesis that the pass-through coefficient equals one is rejected at the significance level of 0.001. Regressing the change in prices from 2013 to 2019 in the data on the predicted consumption price changes, we find a coefficient of 0.507, with a heteroskedasticity-robust standard error of 0.263 and a standard error of 0.540 when clustered at the industry level. With six cities and eleven industries, we are not able to obtain a very precise estimate of the pass-through coefficient. The p-value of our null hypothesis is 0.065 and 0.382 under the robust standard error and the standard error clustered at the industry

[36] Since we adopt the identification assumptions from Goldsmith-Pinkham et al. (2020) instead of Borusyak et al. (2018) and we estimate the key model parameters by matching reduced-form regression coefficients instead of using the orthogonality conditions as in Adão et al. (2022), we cannot establish that the pass-through coefficient has a probability limit of one under the null hypothesis that our model is well-specified and that our identification assumptions hold. However, it is still a useful test for the fit of the model, and is theoretically consistent if ν_i^Y is a classic measurement error and is orthogonal to not only the base-period industry shares but also the model predicted changes $\hat{Y}_i^M$.

level, respectively. These tests suggest that our model may be misspecified. Moreover, the data that we use for calibrating our model, such as industry shares, county-level output, input-output coefficients and consumption shares are all prone to measurement errors. These measurement errors may be amplified by the calibration procedures and cause attenuation biases in the pass-through coefficients.

6.5 Counterfactual Sanctions

In this section, we use our model to predict outcomes under counterfactual scenarios such as a reduction in trade deficits and full export and import sanctions.

Table 8: Aggregate impact under alternative sanctions/trade deficit scenarios

Trade Deficits	Sanctions					
	Export		Export + Import		Full	
	$\Delta\%Q$	$\Delta\%w/P$	$\Delta\%Q$	$\Delta\%w/P$	$\Delta\%Q$	$\Delta\%w/P$
Change as data: $T' = 0.58$	-6.4	-7.7	-12.9	-15.3		
Fixed at pre-sanction: $T' = T = 0.18$	-12.6	-14.3	-18.6	-21.5		
Zero: $T' = 0$	-16.1	-17.3	-22.0	-24.4	-43.7	-55.9

Notes: this table reports the predicted aggregate changes in real output (Q) and real income (w/P) under various scenarios of sanctions and trade deficits. Row 1 assumes that trade deficits are as observed in 2018; Row 2 assumes that the trade deficits have to be at the same level as the pre-sanctions deficits; Row 3 assumes that the post-sanction deficits are zero. For all cases, we report the impact of export sanctions alone as well as the current export and import sanctions. When setting the post-sanction deficits to zero (Row 3), we also report the impact of a full sanction – shutting down all trade and making North Korea autarky.

As we discussed earlier, North Korea's trade deficit increased dramatically after the 2016-2017 UN sanctions. Before the recent sanctions, North Korea was able to finance its trade deficit through the income earned by overseas workers (remittances). This source of income, however, is also prohibited by the UN sanctions. According to UN Resolution 2397 in Dec 2017, member countries were obliged to repatriate all North Korean overseas workers by the end of 2019. Therefore, in the longer run, if all other countries comply with the sanctions, North Korea will eventually run out of foreign reserves and have to reduce its imports of non-sanctioned products. In the baseline, we assume that the national trade deficit, T, increases to the level observed in the 2018 trade data. We now consider two alternative scenarios: (1) T is kept at the pre-sanctions level, i.e., 2011-2015 average and (2) T drops to zero after the sanctions. We compute the general equilibrium under these two assumptions and present the aggregate impact in Rows 2 to 3 of Table 8, where Row 1 displays the aggregate impact of the current sanctions for ease of comparison (same results as in Panel B of Table 7 under "Baseline Model").

Compared to the current sanctions, which reduce the population-weighted county-level real output by 12.9%, forcing North Korea to reduce its trade deficit to the pre-sanctions level and to zero further decreases aggregate real output by 5.7% and 9.1%, respectively. Therefore, if one believes that North Korea will close its trade deficits in the future, we expect aggregate output to decline further. County-population-weighted changes in real income are of similar magnitudes. Such amplification effects also exist when we consider export sanctions alone. For example, moving from current trade deficits to pre-sanction trade deficits, real output declines by 12.6% instead of 6.4%. This is because, even though that imports are not directly sanctioned, the current export sanctions greatly reduce the export revenue thus total imports through the trade balance condition. Since many imported goods are key inputs to production in North Korea, the reduction in import volumes will negatively affect production. Real income may be further reduced because of fewer imports of both final goods and intermediate inputs.

The last two columns in Row 3 of Table 8 report the aggregate impact of a full sanctions regime on all exports and imports, and trade deficits are zero by construction. Manufacturing output declines by 43.7% of the pre-sanctions level, while real income declines by 55.9%. Note that within Row 3, moving from the current export and import sanctions to full sanctions, we are only removing the remaining 10% of the pre-sanction total exports and imports, and this accounts for about half of the decline in output when moving to autarky. These results suggest that the impact of the trade sanctions in our model is highly nonlinear in terms of the shares of goods that are sanctioned, which is consistent with the nonlinear effect of the sanctions on the export-to-GDP ratio. We provide more discussions about this point in Online Appendix D.5.

