The Economic Costs of Trade Sanctions: Evidence from North Korea

Jihee Kim Kyoochul Kim Sangyoon Park Chang Sun*

February 9, 2022

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 they 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 20%. We further quantify the potential impact of alternative sanction scenarios.

JEL Codes: F51, R11, O18, P20

Keywords: Trade Sanction, Regional Economy, Spatial Equilibrium, North Korea

*Jihee Kim: College of Business, KAIST, jiheekim@kaist.ac.kr. Kyoochul Kim: Korea Development Institute, kyoochul@kdi.re.kr. Sangyoon Park: HKU Business School, University of Hong Kong, sangyoon@hku.hk. Chang Sun: HKU Business School, University of Hong Kong, sunc@hku.hk. We are grateful to Lee Crawfurd, Taiji Furusawa, Byung-Yeon Kim, James Kung, Bingjing Li, Chunbo Liu, Hyunjoo Yang, as well as participants at various seminars for helpful comments and discussions. We thank Bingjing Li for kindly sharing the VIIRS data for China. Ruibin Chen, Susang Lee, Jaesurk Yang and Jiaxu Zhang provided excellent research assistance. Financial support from HKGRF (project codes: 17502920 and 17504920) and the National Research Foundation of Korea (No. 519999011) is greatly appreciated.

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 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 sanction 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. Descriptively, 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 as their effectiveness in achieving their stated goals.

A key challenge is 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. 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 nightlight luminosity data as a proxy for regional economic outcomes. To provide an economic interpretation we conduct an auxiliary analysis using Chinese county-level data on GDP and night light and apply the estimated the Gross Domestic Product (GDP)-nightlight 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 first provide reduced-form evidence by estimating the impact of county-level exposures to export and intermediate input sanctions. Using a difference-in-differences specification, we find that a 10 percentage point exposure to export sanctions reduces night light intensity by approximately 5 log points and a ten percentage point exposure to intermediate input sanctions decreases night light intensity by 7.2 log points. To interpret these estimates in economic terms, we estimate the elasticity of Gross Domestic Product (GDP) on night light intensity. 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 7.0 ($= 34 \times 0.497 \times 0.419$) percent.[1] Shifting a county by the same scale for intermediate input sanctions exposure results in a decline in manufacturing GDP by 4.2 percent ($= 14 \times 0.719 \times 0.419$). We conduct extensive tests to show that our results are not confounded by pre-trends and 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.

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 37.5 percent increase in the average price of products that are import sanctioned. Export sanctioned products are shown to have a moderate fall (3.2 percent) in the average price, but the estimate is not statistically significant. Interestingly, a heterogeneity analysis with respect to cities reveals that the a 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. We allow for realistic input-output linkages between sectors to capture the propagation of import sanctions to downstream sectors, consistent with our evidence that the exposure to intermediate input sanctions reduces nighttime light intensity. Our model deviates from standard spatial equilibrium models (Adão, Arkolakis and Esposito, 2020; 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

[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.

[2] Our model accommodates any degree of cross-sector mobility. We set it to zero in the baseline and

open economy that takes foreign demand and prices as exogenous. The export and import sanctions can be modelled 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, each industry's share in aggregate imports and the cross-region relationship between output and sanction exposure measures. We calibrate the domestic and international trade elasticities to common values in the literature and use the road network to predict trade costs between counties. Crucially, the home bias parameter in our model governs the share of domestic goods in total absorption. The home bias lowers the county-level responses to the sanction exposures. We search for the value of this parameter such that the model-predicted relationship between output and sanction indices matches what we observe in the data (reduced-form regression coefficients). With a GDP-nightlight elasticity of 0.419, the calibrated home bias parameter implies that the export-to-GDP ratio of North Korea's manufacturing sector is 0.36.[3] Compared to independent estimates provided by the Bank of Korea (BoK), we find that North Korea's export-to-GDP ratio is 12 percentage point higher and its manufacturing GDP is 30% lower in 2015.

The estimated model implies that the aggregate real output of the industrial sector in North Korea drops by 20% due to the 2016-2017 sanctions. The causal effect of the sanctions on aggregate real output is slightly higher than the cumulative decline of manufacturing GDP estimated by BoK (16.3%), and much higher than a back-of-the-envelope calculation based on the reduced-form estimates assuming away cross-region spillovers (12.3%). The overall impact is robust to parameter values such as the share of labor that is mobile across sectors or the strength of local agglomeration forces, as long as we re-calibrate the other parameters and match the cross-county regression coefficients. 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 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 – and 88%

conduct robustness checks with higher mobility, as our interviews with North Korean defectors reveal that changing jobs is generally difficult.

[3] Adão et al. (2020) advocate an approach that estimates the key elasticities using model-implied optimal instrumental variables. We do not adopt their approach for two reasons. First, their estimating equation requires first-order approximation under small changes of trade costs, which may not apply to North Korea well since the 2016-2017 sanctions cover a large fraction of the exports and imports. Second, their approach requires information about the base period bilateral linkages between couties, such as the bilateral trade shares, which we do not have for North Korea. In contrast, we calibrate trade elasticities and agglomeration parameters so that we can obtain our estimate of the trade shares.

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 its manufacturing output by 14%. In addition, imposition of a full sanctions regime on all exports and imports will drastically reduce its manufacturing output, by 56%. We also consider counterfactual sanctions by industry and examine the potential effects of separate sanctions on each industry to the North Korean economy.

Our paper contributes to three strands of literature. First, it contributes to the recent empirical literature that studies the impact of economic sanctions.[4] 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 2 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.[5]

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

[4] 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.

[5] 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.

priors on which regions might be affected the most. We find that regions that were more 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). In particular, our setting is close to several recent papers that use shift-share research designs through the lens of structural models, including Kovak (2013), Adão, Kolesár and Morales (2019), and Adão et al. (2020).[6] We make a contribution to this literature by showing that such models can be used to infer the extent to which a country relies on external trade when high-quality data are not available. As has been well-known since Dekle, Eaton and Kortum (2007), if all production, consumption, and trade shares are known, one can solve quantitative trade models in changes using the "hat" algebra and without knowing the base period parameters such as the home bias, region-sector productivities and trade costs. However, domestic and international trade shares are not available for North Korea. Our approach is to estimate the key home bias parameter by matching the observed cross-region relationship between the changes in output ($0.419\times$ the observed changes in night light intensity) and the regions' exposures to the export and input sanctions. With our estimated base-period model, we obtain independent estimates of North Korean manufacturing GDP and the export-to-GDP ratio. Our estimates suggest that North Korea has a smaller manufacturing GDP and relies more on external trade than indicated by existing estimates from the Bank of Korea.

Finally, our paper joins the line of research exploiting data from night time 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 night light 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).[7] We

[6]This literature, of course, 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 similar to several papers that examine the aggregate impact of the US-China trade war, including Fajgelbaum, Goldberg, Kennedy and Khandelwal (2019). Though Fajgelbaum et al. (2019) provide predicted welfare changes by US counties, their quantitative model is not disciplined by the observed county-level responses to the trade shocks. In contrast, we rely on and *have to rely on* county-level responses to discipline our model due to data constraints.

[7]Other studies have also utilized night light data to study epidemic fluctuations (Bharti, Tatem, Ferrari,

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 the 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 night light intensity data from satellite imagery, the North Korean economic 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 Trade Sanctions

2.1 Context and Details of Trade Sanctions against North Korea

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.[8] A series of UN sanctions resolutions has been adopted since then, each resolution following a North Korean nuclear test or missile launch. Figure 2 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).

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).

[8] 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.

In contrast, the series of sanctions in 2016-2017 has been more comprehensive, designed to pose a direct threat to the North Korean economy. Most notably, trade sanctions were extensively strengthened, banning the import and export of products crucial to the North Korean economy. For exports, a quota or complete ban was placed on North Korea's top export items, such as coal, iron and iron ore, fisheries products, and textiles, to cut off North Korea's major sources of foreign currency. Moreover, import bans have been placed on items, including, but not limited to, refined petroleum products and industrial machinery, limiting North Korea's manufacturing capacity greatly. We list the sanctioned trade items by each UN resolution in Table A-1. In addition to trade sanctions, other types of sanction measures were also adopted, such as those directed toward the repatriation of North Korean workers.

2.2 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 1, 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 1 also shows the top products (grouped by ISIC Rev.3 2-digit industries) that North Korea exports and imports. Exports concentrate heavily on minerals and apparel. North Korea's imports are more diverse, with the top three categories being textiles, food, and crude oil.

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. The export sanctions apply to a larger share of North Korea's trade than import sanctions: based on pre-sanctions trade data, 88% of exports and 35% of imports would be prohibited, had the sanctions been imposed in 2015. Figure 3 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 are 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.[9] We see similar patterns

[9]We are agnostic about the causes of the decline in the 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

in Figure 4, where we only plot the trade values between North Korea and China. 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.[10]

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

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 4).

[10] 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.

data we use most likely capture manufacturing activities at night.[11] 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 extended manufacturing sector as the "manufacturing" sector.[12]

3.2 List of North Korean Companies

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 B.

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

[11] 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.

[12] 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.

more likely to be mentioned in official news media, especially on issues related to production or facility investment than small companies.

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 in the 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.[13] In sum, the input sanction index captures the share of imported

[13] 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

inputs that are affected by the sanctions for each downstream industry j.

In Table 2, 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.

We next construct the regional exposure measures to export and input sanctions.[14] For each county n, we know the set of companies in each county n and industry j, $\{f \in n, j\}$, and 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 B-1. 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

international input-output tables (Dietzenbacher, Los, Stehrer, Timmer and Vries, 2013).

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

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 B.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.[15] Overall, we find it confirming that our results are robust to using alternative transformation functions $H(\cdot)$ to construct the weights.

Figure 5 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.

In Table 3, 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,

[15] 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 suggest that the correlation between the measurement errors and the true exposure (the change in night light intensities) may be negative (positive).

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.

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[16]). 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 list of products.[17] 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., brand name of 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 employ two approaches for estimation. First, we estimate a long-run difference specification by taking the difference in the annual average night light

[16] 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.

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

intensity between 2014 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 five-year difference in the natural log of annual night light intensity of county n and Export Sanction$_n$ and Input Sanction$_n$ are export and intermediate input sanction exposures of county n, respectively. For our second approach, we estimate a difference-in-differences specification using quarterly average night light intensity as our outcome variable:

$$Y_{nt} = \beta_0 + \beta_1 \text{Export Sanction}_n \times \text{Post}_t + \beta_2 \text{Input Sanction}_n \times \text{Post}_t + \eta_n + \tau_t + \epsilon_{nt}, \tag{5}$$

where Y_{nt} denotes the natural log of night light intensity of county n in time t and Post$_t$ is an indicator variable equal to one if time t is after trade sanctions are imposed.[18] We include county fixed effects to account for time-invariant county-specific factors that might affect night light intensity and time fixed effects to account for time-varying shocks at the national level. The main difference between the two equations is that while equation (4) captures the long-run impact, which may be affected by any regional adjustments to mitigate sanction shocks, equation (5) estimates short-run responses to regional sanction exposures.

Our identification assumption behind the difference-in-differences specification is that, the two key regressors, export and input sanction exposure measures interacted with the post-sanction dummy, are orthogonal to the error term ϵ_{nt} after partialing out the county and time fixed effects. Drawing on the conditions for identification with Bartik estimators (Goldsmith-Pinkham et al., 2020), our assumption amounts to requiring that, conditional on the fixed effects, the other determinants of the outcome variables, ϵ_{nt}, are uncorrelated with the pre-sanction region-industry shares used to construct the export and input sanction exposure measures. In a first-difference or long-difference specification, 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. 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). Since the UN sanctions against North Korea were designed to target specific industries we believe it is unlikely for national-level industry shocks to be exogenous.

[18] In our main specification, we interact aggregate exposure to all five sanctions imposed during 2016-2017 with an indicator variable equal to one if period t is after the fourth quarter of 2016. Later we also present results from separately estimating the differential impact of each U.N. sanction.

For the main analysis, we estimate equations (4) and (5) using county-level VIIRS night light data from Q1 2014 to Q4 2019 across 174 counties.[19] 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 year 2008 and cluster the standard errors at the county level.[20]

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

$$Y_{ct} = \sum_{q=2015Q1}^{2019Q4} (\delta_q \text{Exp Sanc}_c \times 1\{\text{Quar} = q\} + \gamma_q \text{Inp Sanc}_c \times 1\{\text{Quar} = q\}) + \eta_c + \tau_t + \epsilon_{ct}, \quad (6)$$

where δ_q and γ_q estimate quarter-specific parameters of interest, how night light varies with export and input sanction exposures in quarter q relative to year 2014. Importantly, the parameters δ_q and γ_q (for which q is before Q1 2017) capture pre-trends in night light intensity which may be systematically related to regional exposure to sanctions.

4.2 Main Results

Figure 6 provides a visual representation of the relationship between the five-year difference in night light intensity and regional sanction exposures across counties. Panels (a) and (b) plot quarter-to-quarter five-year difference in log night light intensity between 2014 and 2019 against each county's measure of export and intermediate input sanction exposure, respectively. Panel (a) suggests that greater exposure to export sanctions is associated with lower growth in night light intensity during the five-year period. Panel (b) also shows a negative relationship between input sanction exposure and five-year difference in night light intensity.

Table 4 reports coefficient estimates of export and intermediate input sanction exposures. Panel A shows long-difference estimates from estimation 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 3.4 and 5.3 log points, respectively. 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 surpris-

[19] Data for the first two quarters of 2020 were available as this draft was being prepared but we exclude the period following the start of the covid-19 pandemic from our analysis.

[20] The year 2008 is the only one for which official population census data exist.

ing since export sanction and 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.

Panel B explores dynamic responses to sanction exposures and reports coefficients from estimating equation (5) with quarterly night light intensity as the outcome variable. The coefficient of -0.52 on export sanctions indicates that a 10 percentage point increase in export sanction exposure is predicted to reduce night light intensity by 5.2 log points. Similarly, a 10 percentage point increase in intermediate input sanction exposure is predicted to decrease night light intensity by 7.8 log points. The magnitude of estimates in Panel B is about 50 percent larger than those in Panel A. The estimates could be smaller in the long run because of factor adjustments within counties or reallocation of resources across counties in response to the trade sanctions. To take these into account we use the long-run estimates when estimating the quantitative spatial equilibrium model in Section 6.