7 Conclusion

This paper has sought to contribute to our understanding of the economic impacts of trade sanctions in the context of UN sanctions that imposed comprehensive bans on North Korea's exports and imports in 2016 and 2017. Combining a novel firm-level data set with national-level trade data, we construct a Bartik-style measure of regional exposures to export and intermediate input sanctions. We find robust evidence that sanctions on exports led to sharp declines in night light intensities and suggestive evidence that sanctions on intermediate inputs had a similar effect. Using product-level market price data, we also report significant increases in the price of import sanctioned products. These reduced-form findings suggest that trade sanctions took a toll on regional economies but say very little about their general equilibrium effect on the entire North Korean economy.

Our spatial equilibrium model goes a further step in quantifying the general equilibrium effects of the sanctions. The model can match the reduced-form regression coefficients both qualitatively and quantitatively, and it also captures important level effects that are missing from the reduced-form approach. The model predicts that North Korean manufacturing output drops by 12.9% following imposition of the trade sanctions, and the effects would be much larger if the country were forced to reduce or eliminate its current trade deficits. We believe that our approach using regional variation in nighttime luminosity and industry structure combined with spatial equilibrium models, is well suited to other contexts in which researchers want to evaluate the impact of external shocks on countries for which high quality sub-national or national statistics are not readily available.

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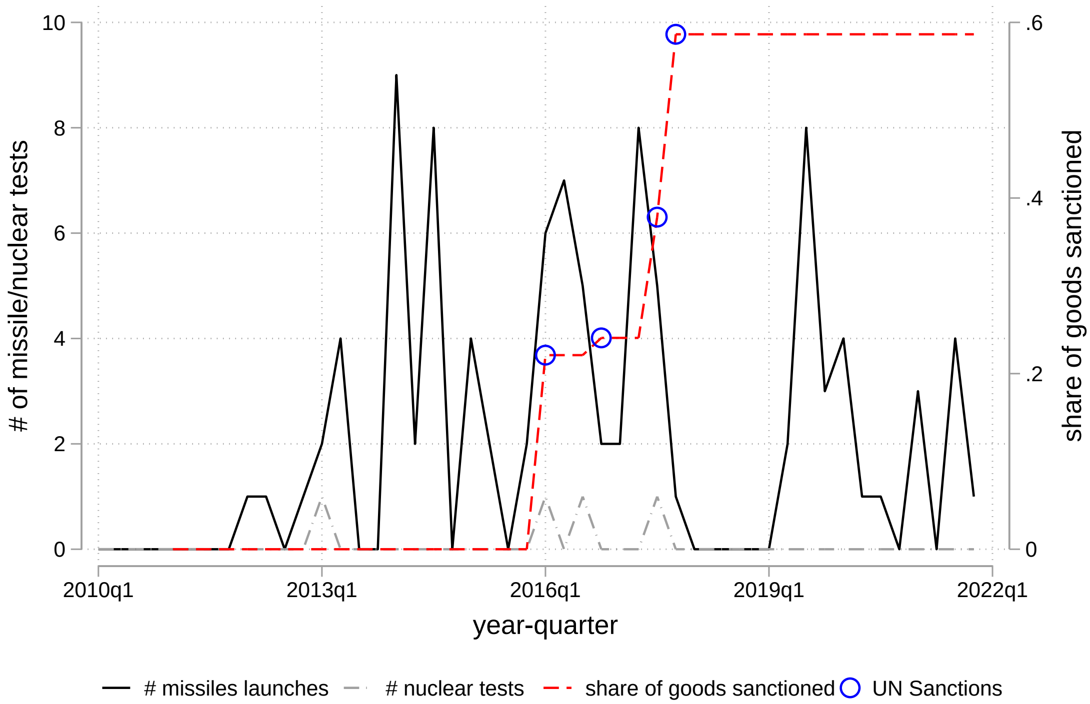
For Online Publication

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

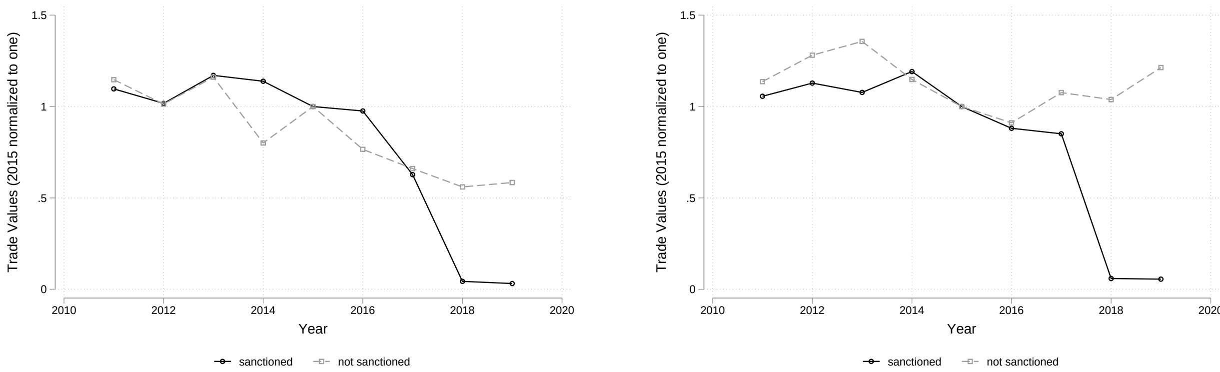
Exports		Imports	
Partner	%	Partner	%
China	79.9	China	84.2
India	1.8	India	4.2
Netherlands	1.4	Russian Federation	2.1
Bahrain	1.4	Thailand	1.7
Pakistan	1.3	Singapore	1.1

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).