Next, we test for pre-trends by restricting the sample from the first quarter of 2014 to the last quarter of 2016 and estimate equation (5). Estimates are reported in Online Appendix Table A-2. Panels A and B test for pre-trends one year and two years prior to the first quarter of 2017, respectively. Overall, we find no evidence of a negative pre-trend in night light intensity associated with sanction exposures. The estimates on export sanction exposure indicate that if anything counties with larger exposure to export sanctions show a positive trend in night light intensities before the sanctions. The estimates on intermediate input sanction exposure are also positive but statistically insignificant rendering the existence of a negative pre-trend unlikely.

More generally, Figure 7 shows quarter-specific estimated coefficients on export (Panel (a)) and intermediate input sanctions (Panel (b)) from estimating equation (6). Panel (a) suggests that counties subject to larger export sanction exposure experienced increases in night light intensity during the second and third quarters of 2016 but their night light intensity declined and remained negative after UN Resolution 2321 was imposed in the fourth quarter of 2016. (We offer a potential explanation for the positive effects in 2016 next) In Panel (b) the estimated coefficient for intermediate input sanction exposure shows no negative pre-trend prior to 2017. 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.

A potential explanation for the positive coefficients in the second and third quarters of 2016 is that, in anticipation of new sanctions on export products, firms were ramping up their production for exports. In Appendix Section B.4, we analyze monthly trade data between China and North Korea. We find temporary growth in exports of sanctioned products in the months immediately before the sanctions; we find no export growth among non-sanctioned products. The export patterns suggest that North Korean firms increased production in anticipation of the later sanctions after the one in 2016Q1, and the exports surged when the sanctions were close. We also want to emphasize that the temporary increases in night light intensity in 2016 are not sufficient to compensate for the decrease since 2017. For example, our long-difference specifications in Panel A of Table 4 focus on the difference in night light intensities between 2019 and 2015. These estimates are not affected by the changes in 2016, and we still find that exposure to export sanctions leads to significant declines in night light intensity. In our quantitative exercise, we use the long-difference regression coefficients to discipline our model, because we do not want to over-estimate the impact of the export sanctions due to the temporary production increase in 2016, and also because our model is meant to capture longer-term changes in the economy instead of short-term fluctuations.

Table 5 examines time-varying impacts of sanctions by providing estimates for each wave of UN sanctions that were imposed between the second quarter of 2016 and first quarter of 2018. Columns 1 and 2 each report UN sanction resolution-specific difference-in-differences estimates on export and intermediate input sanction exposures, respectively. Column 3 includes both sanctions and indicates a statistically significant increase in night light intensity for counties subjected to more export sanctions after UN 2270, which is then followed by a drastic decline after UN 2321. As mentioned above, one possible reason for the increase after UN 2270 is that it 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 is strengthened through UN 2321, which removed the exceptional case for people's livelihood for iron ore exports, export-oriented production activities decreased to the extent at which the overall net effect on production activity was negative. The imposition of intermediate input sanctions displays a similar pattern of increase in night light intensity in response to UN 2270, followed by a large decline after UN 2321. We do not see further declines to night light associated with the last two waves of UN sanction resolutions (UN 2371, 2375, and 2397).

As an alternative to our main specifications, we can construct quarterly sanction exposures representing sanction exposures accumulated up to that quarter. This allows us to examine the evolution of sanction exposures on night light intensity by plotting estimates of quarterly sanction exposures with lead and lag periods. The estimates on quarterly sanction exposures are provided in Online Appendix Figure A-1. Panel (a) shows that export sanctions have an immediate impact on night light intensity: the coefficient is negative in the quarter at which export sanction exposure increases but we see no decline in previous or following quarters. In contrast, an intermediate input sanction seems to take effect one quarter after exposure to the sanction: the coefficient is only negative and statistically significant in the following quarter. Furthermore, we find that including county-specific linear time trends to account for possible pre-trends at the county level causes almost no changes to the estimates.

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 that are similar to North Korean ones. We resort to Chinese data because we do not have measures of county-level GDP in North Korea – in fact, we do not have precise measures of national GDP and want to develop our own estimates of national GDP combining the reduced-form estimates and the structural model in Section 6. We believe that the elasticity estimated from Chinese counties of similar population density and night light intensity as their North Korean counterparts provides a reasonable approximation for the GDP-nightlight elasticity 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, and it is robust to using alternative samples. It is also similar to Chinese prefecture-level estimates from Chor and Li (2021). [21]

[21] Our estimate is at the lower end of the range of estimates in Henderson et al. (2012), who use a different approach (imposing parametric assumptions on the size of the measurement errors in a subset of geographic

Applying our estimated GDP-nightlight elasticity to the long-difference estimates in Column 3, Panel A of Table 4 implies that a 10 percent increase, which corresponds to a 0.45 standard deviation, in export sanction exposure reduces GDP by 1.4 percent (0.329*0.419*10). Increasing the intermediate input sanction exposure by 10 percent, commensurate with an increase by 1.25 standard deviation, reduces GDP by 2.0 percent (0.489*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 and intermediate input sanction exposure by long-difference coefficient estimates. Second, we obtain the population weighted sum of change in nightlight over all counties and then multiply that term by our estimated GDP-nightlight elasticity. An important caveat to this exercise is that it does not take into account spillover effects. In the event of a negative spillover from high- to low-sanction-exposure counties due to, for instance, lower demand for goods from the low-exposure counties by the high-exposure counties, we would underestimate the effect of sanction exposure on night light intensity and, hence, GDP. That said, our back-of-the-envelope calculation implies that North Korea experienced a 12.3 percent fall in GDP due to UN trade sanctions. In Section 6, we quantify the general equilibrium effects using a spatial equilibrium model disciplined by the reduced-form coefficients.

4.4 Robustness Checks and Bartik Decomposition Analysis

4.4.1 Robustness Checks

We next present results from conducting a battery of robustness checks. In Table 6, Columns 1 and 2 show that our results are robust to including separate fixed effects for quarter of year and year as well as a province×quarter fixed effects that controls for province-specific seasonality shocks. Columns 3 and 4 show that dropping the top and bottom 1 percentile and 3 percentile of counties, respectively, does not qualitatively change our results. In Columns 5 and 6 we show estimates from dropping counties in Pyeongyang and counties proximate to the NK-Chinese border. Column 7 suggests that our results are robust to excluding the year 2016 from the sample; our quarter-specific estimates in Figure 7 show strong positive associations between night light intensity and sanction exposures during this year. We further account for potentially spurious correlations between county-level pretrends in night light intensity and regional sanction indices by adding county-specific linear and quadratic time-trends. The estimates in Columns 8 and 9 show that our results are robust and if

units) and focus on the cross-section relationship between GDP and nightlight luminosity. We provide more discussions in Online Appendix C.

anything the magnitudes increase relative to the baseline estimates reported in Column 3 of Table 4.

Table A-3 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 5 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. The estimate on input sanctions has a larger magnitude than the baseline estimate. Columns 4-6 present results by weighing company using the number of mentions instead of the logarithm of number of mentions that we use in our baseline analysis. Compared to the baseline, estimates are smaller in size and statistically less significant, which may be due to the extra measurement errors caused by having firms that are frequently mentioned in the newspapers but their production weights may not be as high.

Table A-4 tests robustness with respect to the input-output table used to construct 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. We report estimates from long-difference specification in Panel A and quarterly difference-in-differences specification in Panel B. Columns 1-2 suggest that using China's 1987 input-output table provides similar estimates to those in Table 4. Estimates in Columns 3-4 further indicates that our main results are robust to using China's 1997 input-output tables for constructing the intermediate input sanction index.

4.4.2 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.[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). 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

[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.

the Rotemberg decomposition in our bivariate, long-difference specifications in Columns (1) and (2) of Panel A, Table 4. 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.[23] (see equation (3) for the notations)

Table 7 reports computed Rotemberg weights (α_j), just-identified coefficient estimates ($\hat{\beta}_j$), and their 95 percent confidence intervals. Panel A shows the top five industries with largest Rotemberg weights for the Bartik coefficients for export sanction exposure. Among the 20 industries that are included in our data set, 14 industries have a positive weight adding up to 1.073. The top five industries account for 89.9 percent (0.965/1.073) of the positive weight on export sanction: the food industry has the largest weight (0.46), followed by machinery (0.19), apparel (0.16), electrical equipment (0.09), and textiles (0.08). Only the food industry has a positive $\hat{\beta}_j$ while the other four industries have negative coefficients. Panel B shows the top five industries with largest weights on input sanction. Similarly, the top five account for 85.6 percent of the positive weights (0.938/1.096): machinery (0.40), basic metals (0.19), electric equipment (0.17), fabricated metals (0.09), and transportation equipment (0.09).[24] Importantly, all five industries with the largest weights on input sanction show negative coefficeint estimates ($\hat{\beta}_j$).

Table 8 shows the relationship between county characteristics and the 2015 share of the top five industries in Table 7 as well as the export and input sanction exposures. 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 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. To address this concern, we include interactions between county characteristics and a post-sanction dummy as controls in equation (5). Online Appendix Table A-5 presents OLS estimates on export and intermediate input sanction exposures. The estimate on export sanctions ranges from -0.17 to -0.27 and is statistically significant in three out of four columns. The estimate on intermediate input sanctions varies between -0.2 and -0.7. Controlling for population and infrastructure seems to reduce the magnitude, leading to statistically insignificant estimates. However, it is worth noting that the signs of estimates on export and intermediate input

[23] 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.

[24] Fourteen out of 20 industries have a positive Rotemberg weight for input sanction.

sanctions exposures are consistently below zero across all columns.

Finally, we examine the parallel pre-trend assumption for industries with the top five Rotemberg weights. Appendix Figure A-2 presents pre-trend figures by regressing equation (6) with county-level industry shares instead of the sanction exposures. Panel (a) combines the top five Rotemberg weights for export sanction and panel (b) combines for input sanctions. Both panels show that industry shares in 2015 are not statistically significant predictors of night light intensity in quarters prior to 2017 Q1.

5 The Impact of Trade Sanctions on Market Price

5.1 Empirical Strategy

We next investigate the impact of sanctions on 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 8 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.

To systematically examine the relationship between trade sanctions and market price we estimate the following difference-in-differences specification:

$$\begin{aligned} Y_{pct} \quad = \quad & \beta_1 \mathbf{1}(p \in P_{EX}) \times \text{Post}_{pt} + \beta_2 \mathbf{1}(p \in P_{IM}) \times \text{Post}_{pt} \\ & + \beta_3 S_{IN,j(p)} \times \text{Post}_{pt} + \delta_p + \delta_c + \delta_t + \epsilon_{pct} \end{aligned} \tag{7}$$

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, and $S_{IN,j(p)}$ is the share of sanctioned inputs for product p, which takes a common value for all products belonging to the same industry j, since the input-output table is at the ISIC 2-digit industry level. 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.

5.2 Estimation Results

Table 9 reports OLS estimates on the product sanction coefficients. Column 1 shows a negative estimate 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 percent after the sanction relative to before. Column 3 also suggests a 35.8 percent rise in the average price of products for which the entire share of inputs were import sanctioned. The results in Columns 2 and 3 are economically and statistically significant. Columns 4 and 5 show that the price increases in import-sanctioned and input-sanctioned products are consistent even when export sanctions are estimated together. Finally, Column 6 reports estimates for all three sanction coefficients and shows that the import sanction estimate is almost unchanged although the estimate for input sanctions becomes insignificant.

The negative coefficients of export sanctions in these regressions, though insignificant, are consistent with typical trade models in which lower foreign demand reduces domestic prices. The positive coefficients of the import-sanctioned dummy suggest that import sanctions have a direct impact on the products that are sanctioned. The indirect impact on the downstream-industry output prices is difficult to isolate because the import and input sanction measures are positively correlated due to each industry's high usage of its own output as input. However, taking the insignificant coefficient of input sanctions in Column (6) together with our earlier results that counties with high exposure to input sanctions see larger declines in night light, one might conjecture that the adjustment of output prices in the downstream sectors falls behind the adjustment of their production. This is likely the case in the short run due to price stickiness and possible in the long run in an economy with strong government interventions in production.

One plausible concern for 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 8, the average quarterly price trend is relatively stable prior to year 2018, which may partly assuage such concerns. Empirically, we conduct placebo tests by moving the sanction period earlier by one or two years. 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 A-6. Across all columns and panels we find no evidence of significant increases in the prices of import-sanctioned products in the first quarters of 2016 or 2017.

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 A-3 separates out Pyeongyang from the other five cities and plots the average quarterly price of products by sanction category for Pyeongyang only and for the other cities. First, before the first quarter of 2018 there is not much difference in prices between Pyeongyang and non-Pyeongyang 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 Pyeongyang 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. Appendix Table A-7 reports estimates from regressing an extended model of equation (7) to incorporate heterogeneity with respect to Pyeongyang city. The estimation results largely support these findings.

6 Quantifying the Aggregate Impact in a Spatial Equilibrium Model

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 $n = 1, \dots, N$ regions (counties) in North Korea. Each region is endowed with L_n workers, and we assume they are not mobile across regions.[25] In each region, there is potentially production in sector $j = 1, \dots, J$. 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

[25] 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.

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, denoting the price index of the domestic composite goods as $P_{n,j}^{dom}$ and the price of foreign goods as $p_{F,j}$, the final price index faced by consumers and producers (for purchasing intermediate inputs) is

$$P_{n,j} = \left(\alpha_{dom} \left(P_{n,j}^{dom} \right)^{1-\sigma} + (1-\alpha_{dom}) p_{F,j}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

The expenditure share of domestic composite goods is

$$s_j^{dom} = \frac{\alpha_{dom} \left(P_{n,j}^{dom} \right)^{1-\sigma}}{\alpha_{dom} \left(P_{n,j}^{dom} \right)^{1-\sigma} + (1-\alpha_{dom}) p_{F,j}^{1-\sigma}}. \tag{8}$$

This share is also closely related to the export-to-GDP ratio of the country. This will be a key parameter in our calibration, and we discipline it using cross-region regression coefficients obtained in Section 4.

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

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

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, $L_{n,j}^m$, and labor that is specific to sector j, $L_{n,j}^s$. 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 cannot move at all ($\alpha_m = 0$) after the sanctions. We use perfect mobility $\alpha_m = 1$ as a robustness check. Due to 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 assume that the iceberg trade costs to ship from origin i to n are 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 ϵ 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. Therefore, the goods market clearing condition can be written as

$$R_{n,j} = \sum_{i\in\mathcal{N}} x_{ni,j}\xi_j E_i + \sum_{i\in\mathcal{N},\|\in\mathcal{J}} x_{ni,j}(1-a_{jL})a_{jk}R_{i,k} + x_{nF,j}E_{F,j}, \tag{9}$$

where $R_{n,j}$ deonotes the output value of sector j in region n. On the right-hand side of

[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 across sectors in our benchmark case, 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.

equation (9), 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 total consumer expenditure, in turn, equals the sum of labor income in region i and an exogenous transfer, T_i, capturing exogenous trade imbalances. 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 Korean $E_{F,j}$ 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

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

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

It is clear from equation (9) that the final goods are consumed by domestic or foreign consumers, or used as intermediate inputs by downstream sectors.[27] We assume that export sanctions have a direct effect on $E_{F,j}$, which will reduce domestic production in equilibrium. Given all equilibrium prices, we can solve $R_{n,j}$ from the $N \times J$ equations (9). Finally, we express the labor market clearing conditions

$$\sum_{j \in \mathcal{J}} L_{n,j}^m = L_n^m, \tag{10}$$

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

Definition 1. *A general equilibrium 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 (9), and labor markets clear according to condition (10).*

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 are sanctioned by the UN in 2016-2017, where zeros mean no sanction at all and ones mean full sanctions. For export sanctions, we simply assume

[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 $E_{F,j}$ as exogenous, the exact usage of exports is irrelevant in our model.

that the foreign expenditure on North Korean goods $E_{F,j}$ drops to $(1 - S_{EX,j})E_{F,j}$. 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 ϵ. The import sanctions block a fraction of $S_{IM,j}$ of these goods from being traded. The foreign price p_{Fj} that we introduced earlier is actually the price index, and the change in $p_{F,j}$ can be written as

$$\hat{p}_{F,j} \equiv \frac{p'_{F,j}}{p_{F,j}} = \frac{\left(\int_0^{1-S_{IM,j}} p_{F,j}(\omega)^{1-\epsilon} d\omega\right)^{1/(1-\epsilon)}}{\left(\int_0^1 p_{F,j}(\omega)^{1-\epsilon} d\omega\right)^{1/(1-\epsilon)}} = (1 - S_{IM,j})^{1/(1-\epsilon)}. \tag{11}$$

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

$$\hat{P}_{n,j} = \frac{P'_{n,j}}{P_{n,j}} = \left(s_j^{dom}(\hat{P}_{n,j}^{dom})^{1-\sigma} + (1 - s_j^{dom})(\hat{p}_{F,j})^{1-\sigma}\right)^{\frac{1}{1-\sigma}},$$

where s_j^{dom} is the expenditure share on domestic goods in the base period as defined in equation (8). Under complete import sanctions, we have $\hat{p}_{F,j} = \infty$ and

$$\hat{P}_{n,j} = \hat{P}_{n,j}^{dom} \left(s_j^{dom}\right)^{\frac{1}{1-\sigma}}, \tag{12}$$

which resonates with the formula for the welfare gains from trade in Arkolakis, Costinot and Rodríguez-Clare (2012).

6.2 Parameterization and the Aggregate Impact

We now parameterize our model, and the calibration and estimation results are summarized in Table 10. Panel A displays the parameters that are calibrated without solving the model. We choose four sets of parameter values from the literature. The domestic trade elasticity, ϵ, is set to four following Simonovska and Waugh (2014) and Adão et al. (2020). The Armington elasticity of substitution between domestic and foreign goods, σ, is set at 1.5, the benchmark value in Backus, Kehoe and Kydland (1994). We do not have direct information about the domestic trade costs or trade flows in North Korea. To discipline the domestic trade costs, τ_{in}, 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 $\tau_{in} = e^{0.042d_{in}}$, where d_{in} is the length of the shortest path from i to n based on the map from www.openstreetmap.org.[28] 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. As in Adão et al. (2020), we allow for an agglomeration force, and set the elasticity of the location-specific productivity to population at 0.56, the same value estimated for the U.S. commuting zones in their paper. We show below that the aggregate predictions of our model are robust to removing the agglomeration force.[29]

As in our reduced-form analysis, we use China's input-output table for the labor and input shares.[30] We use the proportion of firms in each industry j weighted by the log of the number of mentions plus one to approximate the consumption shares ξ_j. We normalize total exports in the base period to one and set the foreign expenditure $E_{F,j}$ to the share of exports in sector j between 2011 and 2015. During this period, North Korea is also running a trade deficit with a value around 18% of total pre-sanctions exports. We treat the overall deficit as an exogenous transfer to North Korea and apportion it to each county according to its population share in 2008.

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 home bias parameter, α_{dom}, we estimate the foreign prices, $p_{F,j}$, and the region-sector-specific productivities, $\tilde{A}_{n,j}$, by matching the share of imports of sector j goods among all imports in the base period and the weighted share of firms in sector j within each county. As in our reduced-form analysis, we interpret the share of firms weighted by log of the number of mentions plus one as a proxy for the local revenue shares of sector j. Since we are matching the shares, we normalize the geometric mean of the prices and the region-sector-specific productivities (within a region) to one. The final productivity in region n sector j is the product of A_n (due to the agglomeration force) and $\tilde{A}_{n,j}$.

In the outer loop, we search for a value of α_{dom} such that the model can generate similar relationships between the sanction exposure measures and the changes in local output. In particular, we solve for the post-sanction equilibrium by changing three sets of parameters: (1) reducing foreign expenditure $E_{F,j}$ to $(1-S_{EX,j})E_{F,j}$; (2) changing foreign prices according to equation (11), i.e., $\hat{p}_{F,j} = (1 - S_{IM,j})^{1/(1-\epsilon)}$; and (3) adjusting the trade deficits to match

[28]We see Fan et al. (2021) as the current best estimate of the semi-elasticity of iceberg trade costs with respect to distance, but it is possible that this elasticity is different in North Korea. Using price data, Atkin and Donaldson (2015) estimate how the level of trade costs (in dollars) vary with 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. We later perform a robustness check with higher trade costs by assuming domestic trade costs in North Korea are four times of those in China, i.e., $\tau_{in} = e^{0.168 d_{in}}$.

[29]Note that we have assumed labor is immobile across locations. Therefore, the location-specific productivities are not responding to shocks.

[30]We use value-added shares for a_{Lj} and interpret "labor" as labor equipped with capital.

the level in 2018. North Korea's trade deficit increased by 2.2 times after the sanctions. We simply increase the overall deficit T to the new level and again apportion it by the population of each county. With both the pre- and post-sanction equilibria, we calculate the changes in real output in each country using base-period prices and regress the output changes on the export and input sanction exposure. We multiply the long-difference regression coefficients from Column 3 of Table 4 by our preferred GDP-nightlight elasticity, 0.419, and obtain the data counterparts of these regression coefficients (replicated in Column 1 of Table 11). We adjust α_{dom} such that the model-predicted regression coefficients are closest to those in the data, which is illustrated in Figure A-4 in the online appendix.

In Column 2 of Table 11, we report more statistics of our calibrated baseline model. We find a value of the home bias parameter $\alpha_{dom} = 0.71$, which makes the regression coefficients of the export and input sanction exposure measures in the model close to what we obtain from the data (Column 1). The value of α_{dom} itself is not informative, since it is affected by other model parameters such as domestic labor productivities A_{nj}, and international trade costs τ_{nF}, τ_{Fn}. A more informative statistic is the export-to-GDP ratio. Under this value of α_{dom}, the manufacturing sector of North Korea has an export-to-GDP ratio of 0.36. The Bank of Korea (BoK)[31] estimates North Korean manufacturing GDP from alternative data sources and a simple calculation shows that North Korea's export-to-GDP ratio would be 0.25 according to their GDP estimates. Using our quantitative model and disciplining the home bias parameter using regional-level variation, we infer the North Korea manufacturing GDP to be 30% lower than the BoK estimate, and the country seems to rely a lot more on foreign markets and goods.[32]

The last three rows of Column 2 report the aggregate impact of the trade sanctions. We first compute the changes in each outcome at the county level and then aggregate them across counties using county population as weights. According to these measures, aggregate real manufacturing output, GDP and wage decline by 20%, 19% and 22%, respectively. Compared to the back-of-the-envelope calculation based on the reduced-form coefficients assuming away general equilibrium effects (12.3%), the model predicts a much higher overall impact, suggesting large negative spillover effects across counties. To put the aggegate effect (-20%) in context, according to independent estimates from the Bank of Korea (BoK), the cumulative decline of manufacturing output from 2017 to 2019 is 16.3%. With all the caveats of cross-country comparisons and differences in methodologies, our results are comparable to other estimates of the aggregate impact of actual or counterfactual removal of trade. For

[31] See Online Appendix D on how the Bank of Korea estimates North Korea's GDP

[32] Despite that we find a larger export-to-GDP ratio than the BoK estimate, we notice that this ratio is much lower compared to those of other countries. We visualize the comparison in Online Appendix Figure A-5.

example, Etkes and Zimring (2015) estimate the blockade imposed on the Gaza Strip reduced real consumption by 14 to 27% from 2007 to 2010, and Costinot and Rodríguez-Clare (2014) quantify the welfare loss from economic autarky for Eastern European countries at 27 - 38%.

In Columns 3-6 of Table 11, we investigate the robustness of our baseline calibration and results by changing the value of some parameters and recalibrating the other model parameters. We have assumed that local agglomeration in North Korea is as strong as that in the United States, i.e., we specify the region-specific productivity as a function of population, $A_n = L_n^{\psi}$, where ψ is set at 0.56, an estimate for the U.S. in Adão et al. (2020). In Column 3, we change it to zero (no agglomeration) and calibrate the other parameters of the model. To match the reduced-form regression coefficients, we find that the implied base period export-to-GDP ratio is almost identical to that in Column 2.[33] The aggregate impacts are also quantitatively similar. Columns 4 and 5 assume that the shares of labor that is mobile across sectors in each region are 0.5 and 1.0 (some mobility and perfect mobility), respectively. We see slightly worse matches between the regression coefficients in the model and those in the data, but the value of α_{dom}, the base-period export-to-GDP ratios and the aggregate changes in output are similar to those in the baseline. Finally, in Column 6, we recalibrate the model under the assumption that the semi-elasticity of domestic trade costs with respect to distance in North Korea is four times of those in China (baseline). The inferred export-to-GDP ratio becomes smaller (0.31 instead of 0.36), while the decline of aggregate real output is 17%.

In Online Appendix Table A-8, we further examine the relationship between industry sanction indices and the model predicted changes in $P_{n,j}$, the price of the composite good in industry j, county n, and compare them to the empirical estimates using product prices in Section 5. Two points are worth mentioning before we discuss the results. First, the price data are not used or targeted in our calibration procedure, so one can see this as a measure of the goodness of fit of the model. Second, we need to be cautious about this comparison since the average price of products in the data is not calculated in the same way as the optimal price index $P_{n,j}$ in the model, and the products covered in the price data may not be a representative sample of products consumed in each industry. With these caveats in mind, we find that export sanction reduces the price index by an average of 0.145 log points, with a standard error of 0.173. Import sanction increases the price index by 0.571 log points (s.e. = 0.181) and the coefficient of input sanction index is 0.573 (s.e. = 0.190). These signs of these coefficients are consistent with their empirical counterparts in Table 9, though the model predicts slightly larger effects of sanctions on prices. However, the 95% confidence

[33] The calibrated α_{dom} is different mainly because the level of domestic productivities A_{nj} has been changed due to the removal of agglomeration.

intervals of the model estimates contain the point estimates using the product price data, suggesting that the observed changes in prices are consistent with the calibrated model.

6.3 Counterfactual Sanctions

In this section, we consider alternative outcomes under counterfactual sanctions. We first consider further strengthening the current sanctions on North Korea, either by forcing North Korea to reduce or eliminate its trade imbalances by enforcing a full sanctions regime. We also examine the potential impact of industry-specific export and import sanctions.

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 the 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 spatial equilibria under these two assumptions and present the aggregate impact in Rows 2 to 3 of Table 12, where Row 1 displays the aggregate impact of the current sanctions for ease of comparison (same results as in Column 2 of Table 11). Compared to the current sanctions, which reduce the population weighted county-level real output by 20%, forcing North Korea to reduce its trade deficit to the pre-sanctions level and to zero further decreases aggregate real output by 8% and 14%, respectively. Therefore, if one believes that North Korea will close its trade deficits in the mid to long term, we expect aggregate output to decline further. County-population-weighted changes in real GDP and real wages are of similar magnitudes, with the change in real wages being slightly larger.

The last row of Table 12 reports the aggregate impact of a full sanctions regime on all exports and imports, and trade deficits are zero by construction. Manufacturing output declines even further to 44% of the pre-sanctions level. Note that from Row 3 to Row 4, we are only removing the remaining 10% of the pre-sanction total exports and imports, and this accounts for about one-third of the final decline in output. These results suggest that the impact of the trade sanctions could be highly nonlinear.

We next consider sanctions by sector. We first consider complete export sanctions on each of the 21 industries in our sample. Panel (a) of Figure 9 plots the impact of complete export sanctions in each sector on the aggregate manufacturing output against the pre-sanctions export value of each sector (the sum is normalized to one). Each dot represents a counterfactual equilibrium under the corresponding sanction. Panel (b) plots the same predicted change against the "total usage" of these exports, i.e., the direct loss in output due to sanctions as well as the indirect loss due to reduced demand for upstream industries.[34] We see that overall the predicted aggregate impact is highly correlated with the base-period exports, whether we take into account the input-output linkages or not. Among the manufacturing sectors that we consider, Sector 18 (Apparel) has the highest exports in the base period, and therefore an export sanction on this industry alone creates the largest impact (around -10%) on total manufacturing output.