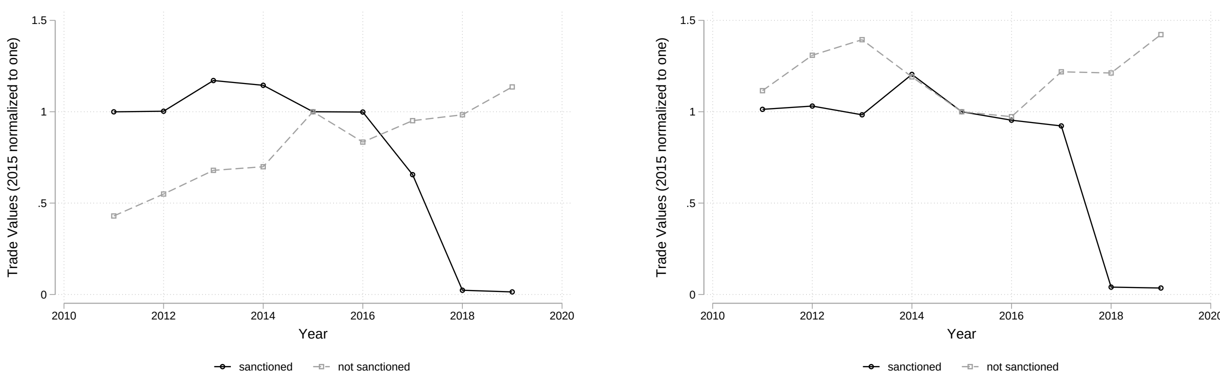
Figure A-2: Total Trade in Sanctioned and Non-sanctioned Categories



(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

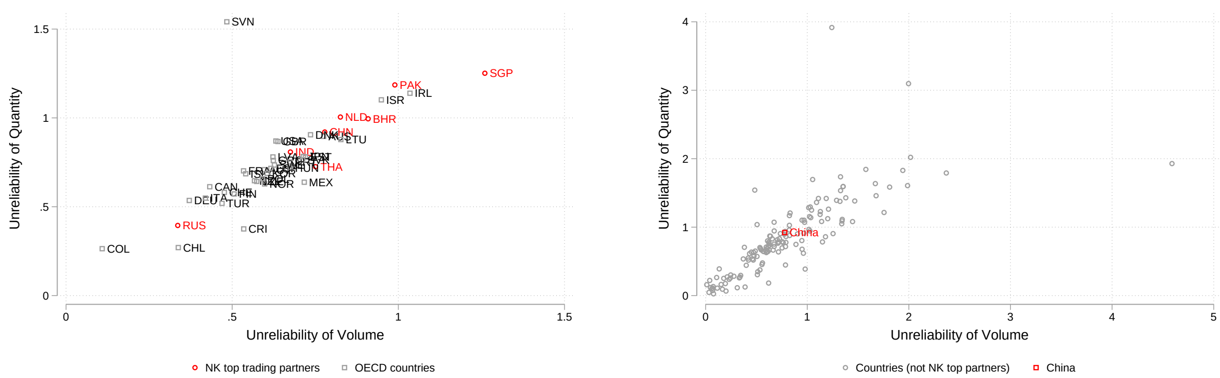
Notes: Data are normalized by the 2015 trade values for each category of products.

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

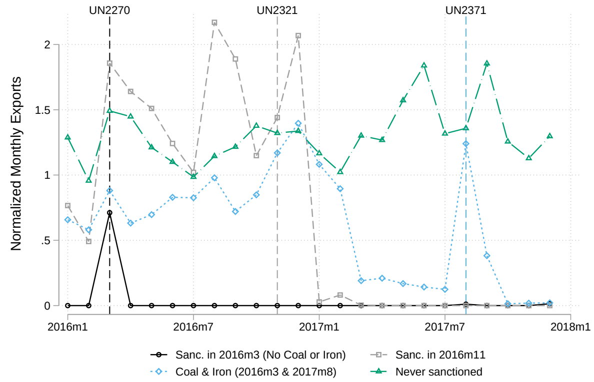
In this section, we describe the monthly trade patterns between North Korea and China and present suggestive evidence that exports of sanctioned products increase temporarily before the corresponding sanctions are imposed. We obtain the monthly trade data reported by China to the UN Comtrade database. 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.

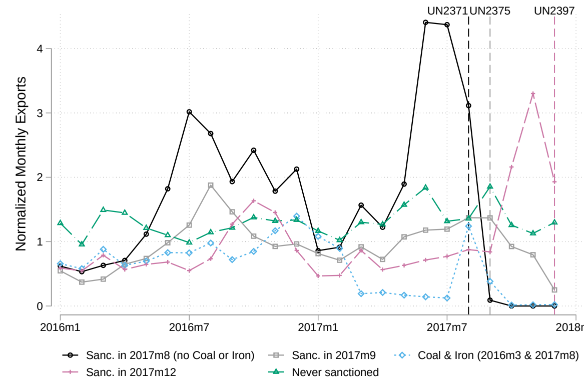
In contrast, we do not observe such temporary growth in trade on the import side. In Panel (c), we isolate three groups that are affected: vessels (sanctioned twice in Nov 2016 and Dec 2017), petroleum products (sanctioned twice in Sep 2017 and Dec 2017) and products sanctioned in Dec 2017, excluding 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.