Panels (c) and (d) plot the impact of full import sanctions on each sector against two measures of the importance of the imports of each sector's products. The first measure is the share of imports in total absorption, i.e., $1 - s_j^{dom}$, where s_j^{dom} is defined in equation (8). A full import sanction of sector j goods causes a larger decline in aggregate output if this share is larger, as we see from equation (12) that a smaller s_j^{dom} is associated with a larger change in the prices of sector j goods, taking domestic prices as fixed. The second measure is $1 - s_j^{dom}$ scaled by the Domar weights. Domar weights of sector j are the output of this sector to value added of all sectors, which captures the downstream propagation of supply shocks to sector j and is a sufficient statistic of the impact of a productivity shock to sector j on the aggregate value added under first-order approximation (Hulten, 1978). For domestic production, foreign input price shocks can be seen as supply-side shocks, and we use the Domar weights to capture the indirect effects of import sanctions on downstream sectors. As seen in panel (d), the Domar-weights-adjusted import shares better predict the aggregate impact of full import sanctions than using import shares alone in panel (c). For example, in panel (c), a full import sanction on motor vehicles seems to generate a relatively small aggregate output loss despite its strong reliance on foreign imports. In panel (d), it is clear that the Domar weight for this sector (Sector 34) is small, and after the adjustment the economy appears to rely much less on foreign motor vehicles, likely because they are not an important intermediate input for downstream manufacturing sectors.

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-

[34] Formally, the total usage of sector j's export is $m_j^u E_{F,j}$, where m_j^u is the upstream multiplier which equals the j-th element of the vector $(\mathbf{I} - \mathbf{A}')^{-1}\mathbf{e}_J$, where $\mathbf{I}$ is the $J \times J$ identity matrix, $\mathbf{A} = \{a_{jk}\}_{j,k}$ is the input-output matrix, and $\mathbf{e}_J$ is a vector of ones.

level trade data, we construct a Bartik-style measure of regional exposures to export and intermediate input sanctions. We find that sanctions on exports and intermediate inputs led to sharp declines in night light intensity. 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 impact on the aggregate economy of North Korea.

The 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 regional spillovers that are missing from the reduced-form approach. The model predicts that North Korean manufacturing GDP drops by 20% 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 night light changes 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.

References

Abrahams, Alexei, Christopher Oram, and Nancy Lozano-Gracia, "Deblurring DMSP nighttime lights: A new method using Gaussian filters and frequencies of illumination," *Remote Sensing of Environment*, 2018, *210*, 242–258.

Adão, Rodrigo, Costas Arkolakis, and Federico Esposito, "General Equilibrium Effects in Space: Theory and Measurement," Working Paper 2020.

____, Michal Kolesár, and Eduardo Morales, "Shift-Share Designs: Theory and Inference," *The Quarterly Journal of Economics*, November 2019, *134* (4), 1949–2010.

Ahn, Daniel P. and Rodney D. Ludema, "The sword and the shield: The economics of targeted sanctions," *European Economic Review*, November 2020, *130*, 103587.

Arkolakis, Costas, Arnaud Costinot, and Andrés Rodríguez-Clare, "New Trade Models, Same Old Gains?," *American Economic Review*, 2012, *102* (1), 94–130.

Atkin, David and Dave Donaldson, "Who's Getting Globalized? The Size and Implications of Intra-national Trade Costs," Working Paper 2015.

Autor, David H., David Dorn, and Gordon H. Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, October 2013, *103* (6), 2121–2168.

Backus, David K., Patrick J. Kehoe, and Finn E. Kydland, "Dynamics of the Trade Balance and the Terms of Trade: The J-Curve?," *The American Economic Review*, 1994, *84* (1), 84–103.

Bank of Korea, "Gross Domestic Product Estimates for North Korea in 2020," 2021.

Bartik, Timothy J., *Who benefits from state and local economic development policies?*, Kalamazoo, MI: WE Upjohn Institute for Employment Research, 1991.

Beyer, Robert, Yingyao Hu, and Jiaxiong Yao, "Measuring Quarterly Economic Growth from Outer Space," 2022.

Bharti, Nita, Andrew J Tatem, Matthew J Ferrari, Rebecca F Grais, Ali Djibo, and Bryan T Grenfell, "Explaining seasonal fluctuations of measles in Niger using nighttime lights imagery," *Science*, 2011, *334* (6061), 1424–1427.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, "Quasi-Experimental Shift-Share Research Designs," NBER Working Paper w24997 September 2018.

Caliendo, Lorenzo and Fernando Parro, "Estimates of the Trade and Welfare Effects of NAFTA," *The Review of Economic Studies*, 2015, *82* (1), 1–44.

____, ____, Esteban Rossi-Hansberg, and Pierre-Daniel Sarte, "The impact of regional and sectoral productivity changes on the US economy," *The Review of Economic Studies*, 2018, *85* (4), 2042–2096.

Central Bureau of Statistics of the DPR Korea, *DPR Korea 2008 Population Census: National Report*, Central Bureau of Statistics of the DPR Korea, Pyongyang, 2009.

Chen, Xi and William D. Nordhaus, "Using luminosity data as a proxy for economic statistics," *Proceedings of the National Academy of Sciences of the United States of America*, 2011, *108*, 8589–8594.

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

Costinot, Arnaud and Andrés Rodríguez-Clare, "Chapter 4 - Trade Theory with Numbers: Quantifying the Consequences of Globalization," in Gita Gopinath, Elhanan Helpman, and Kenneth Rogoff, eds., *Handbook of International Economics*, Vol. 4 of *Handbook of International Economics*, Elsevier, January 2014, pp. 197–261.

Dekle, Robert, Jonathan Eaton, and Samuel Kortum, "Unbalanced trade," *American Economic Review*, 2007, *97* (2), 351–355.

Dietzenbacher, Erik, Bart Los, Robert Stehrer, Marcel Timmer, and Gaaitzen de Vries, "The Construction of World Input–Output Tables in the Wiod Project," *Economic Systems Research*, March 2013, *25* (1), 71–98. Publisher: Routledge _eprint: https://doi.org/10.1080/09535314.2012.761180.

Dingel, Jonathan I, Antonio Miscio, and Donald R Davis, "Cities, lights, and skills in developing economies," *Journal of Urban Economics*, 2019, pp. 103–174.

Eaton, Jonathan and Samuel Kortum, "Technology, Geography, and Trade," *Econometrica*, 2002, *70* (5), 1741–1779.

Elvidge, Christopher, Kimberly Baugh, Mikhail Zhizhin, and Feng Chi Hsu, "Why VIIRS data are superior to DMSP for mapping nighttime lights," *Proceedings of the Asia-Pacific Advanced Network*, 2013, *35*, 62–69.

Etkes, Haggay and Assaf Zimring, "When trade stops: Lessons from the Gaza blockade 2007–2010," *Journal of International Economics*, January 2015, *95* (1), 16–27.

Fajgelbaum, Pablo D, Pinelopi K Goldberg, Patrick J Kennedy, and Amit K Khandelwal, "The Return to Protectionism," Working Paper 25638, National Bureau of Economic Research March 2019.

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

Felbermayr, Gabriel J., Constantinos Syropoulos, Erdal Yalcin, and Yoto Yotov, "On the Effects of Sanctions on Trade and Welfare: New Evidence Based on Structural Gravity and a New Database," SSRN Scholarly Paper ID 3422152, Social Science Research Network, Rochester, NY 2019.

Gibson, John, Susan Olivia, Geua Boe-Gibson, and Chao Li, "Which Night Lights Data Should We Use in Economics, and Where?," *Journal of Development Economics*, 2021, *149*, 102602.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik Instruments: What, When, Why, and How," *American Economic Review*, August 2020, *110* (8), 2586–2624.

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

Hodler, Roland and Paul A. Raschky, "Regional Favoritism," *Quarterly Journal of Economics*, 2014, *129*, 995–1033.

Hong, Min, *Analysis of North Korea's Nuclear and Missile Activities (in Korean)*, Korea Institute for National Unification, 2017.

Hu, Yingyao and Jiaxiong Yao, "Illuminating economic growth," Working Paper, International Monetary Fund 2019.

Hufbauer, Gary Clyde, Jeffrey Schott, Kimberly Ann Elliott, and Barbara Oegg, *Economic Sanctions Reconsidered*, Peterson Institute for International Economics, 2009.

Hulten, C. R., "Growth Accounting with Intermediate Inputs," *The Review of Economic Studies*, 1978, *45* (3), 511–518.

Jung, Euni, Suho Lim, Seung-Ho Jung, Seung-Yeop Lee, and Hyuk Kim, *Analysis of determinants of the current status and utilization rate of companies in western cities during the Kim Jong-un era*, Korea Institute for National Unification, Seoul, 2019.

Kahn-Lang, Ariella and Kevin Lang, "The Promise and Pitfalls of Difference-in-Differences: Reflections on 16 and Pregnant and Other Applications," *Journal of Business and Economic Statistics*, 2020, *38*, 613–620.

Kovak, Brian K., "Regional effects of trade reform: What is the correct measure of liberalization?," *American Economic Review*, 2013, *103* (5), 1960–76.

Kwon, Bo Ram, "The conditions for sanctions success: a comparison of the Iranian and North Korean cases," *Korean Journal of Defense Analysis*, 2016, *28* (1), 139–161.

Lee, Yong Suk, "International isolation and regional inequality: Evidence from sanctions on North Korea," *Journal of Urban Economics*, 2018, *103*, 34–51.

Michalopoulos, Stelios and Elias Papaioannou, "Pre-colonial ethnic institutions and contemporary African development," *Econometrica*, 2013, *81* (1), 113–152.

____ **and** ____ , "Spatial patterns of development: A meso approach," *Annual Review of Economics*, 2018, *10*, 383–410.

Morgan, T Clifton, Navin Bapat, and Yoshiharu Kobayashi, "Threat and imposition of economic sanctions 1945–2005: Updating the TIES dataset," *Conflict Management and Peace Science*, 2014, *31* (5), 541–558.

National Spatial Data Infrastructure Portal, "Digital Map of Korea," 2018.

Neuenkirch, Matthias and Florian Neumeier, "The impact of UN and US economic sanctions on GDP growth," *European Journal of Political Economy*, 2015, *40*, 110–125.

Paek, Yilsoon, Hyunjoo Jung, and Seung pyo Hong, "Re-reading Kaesung Industrial District with the (New) Mobilities Paradigm: Production of Socio-spaces through Commuter Buses as a New Mobility System," *Journal of the Korean Geographical Society*, 2020, *55*, 521–540.

Pape, Robert A, "Why Economic Sanctions Do Not Work," *International Security*, 1997, *22* (2), 90–136.

Pinkovskiy, Maxim and Xavier Sala-i-Martin, "Lights, camera… income! Illuminating the national accounts-household surveys debate," *The Quarterly Journal of Economics*, 2016, *131* (2), 579–631.

Redding, Stephen J. and Esteban Rossi-Hansberg, "Quantitative Spatial Economics," *Annual Review of Economics*, 2017, *9* (1), 21–58.

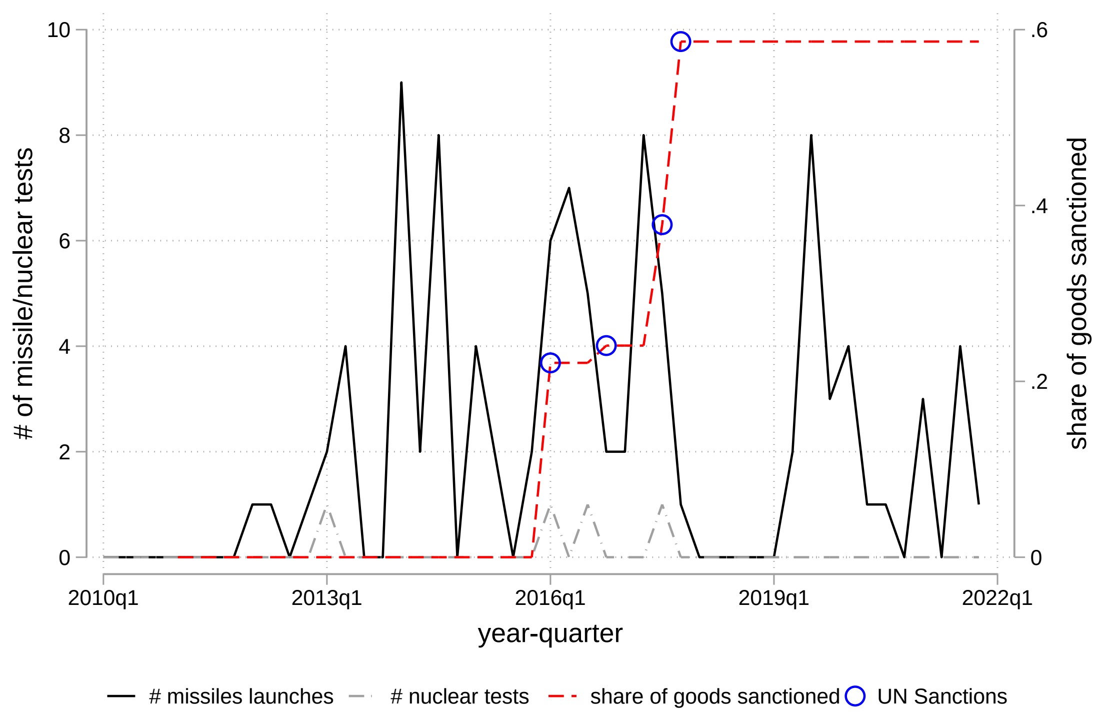
Simonovska, Ina and Michael E. Waugh, "The elasticity of trade: Estimates and evidence," *Journal of International Economics*, January 2014, *92* (1), 34–50.

Storeygard, Adam, "Farther on down the road: transport costs, trade and urban growth in sub-Saharan Africa," *The Review of Economic Studies*, 2016, *83* (3), 1263–1295.

The United Nations Human Rights Council, "Report of the detailed findings of the commission of inquiry on human rights in the Democratic People's Republic of Korea," 2014.

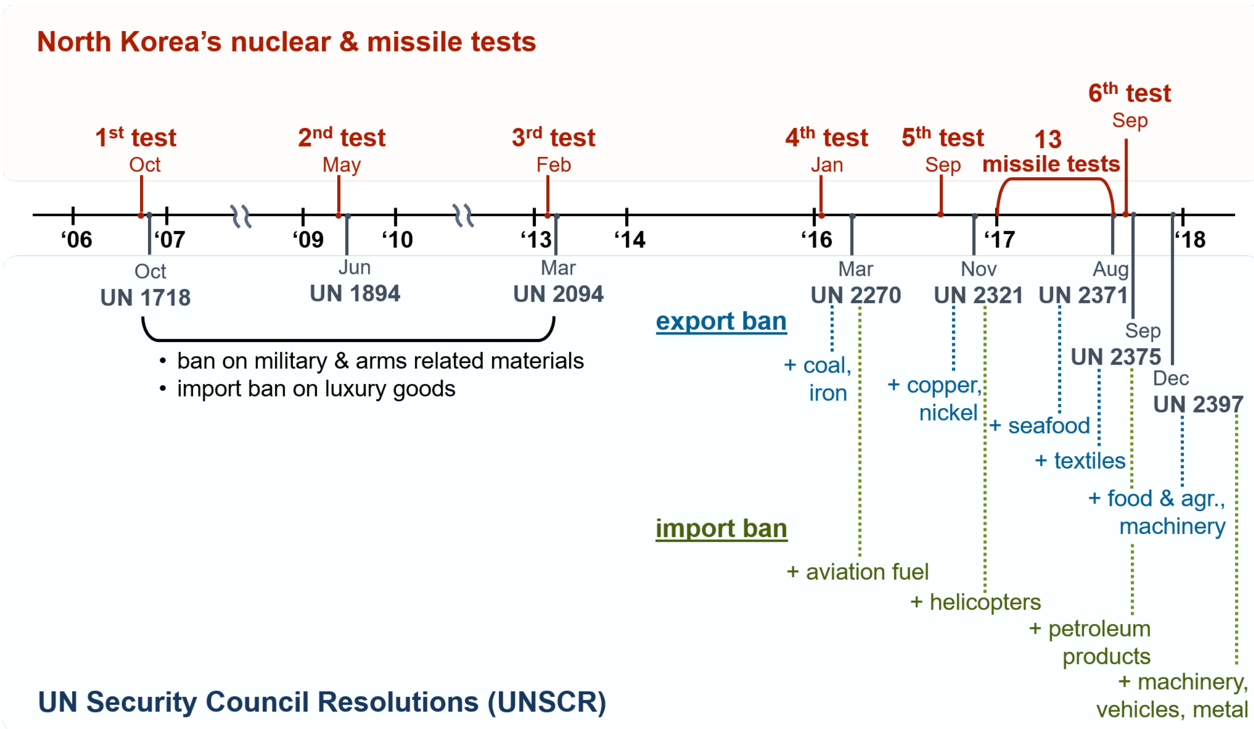
Yang, Moon Soo, *Systems and Status of North Korean Trade*, Korea Development Institute, 2008.

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



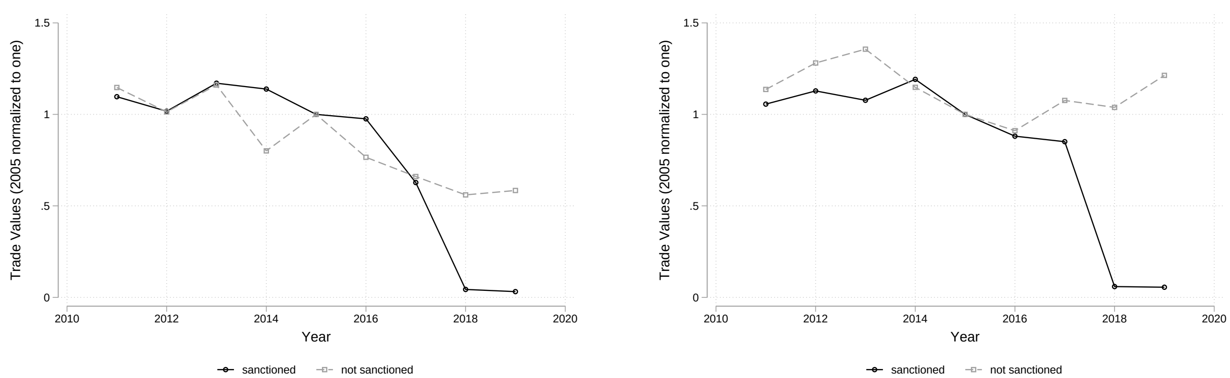
Notes: The solid line indicates the number of missile launches and nuclear tests in each quarter from 2010 to 2021. The grey, dash-dotted line indicates the quarters in which North Korea conducted nuclear tests. The red dashed line shows the share of pre-sanctions exports and imports (2011-2015) that 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.

Figure 2: The Timeline of UN Sanctions against North Korea



Notes: This figure shows the timeline of the 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.

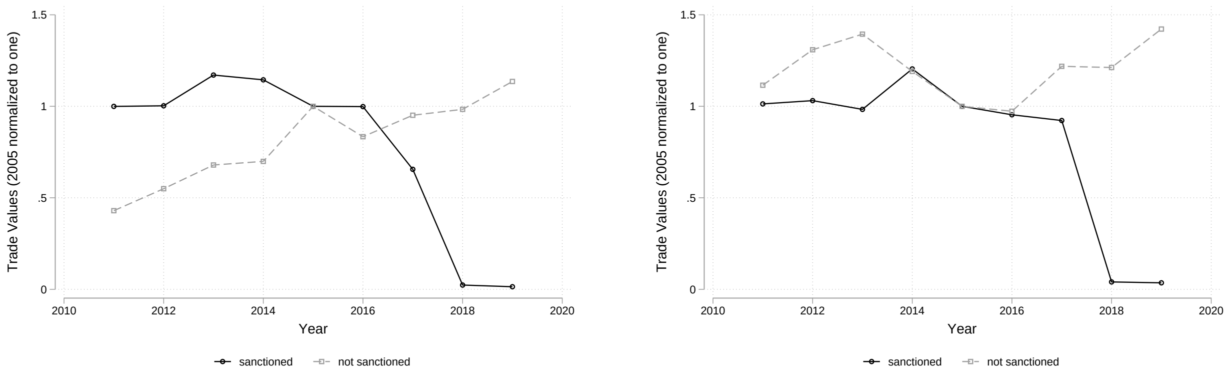
Figure 3: Total Trade in Sanctioned and Non-sanctioned Categories



(a) Exports (b) Imports

Notes: Data are normalized by the 2015 trade values for each category of products. In 2015 (before the sanctions), North Korea exported 2,714 million USD of goods to the rest of the world (RoW) in the sanctioned product categories and 377 million USD in the non-sanctioned categories. It imported 1213 million USD of goods from RoW in the sanctioned product categories and 2254 million USD in the non-sanctioned categories.

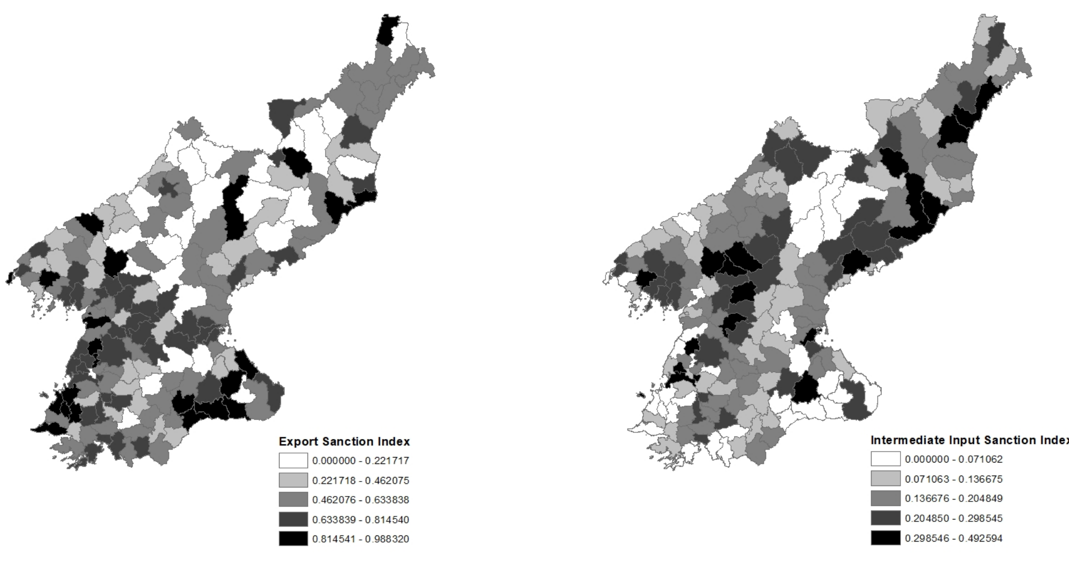
Figure 4: Total Trade with China in Sanctioned and Non-sanctioned Categories



(a) Exports (b) Imports

Notes: Data are normalized by the 2015 trade values for each category of products. In 2015 (before the sanctions), North Korea exported 2,413 million USD of goods to the rest of the world (RoW) in the sanctioned product categories and 155 million USD in the non-sanctioned categories. It imported 1151 million USD of goods from RoW in the sanctioned product categories and 1792 million USD in the non-sanctioned categories.

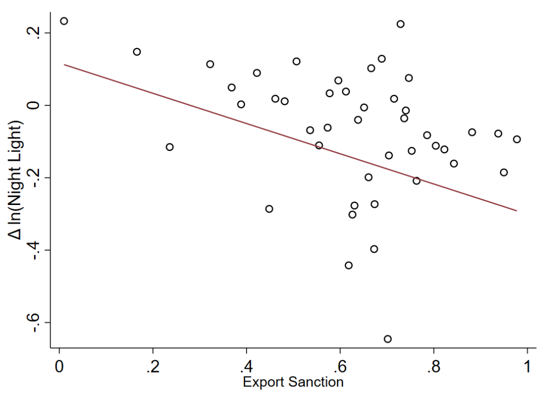
Figure 5: Spatial Distribution of Sanction Exposures



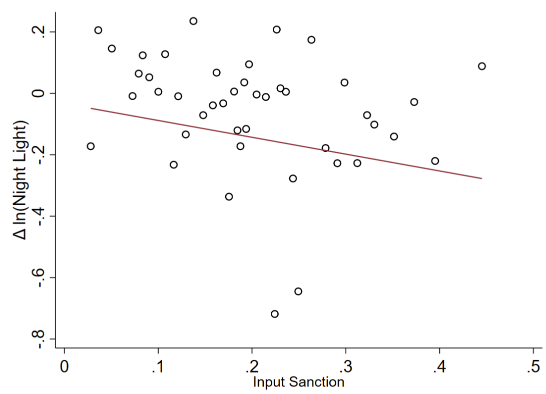
(a) Export Sanction Exposure (b) Intermediate Input Sanction Exposure

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

Figure 6: Long-difference relationship between night light and sanction exposures



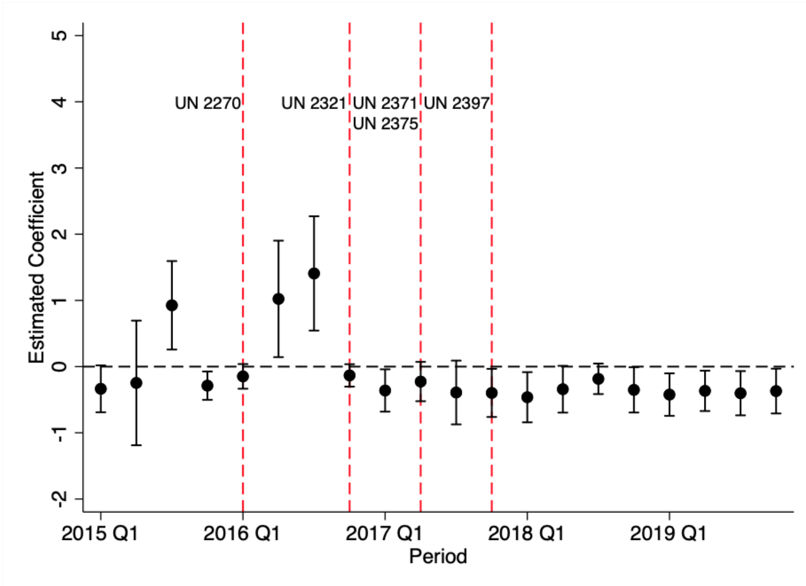
(a) Export sanction exposure



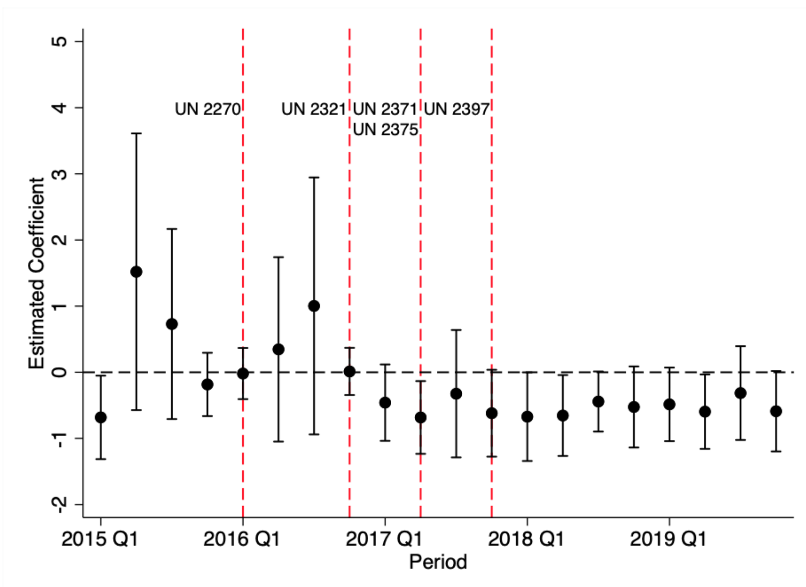
(b) Intermediate input sanction exposure

Notes: The vertical axis indicates the quarter-to-quarter difference in log night light intensity between two years, 2014 and 2019. Night lights are residualized by year to account for year-specific shocks. County × quarter observations are grouped into 50 bins based on the horizontal axis. The solid red line depicts the linear fit with population share in 2008 as weights.