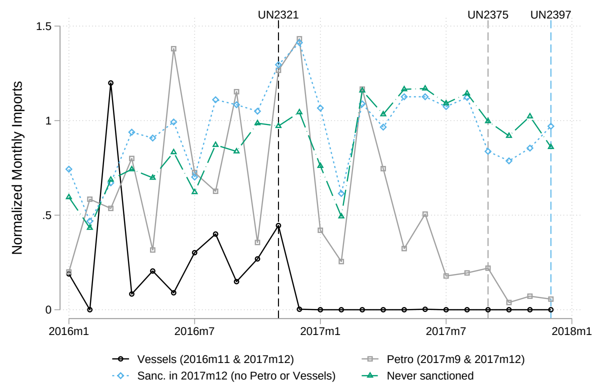
Figure A-5: North Korean monthly exports to and imports from China



(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.

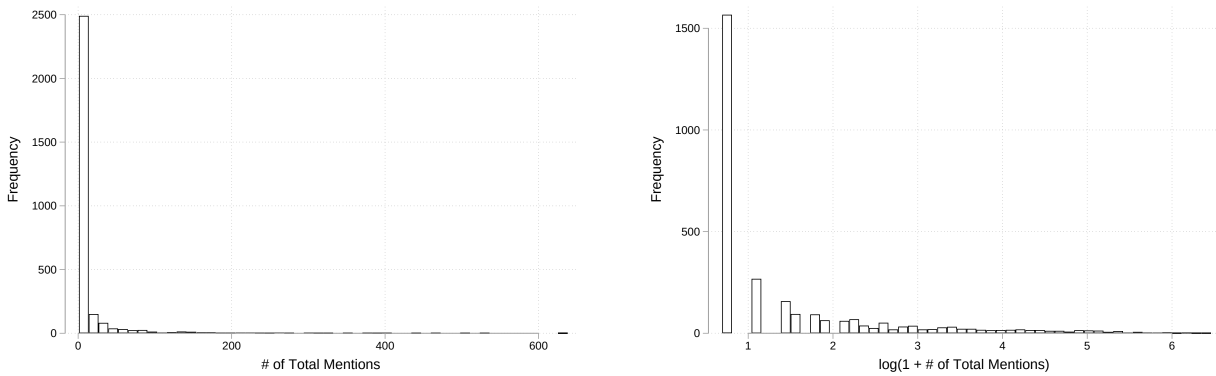
4) July 21, 2019.

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

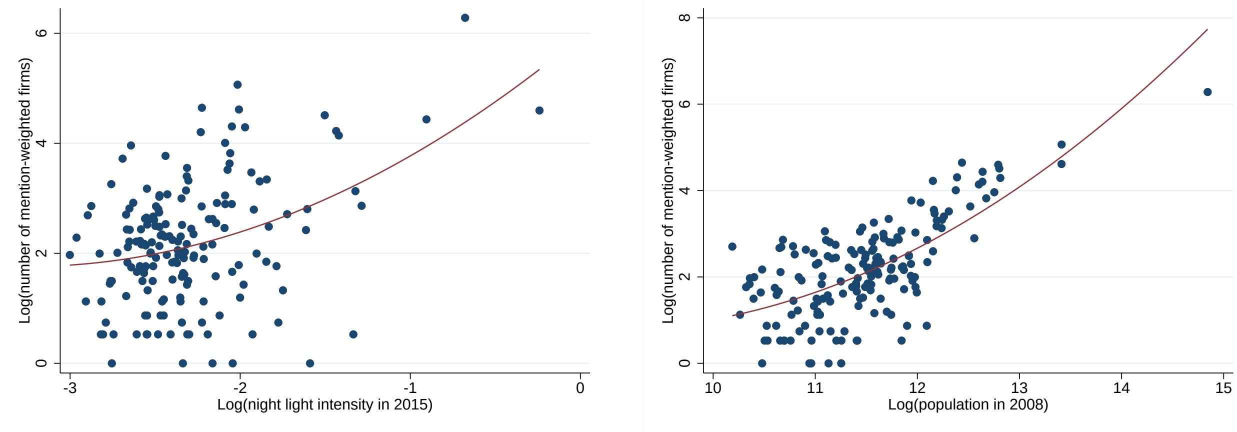
KSIC code	KSIC description	ISIC
10000	Manufacture of food products	15
10600	Manufacture of grain mill products, starches and starch products	15
10700	Manufacture of other food products	15
10800	Manufacture of prepared animal feeds and feed additives	15
11100	Manufacture of alcoholic beverages	15
11200	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.