Figure 7: Generalized DID estimates of sanction exposures on night light intensity



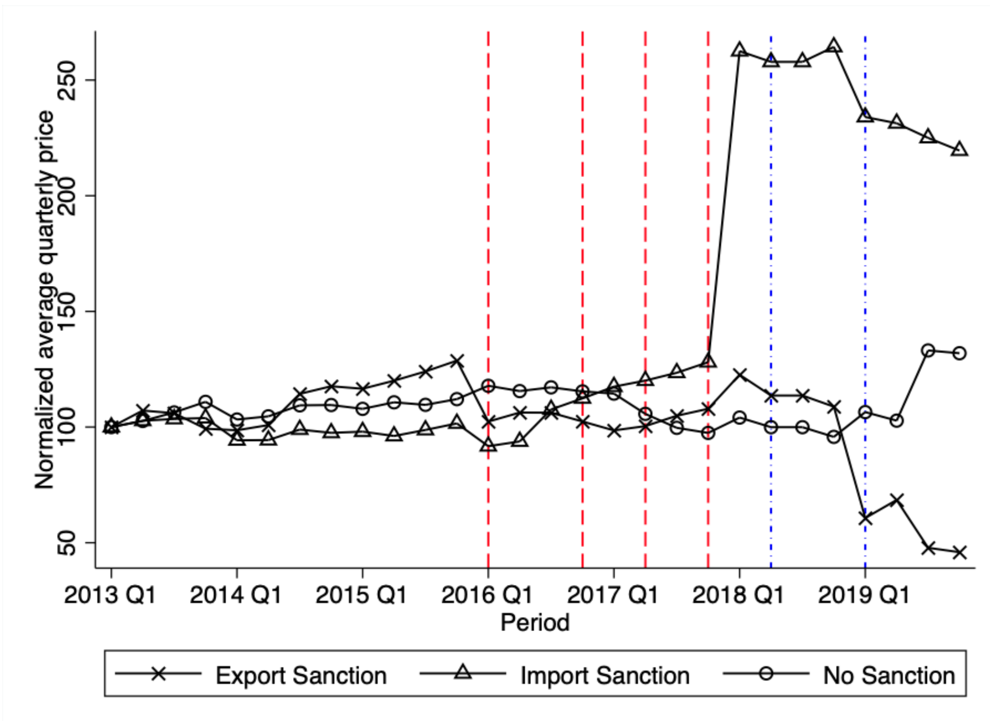
(a) Export sanction exposure



(b) Intermediate input sanction exposure

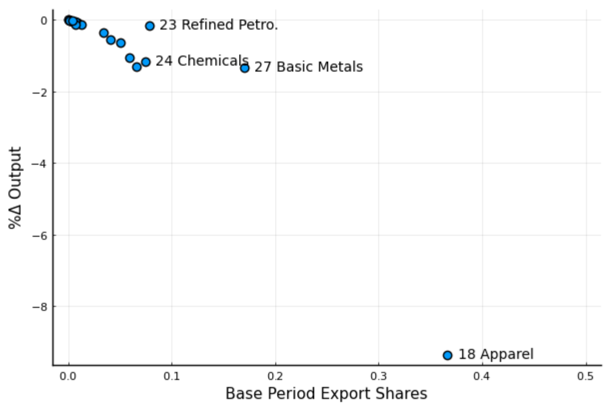
Notes: This figure presents quarter-specific coefficient estimates of (a) export sanction and (b) input sanction exposures on nighttime light intensity. UN 2270 - Export ban of coal and iron ore except for people's livelihood. UN 2321 - Upper limit on coal and iron exports. UN 2371 - Total ban on coal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

Figure 8: Price trend by product's sanction status

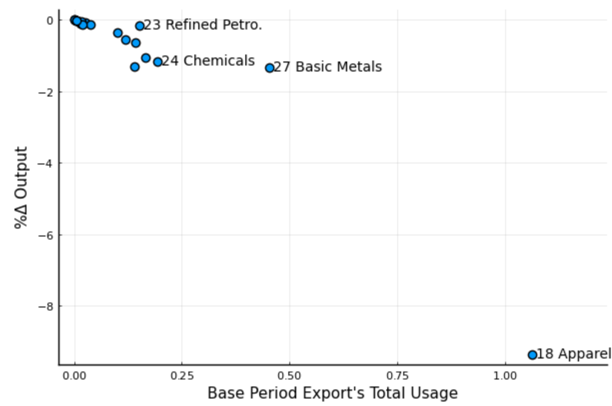


Notes: This figure plots normalized average quarterly price trends of products grouped by sanction type. Average quarterly price is obtained by averaging across six cities in North Korea (Pyeongyang, Shineuijoo, Kwaksan, Wonsan, Hweiryoung, and Hamheung) and is normalized with respect to the first quarter 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: the Singapore summit in June 12, 2018 and the Hanoi summit in February 27, 2019.

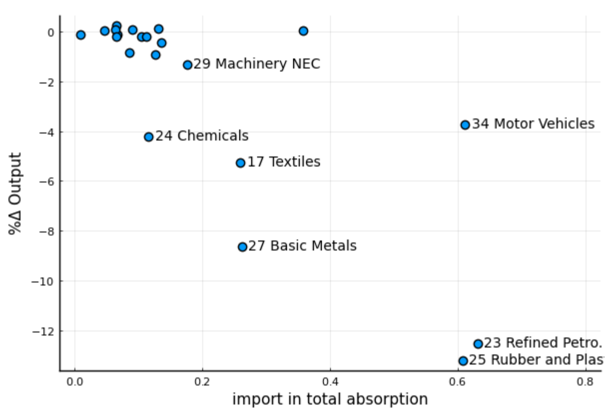
Figure 9: The impacts of by-sector sanctions and their determinants



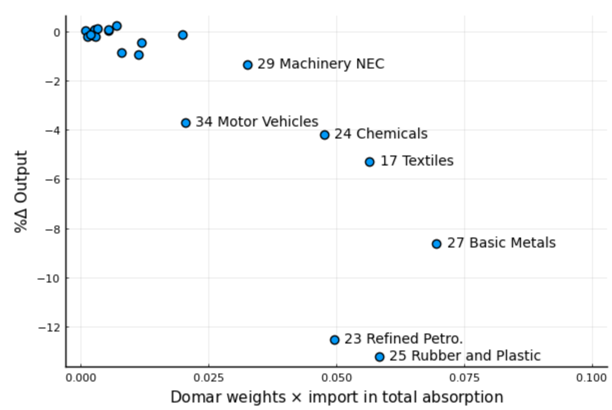
(a) Impact of full exp. sanc. by sector and base-period exports



(b) Impact of full exp. sanc. by sector and base-period exports' total usage



(c) Impact of full import sanc. and import shares in total absorption



(d) Impact of Full Import Sanc. and Import Shares Adjusted by Domar Weights

Notes: Each dot in the figure represents a counterfactual sanction of a particular industry, either on the export side (panels a-b) or on the import side (panel c-d). %Δ Output refers to the percentage change in aggregate industrial output caused by corresponding sanctions.

Table 1: Top 5 Industries and Trading Partners, 2011 - 2015

Exports				Imports			
Partner	%	Products in Industry	%	Partner	%	Products in Industry	%
China	79.9	10 Coal	32.8	China	84.2	17 Textiles	12.4
India	1.8	18 Apparel	15.6	India	4.2	15 Food	10.5
Netherlands	1.4	13 Metal Ores	15.5	Russian Federation	2.1	11 Crude Oil	8.8
Bahrain	1.4	27 Basic Metals	7.2	Thailand	1.7	24 Chemicals	8.2
Pakistan	1.3	15 Food	5.2	Singapore	1.1	29 Machinery NEC	7.8

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. We map HS 6-digit products to ISIC 2-digit industries using the concordance map provided by the World Integrated Trade Solution (WITS, https://wits.worldbank.org/product_concordance.html).

Table 2: 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).

Table 3: 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 light intensity	4045	0.192	0.137	0.007	0.097	0.201	0.252	0.783

Notes: This table provides summary statistics on county-level characteristics. Mean nighttime light intensity is shown at the county $\times$ quarter level from the first quarter of 2014 to fourth quarter of 2019.

Table 4: Estimates of the Impact of Sanction Exposures

	Log(Night light intensity)		
	(1)	(2)	(3)
Panel A. Five-year difference in annual average (2014-2019)			
Export sanction exposure	-0.341**		-0.329**
	(0.149)		(0.145)
Intermediate input sanction exposure		-0.528*	-0.489*
		(0.275)	(0.264)
R-squared	0.05	0.03	0.08
Observations	174	174	174
Panel B. Difference-in-Differences in quarterly average			
Export sanction exposure × Post(2017 Q1-)	-0.516***		-0.497**
	(0.197)		(0.192)
Intermediate input sanction exposure × Post(2017 Q1-)		-0.778*	-0.719*
		(0.397)	(0.380)
R-squared	0.82	0.82	0.83
Observations	4045	4045	4045
County FE	Yes	Yes	Yes
Quarter × Year FE	Yes	Yes	Yes

Notes: Dependent variable is the natural log of nighttime light intensity aggregated at the county level. Monthly VIIRS nighttime light data are averaged by year (Panel A) and by quarter (Panel B), respectively. Observations are weighted by county's share of population in 2008. 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 5: Estimated Impacts of Sanction Exposures by Sanction Wave

	Log(Night light intensity)				
	(1)	(2)	(3)	(4)	(5)
Export sanction × UN 2270 (2016 Q2-)	0.652***		0.643***	0.675***	0.696***
	(0.226)		(0.225)	(0.258)	(0.236)
Export sanction × UN 2321 (2017 Q1-)	-0.965***		-0.938***	-0.944***	-0.943***
	(0.339)		(0.334)	(0.332)	(0.333)
Export sanction × UN 2371, UN2375 (2017 Q3-)	-0.099		-0.101	-0.095	-0.082
	(0.073)		(0.071)	(0.065)	(0.069)
Export sanction × UN 2397 (2018 Q1-)	0.030		0.032	0.048	0.092
	(0.072)		(0.070)	(0.102)	(0.088)
Intermediate input sanction × UN 2270 (2016 Q2-)		0.389	0.322	0.204	0.297
		(0.501)	(0.476)	(0.513)	(0.494)
Intermediate input sanction × UN 2321 (2017 Q1-)		-1.107	-1.004	-1.061	-1.039
		(0.702)	(0.670)	(0.682)	(0.677)
Intermediate input sanction × UN 2371, UN 2375 (2017 Q3-)		0.088	0.100	0.056	0.073
		(0.184)	(0.178)	(0.164)	(0.174)
Intermediate input sanction × UN 2397 (2018 Q1-)		-0.059	-0.063	-0.172	-0.149
		(0.176)	(0.172)	(0.245)	(0.216)
County FE	Yes	Yes	Yes	Yes	Yes
Quarter × Year FE	Yes	Yes	Yes	Yes	Yes
County-specific linear time trend	No	No	No	Yes	No
County-specific quadratic time trend	No	No	No	No	Yes
Mean night light intensity (in levels)	0.14				
R-squared	0.83	0.82	0.83	0.85	0.85
Observations	4045	4045	4045	4045	4045

Notes: Dependent variable is the natural log of nighttime light intensity aggregated by county and quarter using monthly VIIRS nighttime light data. For description of sanctions see notes in Figure 6. Observations are weighted by county's share of population in 2008. 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 6: Robustness Check - Difference-in-Differences Estimates

	Log(Night light intensity)								
	Alternative Fixed Effects		Drop counties from sample				Exclude Year 2016	Add county-specific time trends	
			top and bottom		Pyeongyang	China Border			
			1 perc.	3 perc.				Linear	Quadratic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Export sanction exposure × Post(2017 Q1-)	-0.439**	-0.437**	-0.537***	-0.365***	-0.343***	-0.463**	-0.377**	-0.798***	-0.602**
	(0.193)	(0.197)	(0.198)	(0.104)	(0.118)	(0.203)	(0.168)	(0.283)	(0.235)
Intermediate input sanction exposure × Post(2017 Q1-)	-0.725*	-0.722*	-0.578	-0.407	-0.477	-0.689*	-0.669**	-0.994	-0.848*
	(0.371)	(0.373)	(0.368)	(0.281)	(0.299)	(0.374)	(0.325)	(0.616)	(0.492)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	No	No	No	No	No	No	No
Province × Quarter FE	No	Yes	No	No	No	No	No	No	No
Quarter × Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-specific linear time trend	No	No	No	No	No	No	No	Yes	No
County-specific quadratic time trend	No	No	No	No	No	No	No	No	Yes
Mean nighttime light (in levels)	0.14	0.14	0.14	0.14	0.14	0.14	0.17	0.14	0.14
R-squared	0.75	0.75	0.82	0.81	0.82	0.83	0.85	0.85	0.85
Observations	4045	4045	3950	3758	3925	3689	3423	4045	4045

Notes: Dependent variable is the natural log of nighttime light intensity aggregated by county and quarter using monthly VIIRS nighttime light data. Dropped counties are at the top or bottom 1 percentile (Column 3) and 3 percentile (Column 4) of the night light intensity distribution in the first quarter of 2015. Observations are weighted by county's share of population in 2008. 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 7: Industries with the largest Rotemberg weights

Industry j	α_j	Sanction index g_j	$Z'_j B$	$\hat{\beta}_j$	95% CI	
Panel A. Export sanction						
Food	0.442	0.944	3.209	0.316	-0.236	0.868
Machinery NEC	0.180	0.994	1.243	-0.075	-0.664	0.515
Apparel	0.149	0.997	1.027	-0.972	-2.231	0.287
Elec. Equip.	0.083	0.997	0.568	-1.787	-4.197	0.623
Textiles	0.075	0.999	0.516	-0.977	-2.306	0.352
Panel B. Intermediate input sanction						
Machinery NEC	0.418	0.619	0.997	-0.093	-0.830	0.644
Basic Metals	0.184	0.498	0.545	-0.343	-1.220	0.534
Elec. Equip.	0.181	0.560	0.477	-2.130	-5.351	1.090
Fabricated Metals	0.096	0.631	0.225	-2.410	-6.290	1.471
Trans Equip. NEC	0.092	0.706	0.192	-1.730	-3.313	-0.147

Notes: We perform the Rotemberg decomposition of the long-difference regressions in Columns 1 and 2 of Panel A, Table 4, 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 4 equals the weighted average of all the coefficients from the IV regressions, i.e., $\sum_j \alpha_j \beta_j$.