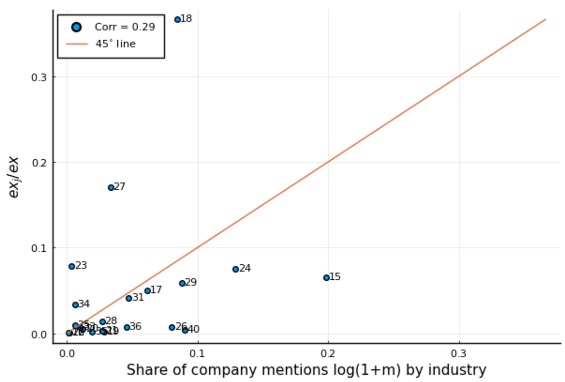
the consumption share of the Manufacturing of Food (Sector 15) is much higher than its share of company mentions, but the model implied share of output is closer to the company mention share, largely due to the large net imports in this sector. Though we are not directly comparing the share of total 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

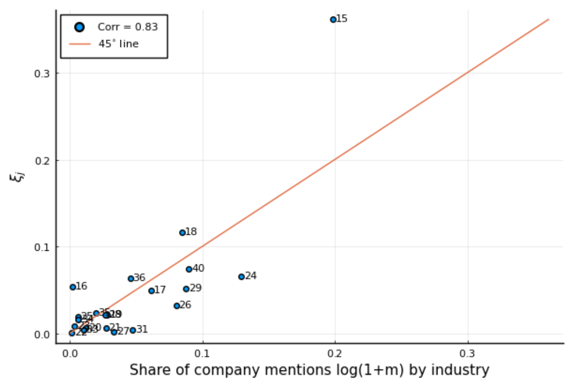
	Log(Nightlight intensity 2015)		
	(1)	(2)	(3)
Total company mentions in 2000-2015 (unit: 1,000)	0.435***	0.453***	0.337***
	(0.014)	(0.066)	(0.113)
Log (population in 2008)			0.104
			(0.120)
Log (road length in 2017)			0.052
			(0.100)
Log (building area in 2014)			-0.025
			(0.130)
Log distance to 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.

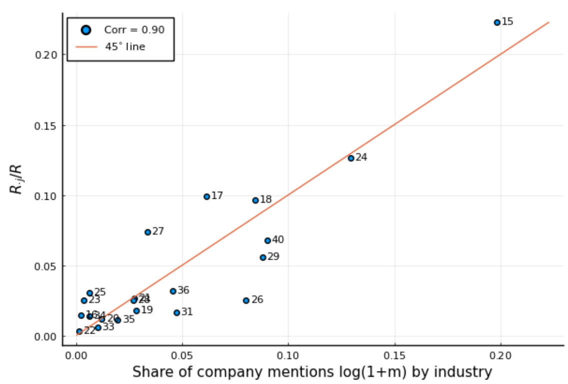
Figure A-8: Compare share of company mentions to industry-level exports, consumption and output



(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?

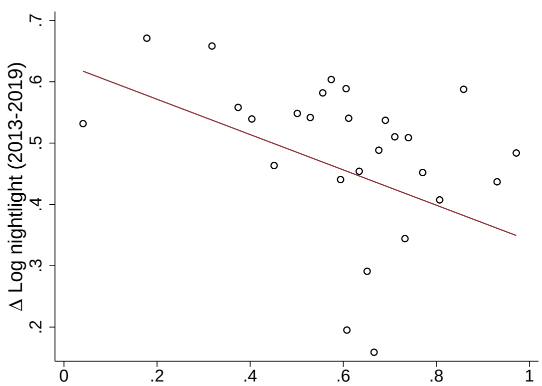
In a press release, the Bank of Korea (2021) explains officially how North Korea's GDP is estimated as follows.

- 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.

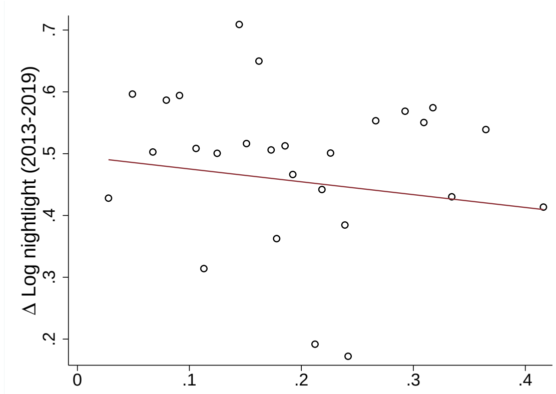
B Additional Reduced-form Results

B.1 Impact of Trade Sanctions on Regional Economies

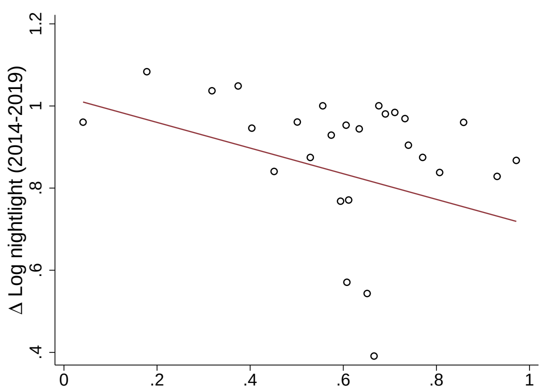
Figure B-1: Long-difference relationship between night light and sanction exposures