Table 8: Relationship between Industry Share and Characteristics

	Industry share of firms in 2015								Sanction exposure	
	Food	Apparel	Machinery	Textile	Electrical Equip.	Basic metal	Transport Equip.	Fabricated metal	Export	Intermed. input
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ln(size of population in 2008)	-0.046	-0.002	0.028	0.022	0.032***	0.043**	0.020***	0.017	0.127**	0.057**
	(0.039)	(0.022)	(0.025)	(0.030)	(0.008)	(0.017)	(0.005)	(0.013)	(0.046)	(0.023)
ln(sum of building area in 2014)	-0.097**	0.032	0.066	0.031	-0.018	-0.038**	-0.002	-0.011	-0.043	0.006
	(0.042)	(0.035)	(0.038)	(0.035)	(0.014)	(0.017)	(0.005)	(0.019)	(0.069)	(0.020)
ln(road length in 2017)	0.066	-0.027	-0.052*	-0.046***	-0.003	0.010	-0.005	-0.006	-0.066	-0.016
	(0.041)	(0.015)	(0.023)	(0.009)	(0.006)	(0.016)	(0.004)	(0.009)	(0.050)	(0.015)
ln(distance to border)	0.039	0.006	-0.004	0.001	-0.005	-0.013	0.004	-0.001	0.020	-0.014
	(0.027)	(0.009)	(0.008)	(0.002)	(0.005)	(0.013)	(0.004)	(0.003)	(0.015)	(0.014)
ln(distance to Pyeongyang)	-0.019	-0.003	0.028**	-0.002	-0.016	0.013	0.011*	-0.003	0.015	0.016**
	(0.013)	(0.013)	(0.010)	(0.006)	(0.011)	(0.007)	(0.006)	(0.002)	(0.029)	(0.007)
ln(distance to major port)	0.009	0.003	0.006*	0.006**	-0.002	-0.022**	-0.003	-0.002	-0.002	-0.010*
	(0.007)	(0.004)	(0.003)	(0.002)	(0.003)	(0.008)	(0.003)	(0.001)	(0.004)	(0.004)
Nuclear site	-0.070	-0.050***	0.019	0.123**	-0.013	-0.009	-0.005	-0.008**	0.020	-0.001
	(0.046)	(0.013)	(0.035)	(0.048)	(0.018)	(0.010)	(0.004)	(0.003)	(0.041)	(0.033)
Special industrial zone	0.001	-0.007	-0.032	0.039*	0.006	-0.047*	0.002	-0.015	-0.075	-0.036
	(0.054)	(0.035)	(0.032)	(0.019)	(0.024)	(0.022)	(0.014)	(0.010)	(0.065)	(0.025)
ln(mean night light intensity in 2015)	0.054	0.034	0.015	-0.002	-0.042*	-0.010	0.023	0.010	0.068	-0.024
	(0.071)	(0.045)	(0.030)	(0.020)	(0.020)	(0.014)	(0.026)	(0.013)	(0.086)	(0.022)
Mean	0.28	0.07	0.06	0.04	0.02	0.02	0.01	0.01	0.55	0.17
R-squared	0.12	0.11	0.12	0.17	0.18	0.35	0.32	0.11	0.12	0.21
Observations	174	174	174	174	174	174	174	174	174	174

Notes: Each column reports results from separate regressions of 2015 industry share on county-level characteristics. Regressions are weighted by population in 2008. Standard errors are clustered at the province level and reported in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table 9: Estimated Impacts of Sanctions on Market Price

	Log(Normalized quarterly price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Export sanctioned $\times\mathbf{1}$(Post sanction)	-0.032			-0.040	-0.052	-0.042
	(0.066)			(0.063)	(0.064)	(0.064)
Import sanctioned $\times\mathbf{1}$(Post sanction)		0.319***		0.322***		0.303*
		(0.055)		(0.050)		(0.158)
Input sanction index $\times\mathbf{1}$(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
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 its price in the 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 the product level and reported in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table 10: Calibrated and Estimated Parameters

Parameters	Description	Value	Source
Panel A: Calibrated (without solving the model)			
ϵ	Domestic trade elasticity	4	Adão et al. (2020)
σ	Armington elasticity	1.5	Backus et al. (1994)
τ_{in}	Domestic iceberg trade costs	$e^{0.042d_{in}}$	Fan et al. (2021)
A_n	Location-specific productivity	$L_n^{0.56}$	Adão et al. (2020)
$\tau_{nF}=\tau_{Fn}$	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		Nationwide share of firms weighted by log(# mention + 1)
$E_{F,j}$	Foreign expenditure on domestic goods in sector j		Yearly exports 2011-2015
T_n	Exogenous transfers to residents in county n	$\frac{L_n}{L}\times T$	Total trade deficits in 2011-2015 scaled by population share
Panel B: Estimated (solving the model and matching moments)			
p_{Fj}	Foreign prices in the base period		Shares of j goods in yearly imports, 2011-2015
$\tilde{A}_{nj}$	Productivity of sector j in region n		County share of firms weighted by log(# mention + 1)
α_{dom}	Home bias parameter	0.71	Reduced-form coefficients

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.

Table 11: Baseline Results and Alternative Models

	(1) Data	(2) Baseline	(3) No Agglomeration	(4) Some Mobility	(5) Perfect Mobility	(6) High τ_{in}
Parameters varied (α_m, ψ)		(0,0.56)	(0,0)	(0.5,0.56)	(1,0.56)	(0,0.56)
Estimated α_{dom}		0.71	0.43	0.73	0.75	0.76
Panel A: Regressions						
Dep. Var.	0.419 $\times\Delta$ log(light)	Δ log(real output)				
Exp. Sanc. Coef.	-0.138	-0.130	-0.145	-0.121	-0.113	-0.094
	(0.061)	(0.020)	(0.021)	(0.019)	(0.018)	(0.018)
Input Sanc. Coef.	-0.205	-0.211	-0.196	-0.198	-0.186	-0.228
	(0.111)	(0.029)	(0.030)	(0.027)	(0.026)	(0.033)
N	174	174	174	174	174	174
R-squared	0.078	0.381	0.371	0.375	0.370	0.371
Panel B: Aggregate Outcomes						
Base Period Export/Output		0.14	0.15	0.14	0.13	0.12
Base Period Export/GDP		0.36	0.36	0.34	0.32	0.31
$\widehat{\text{real output}}$		0.80	0.80	0.81	0.82	0.83
$\widehat{\text{real GDP}}$		0.81	0.80	0.82	0.83	0.85
$\widehat{\text{real wage}}$		0.78	0.77	0.79	0.80	0.81

Notes: We change the values of α_m (labor mobility across sectors) and ψ (the strength of agglomeration) across model specifications in Columns 2 to 5, and present the estimated home bias α_{dom} for each model. Column 6 reports the calibration of the "high trade costs" scenario, where we assume that the semi-elasticity of trade costs with respect to road network distance in North Korea is four times of those in China. Panel (A) displays the cross-county regressions in the model and in the data. We estimated α_{dom} by minimizing the difference between the regression coefficients in the model and those in the data (Column 1). GDP-to-nightlight elasticity is set at 0.419. In panel (B), we report aggregate outcomes in different models. Statistics with a "hat" indicate ratios of these variables in the post-sanction equilibrium to those in the base period.

Table 12: The impacts under alternative scenarios/sanctions

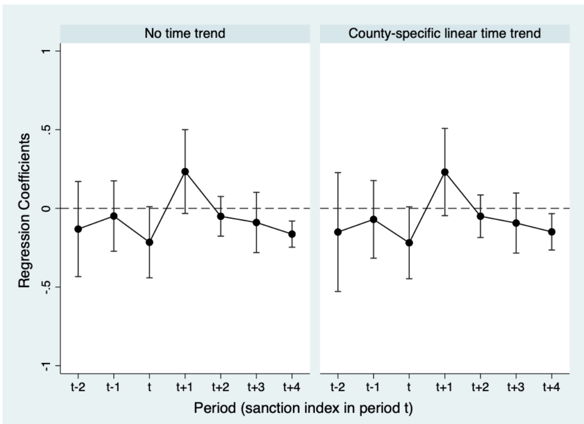
	Sanction	Deficit	$\widehat{\text{real output}}$	$\widehat{\text{real GDP}}$	$\widehat{\text{real wage}}$
1	Current	change as data	0.80	0.81	0.78
2	Current	fixed at pre-sanction	0.72	0.71	0.68
3	Current	zero	0.66	0.64	0.61
4	Full	zero	0.44	0.39	0.33

Notes: The table compares ratios of population-weighted aggregate outcomes of each county after the sanctions with those in the base period. We consider the current sanction in Rows 1 to 3 and vary assumptions about the trade deficits after sanctions. 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; and Row 4 displays the aggregate outcome under complete export and import sanctions.

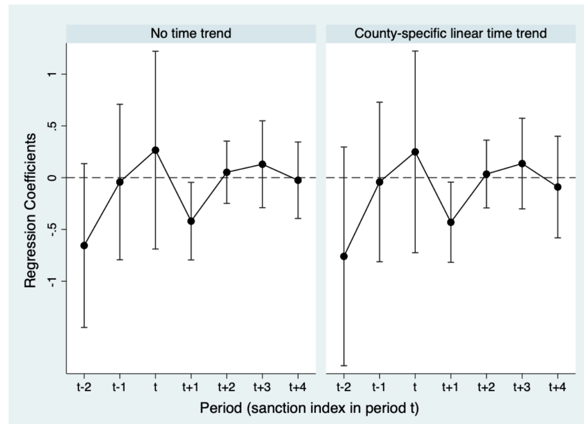
For Online Publication

A Appendix: Figures & Tables

Figure A-1: Evolution of the impact of sanction exposures on night light intensity



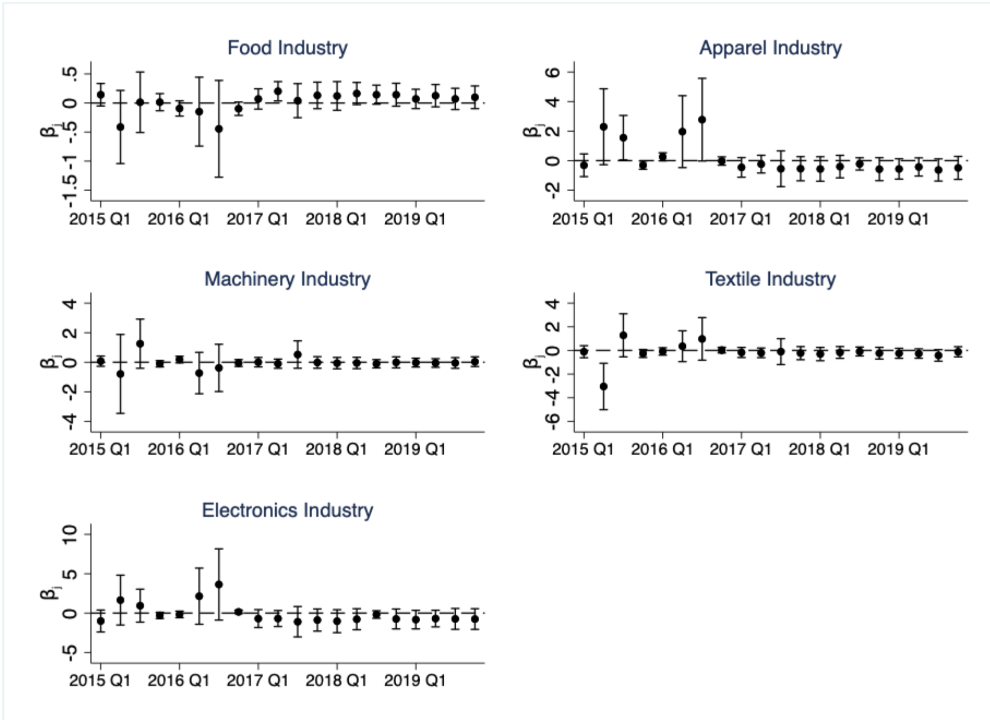
(a) Export sanction



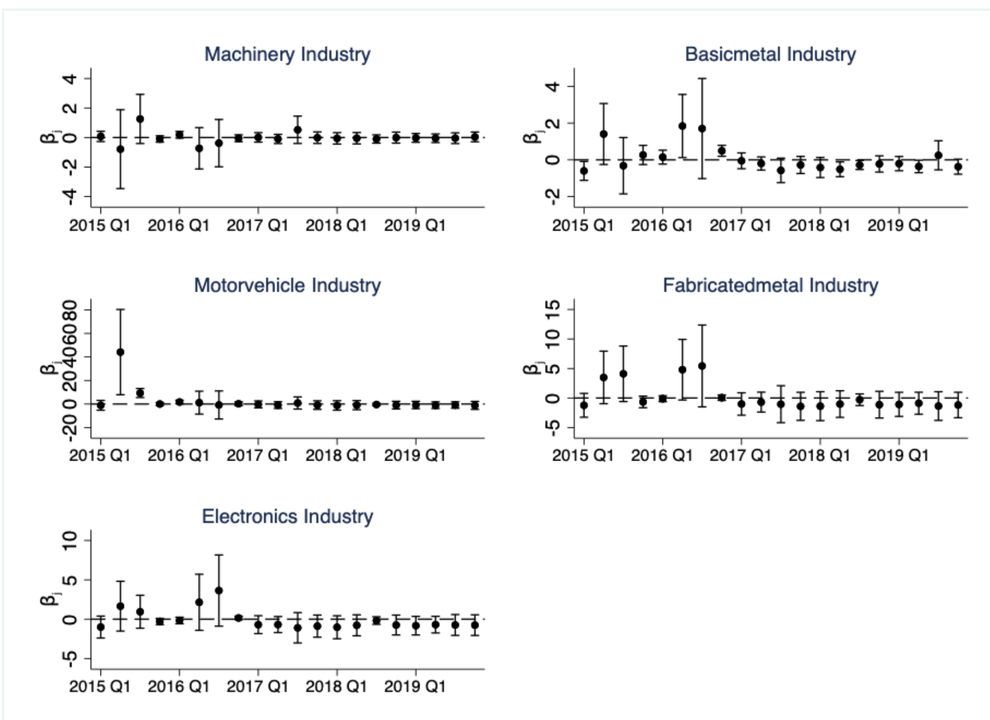
(b) Intermediate input sanction

Notes: This figure plots regression coefficients of sanction exposure with lead and lag periods. In panels (a) and (b), the left graph shows coefficients estimated without a linear time trend and the right graph shows coefficients estimated with a county-specific linear time trend.