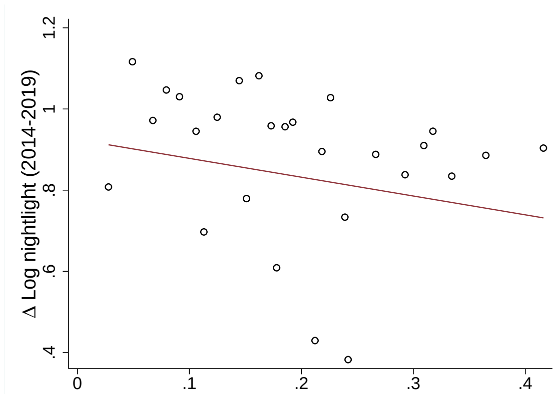
(a) Export sanction exposure



(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

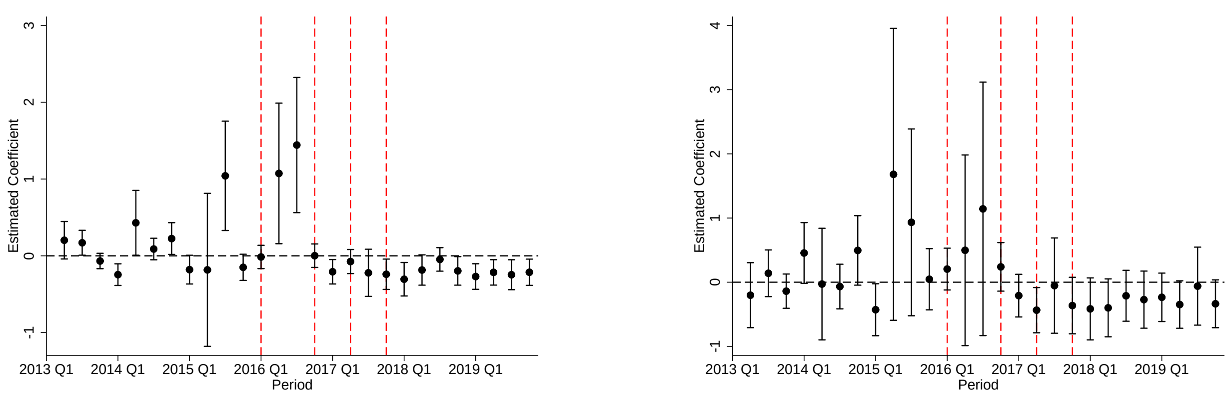
Notes: Dependent variable is the quarterly difference in log of nighttime light intensity between 2013 Q1 and 2019 Q4. Δ Sanction Exposure is the quarterly differential changes in exposure to export and input sanctions. Observations are weighted by share of population in 2008. All specifications include 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

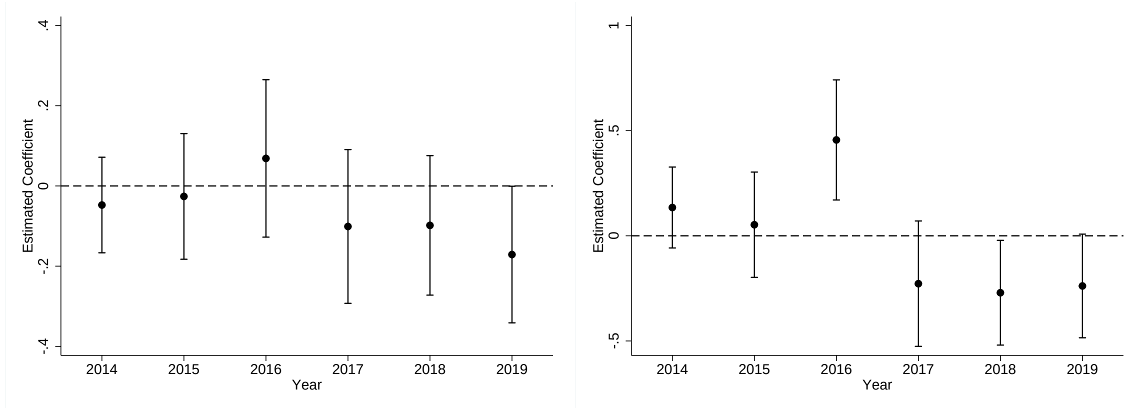
Notes: We perform the Rotemberg decomposition of the long-difference regressions in Columns 1 and 2 of Panel A, Table 3, following the method described in Goldsmith-Pinkham et al. (2020). We leave out one sector, Manufacturing of Tobaccos, to avoid the colinearity issue. The industry-level shocks, g_j, 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

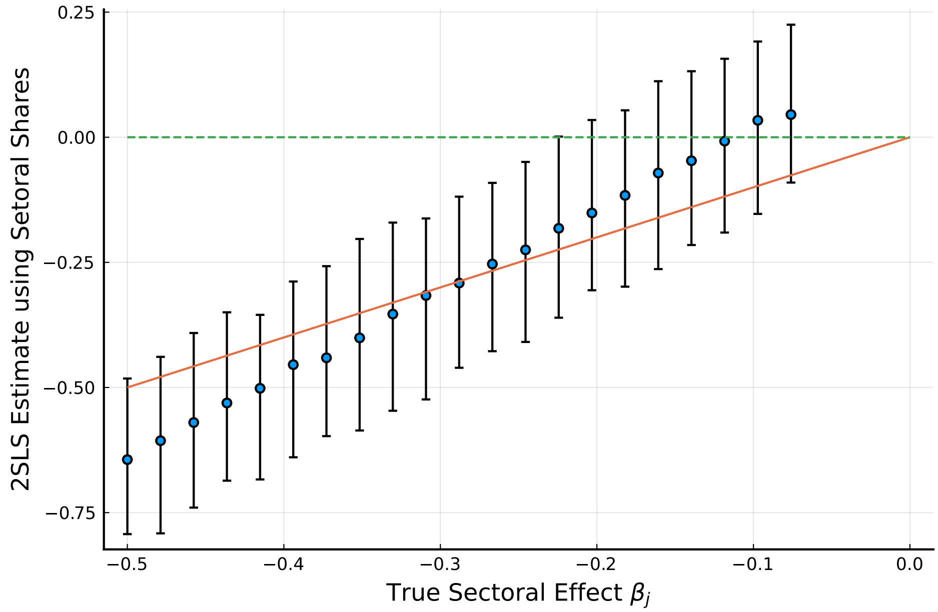
$$\text{plim}_{N\to\infty} \hat{\beta}_j = \frac{Cov(\sum_j \beta_j r_{nj} S_{EX,j}, r_{nj})}{Cov(\sum_k r_{nk} S_{EX,k}, r_{nk})} = \sum_j \beta_j \frac{Cov(r_{nj} S_{EX,j}, r_{nj})}{\sum_k Cov(r_{nk} S_{EX,k}, r_{nk})}. \tag{B-2}$$

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.

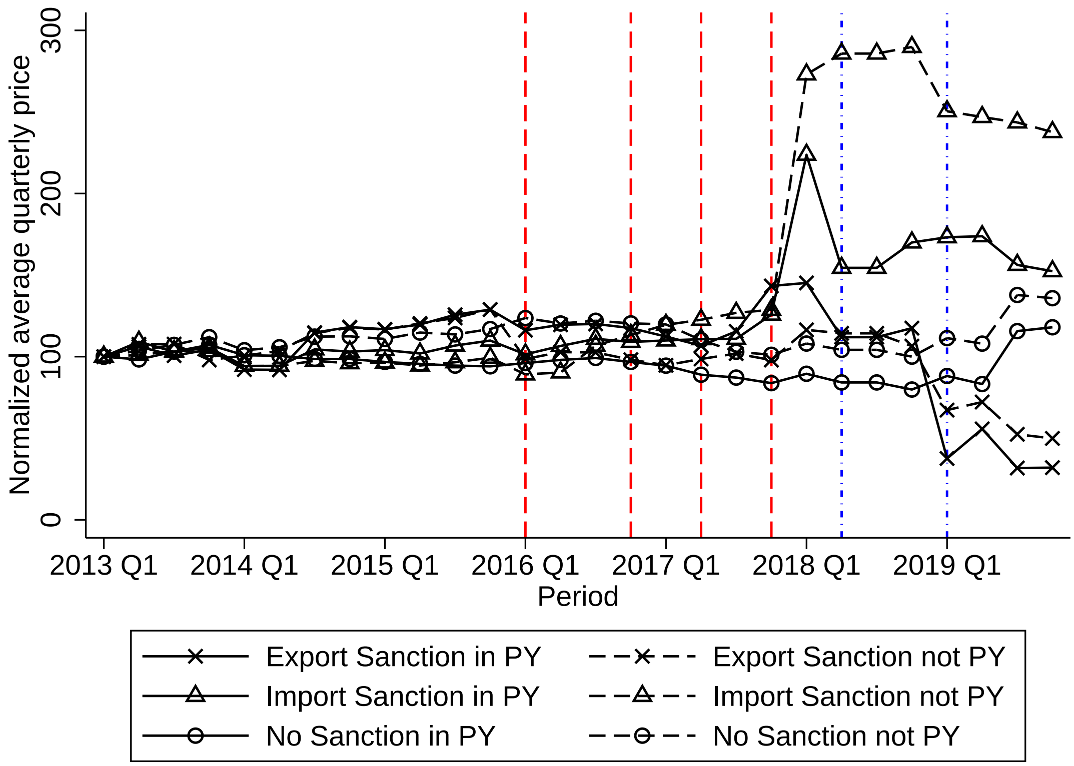
B.4 Impact of Trade Sanctions on Market Price

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:

$$
\begin{aligned}
z_{nt} &= y_{nt} + \varepsilon_{z,nt}, \\
x_{nt} &= \beta y_{nt} + \varepsilon_{x,nt},
\end{aligned}
$$

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 region-specific 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,

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

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

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

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

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

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.,

$$\begin{aligned} & R_0\hat{p}_0 + \sum_{n=1}^{N} R_n \frac{-(\eta-1)a_0\hat{p}_0 - (\sigma-1)za_0\hat{p}_0}{1+(\eta-1)a_L+(\sigma-1)za_L} \\ &= a_0 R\hat{p}_0 - R\frac{-(\eta-1)a_0\hat{p}_0 - (\sigma-1)za_0\hat{p}_0}{1+(\eta-1)a_L+(\sigma-1)za_L} \\ &= a_0 R\hat{p}_0 \frac{1-(\eta-1)-(\sigma-1)\frac{1-x}{a_L}}{1+(\eta-1)a_L+(\sigma-1)za_L} \end{aligned}$$

It is positive if and only if

$$\eta - 1 + \frac{1}{a_L}(\sigma - 1)(1 - x) < 1.$$

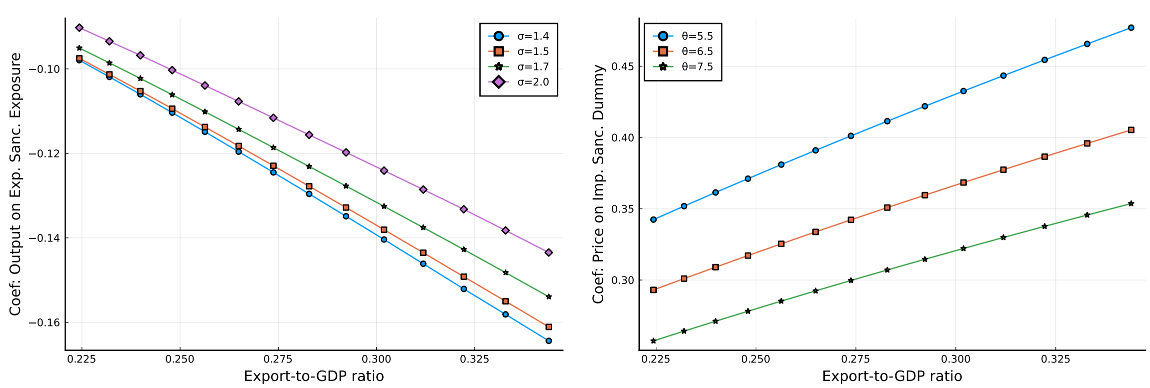
□

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 ×Δ 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 × 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 × 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

	$\Delta \log(\text{real output}_n)$		$\Delta \log(\text{price}_{nj})$	
	(1)	(2)	(3)	(4)
Fit Coef. (ρ^Y)	0.178	0.206	0.507	0.507
	(0.091)	(0.142)	(0.263)	(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 $\Delta\%$		
	σ	θ	α_{dom}	Exp. Sanc. on Output	Imp. Sanc. on Prices	Export/GDP	Real Output		Real Income
							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

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

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

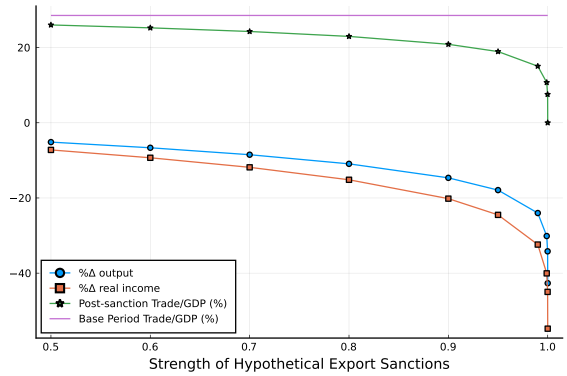
$$B'_{F,j} = (1 - S_{EX})B_{F,j}, \quad \forall\, j.$$

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.

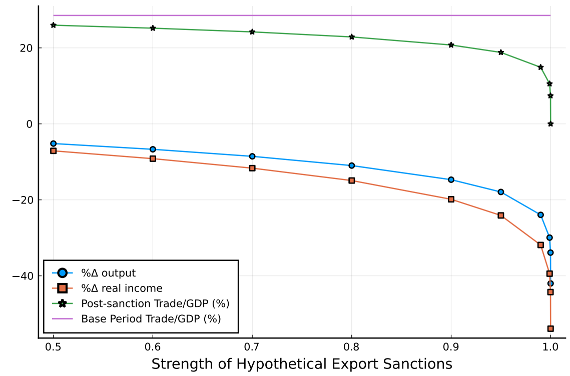
Panel (a) of Figure D-2 shows the effects of the hypothetical export sanctions under the baseline parameters. As expected, the effects on aggregate output and real income are nonlinear – the decline in output is less than 20% even when 95% of the foreign demand has disappeared. However, as the sanction 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.

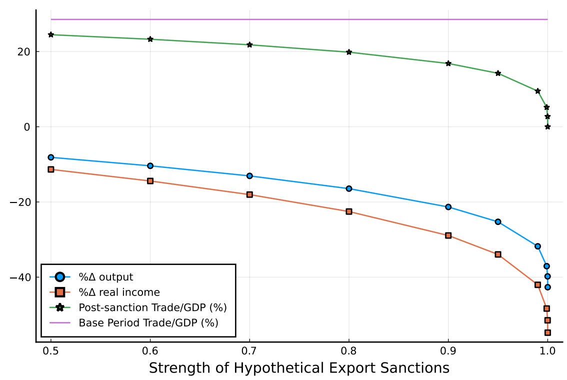
Figure D-2: Nonlinear Effects of Hypothetical Export Sanctions



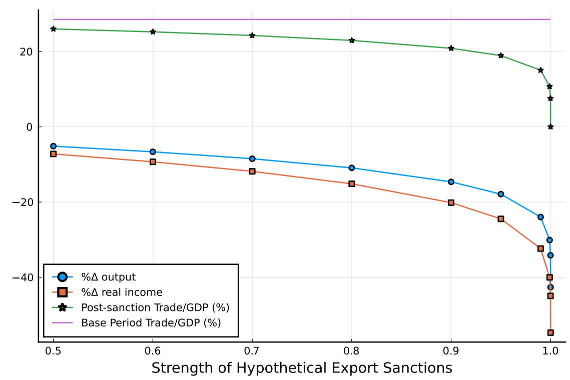
(a) Baseline, $\alpha_m = 0, \eta = 2, \epsilon = 5$



(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.

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