Figure A-2: Pre-trends in top-5 Rotemberg weight industries



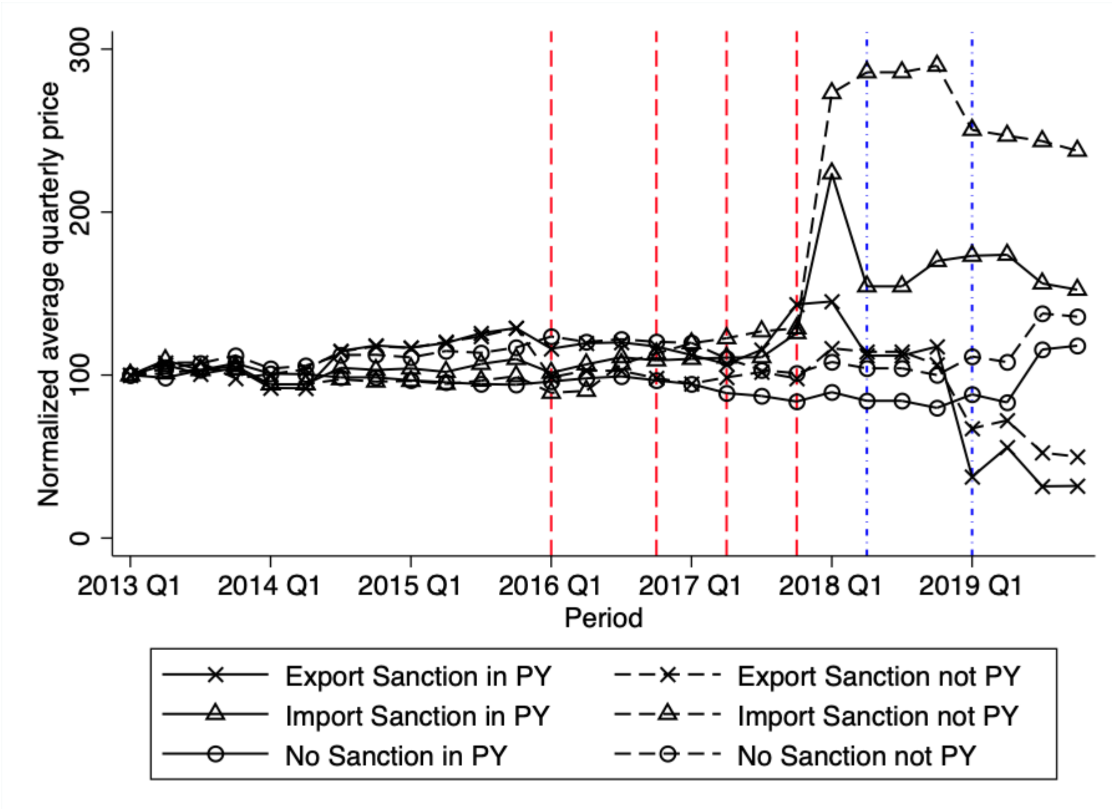
(a) Export sanction



(b) Intermediate input sanction

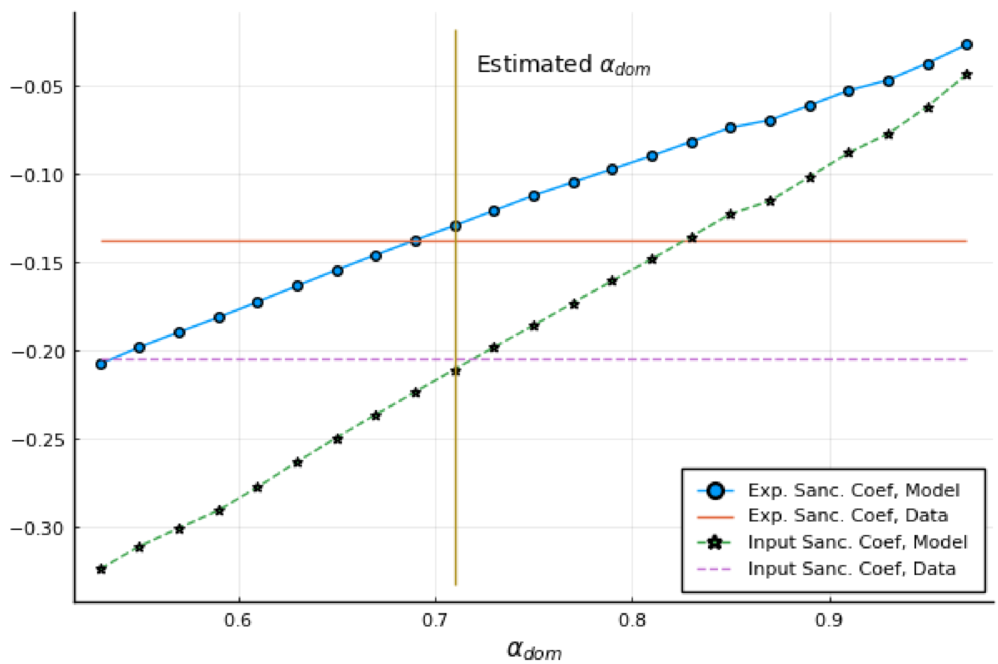
Notes: This figure presents quarter-specific estimates of industry share on night light intensity for industries with top-5 Rotemberg weights. Panels (a) and (b) include the five industries with largest Rotemberg weights for export and intermediate input sanction exposure, respectively.

Figure A-3: Price trends by product's sanction status: City heterogeneity



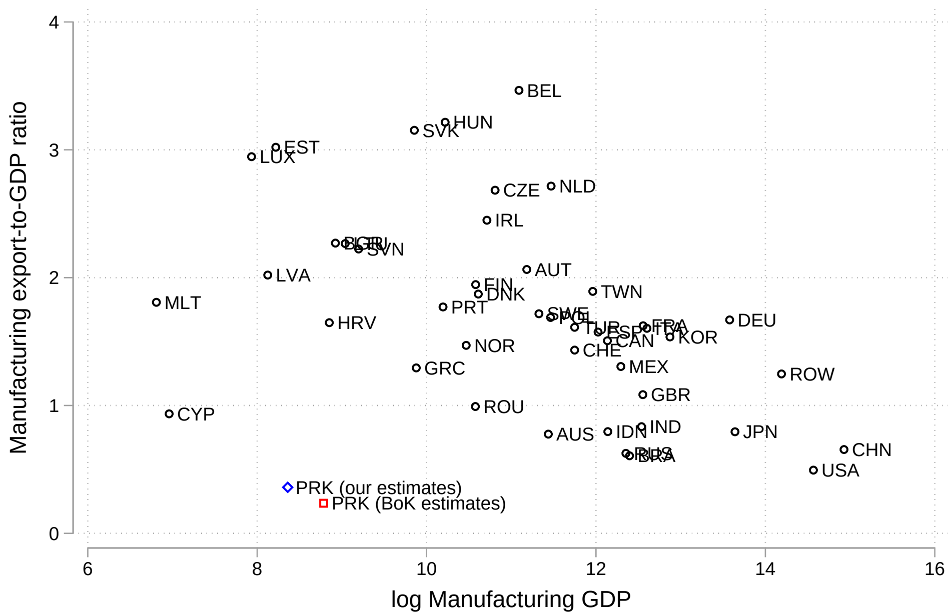
Notes: This figure plots normalized average quarterly price trends of products grouped by sanction type. Solid lines indicate price in Pyeongyang and dashed lines indicate the average price across five cities excluding Pyeongyang. Red dashed horizontal lines indicate periods in which sanctions were imposed.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

Figure A-4: Identifying the Parameter α_{dom}



Notes: For each guess of α_{dom}, we calibrate all the other parameters of the model so that the base-period region-industry shares match those observed in the data. We then shock the model with the export and import sanctions and solve for the changes in county-level output, and regress the changes on the export and input sanction exposure measures as we do in the empirical sections. The solid line with blue dots represents the coefficient of export sanction exposure and the green dashed line with stars represents the coefficient of input sanction exposure. The two horizontal lines represent the data coefficients we target. The vertical line indicates the calibrated value of α_{dom}.

Figure A-5: Manufacturing Export-to-GDP ratio across countries



Notes: Each dots represents the export-to-GDP ratio and GDP in current USD of the manufacturing sector in a country. For the red dot (BoK estimates for North Korea), we use exports data obtained from UN Comtrade and GDP estimates from the Bank of Korea. The Bank of Korea provided North Korean GDP in Korean won, which we converted to USD using Korean won-USD exchange rates. We use the average exports and GDP between 2011 and 2015 to smooth year-to-year fluctuations. For the blue dot (our estimates for North Korea), we use the export-to-GDP ratio implied by our model, 0.36, and infer its GDP using yearly exports from UN Comtrade. The statistics of the remaining countries come from the World Input Output Table for the year 2014.

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: Pre-trend Estimates of Sanction Exposures

	Log(Night light intensity)		
	(1)	(2)	(3)
Export sanction exposure × Post(2016 Q1-)	0.421***		0.415***
	(0.152)		(0.152)
Intermediate input sanction exposure × Post(2016 Q1-)		0.265	0.217
		(0.356)	(0.338)
R-squared	0.79	0.79	0.79
Observations	1957	1957	1957
Export sanction exposure × Post(2015 Q1-)	0.243**		0.236**
	(0.111)		(0.108)
Intermediate input sanction exposure × Post(2015 Q1-)		0.299	0.271
		(0.294)	(0.291)
R-squared	0.79	0.79	0.79
Observations	1957	1957	1957
County FE	Yes	Yes	Yes
Quarter × Year FE	Yes	Yes	Yes

Notes: Dependent variable is the natural log of nighttime light intensity aggregated by county and quarter using monthly VIIRS nighttime light data. Sample period is from 2014 Q1 to 2016 Q4. Observations are weighted by county's share of population in 2008. 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 A-3: Robustness Check: Alternative Company Weights

	Log(Night light intensity)								
Company weights:	None			Num. of mentions			Log(num. of mentions)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Export sanction exposure × Post(2017 Q1-)	-0.551***		-0.553***	-0.382**		-0.362**	-0.516***		-0.497**
	(0.197)		(0.197)	(0.184)		(0.183)	(0.197)		(0.192)
Intermediate input sanction exposure × Post(2017 Q1-)		-1.168*	-1.175**		-0.392*	-0.301		-0.778*	-0.719*
		(0.593)	(0.574)		(0.204)	(0.203)		(0.397)	(0.380)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.82	0.82	0.83	0.82	0.82	0.82	0.82	0.82	0.83
Observations	4045	4045	4045	4045	4045	4045	4045	4045	4045

Notes: Dependent variable is the natural log of nighttime light intensity aggregated by county and quarter using monthly VIIRS nighttime light data. Observations are weighted by county's share of population in 2008. Number of company mentions is sourced from KIET data from 2000 to 2015. 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 A-4: Robustness Check: Alternative Input-Output Table

	Log(Night light intensity)			
	(1)	(2)	(3)	(4)
Panel A. Five-year difference in annual average (2014-2019)				
Intermediate Input Sanction Exposure (1987 China IO)	-0.443*	-0.396*		
	(0.226)	(0.217)		
Intermediate Input Sanction Exposure (1997 China IO)			-0.434*	-0.394*
			(0.235)	(0.227)
Export Sanction Exposure		-0.326**		-0.330**
		(0.146)		(0.147)
R-squared	0.02	0.07	0.02	0.07
Observations	174	174	174	174
Panel B. Difference-in-Differences in quarterly average				
Input Sanction Exposure (1987 China IO) × Post(2017 Q1-)	-0.667**	-0.597*		
	(0.334)	(0.322)		
Input Sanction Exposure (1997 China IO) × Post(2017 Q1-)			-0.627*	-0.566*
			(0.349)	(0.339)
Export Sanction Exposure × Post(2017 Q1-)		-0.493**		-0.499**
		(0.192)		(0.193)
R-squared	0.82	0.83	0.82	0.83
Observations	4045	4045	4045	4045
County FE	Yes	Yes	Yes	Yes
Quarter × Year FE	Yes	Yes	Yes	Yes

Notes: Dependent variable is the natural log of nighttime light intensity aggregated at the county level. Monthly VIIRS nighttime light data are averaged by year (Panel A) and by quarter (Panel B), respectively. Intermediate Input Sanction Exposure indices are created based on China's 1987 or 1997 input-output table. Observations are weighted by county's share of population in 2008. 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 A-5: Robustness check: Controlling for county characteristics

	Log(Night light intensity)			
	(1)	(2)	(3)	(4)
Export sanction exposure × Post(2017 Q1-)	-0.245**	-0.266**	-0.173	-0.201*
	(0.114)	(0.113)	(0.116)	(0.115)
Intermediate input sanction exposure × Post(2017 Q1-)	-0.704**	-0.594**	-0.308	-0.228
	(0.315)	(0.294)	(0.326)	(0.326)
County FE	Yes	Yes	Yes	Yes
Quarter × Year FE	Yes	Yes	Yes	Yes
County characteristics × Post(2017 Q1-):				
Distance to Pyeongyang (quartile)	Yes	Yes	Yes	Yes
Distance to Chinese border (quartile)	Yes	Yes	Yes	Yes
Distance to major seaport (quartile)	Yes	Yes	Yes	Yes
Nuclear site	No	Yes	No	Yes
Special industrial zone	No	Yes	No	Yes
Population (quartile)	No	No	Yes	Yes
Building area (quartile)	No	No	Yes	Yes
Road length (quartile)	No	No	Yes	Yes
R-squared	0.84	0.84	0.85	0.85
Observations	4045	4045	4045	4045

Notes: VIIRS nighttime light data are aggregated by county and quarter from 2014 to 2019. Observations are weighted by share of population in 2008. 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 A-6: Placebo test of sanction impacts on market price

	Log(Normalized quarterly price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Placebo sanction quarter = T-4						
Export sanctioned ×**1**(Post placebo sanction)	0.123			0.126	0.121	0.123
	(0.081)			(0.079)	(0.080)	(0.082)
Import sanctioned ×**1**(Post placebo sanction)		0.151		0.156*		0.033
		(0.094)		(0.080)		(0.234)
Input sanction index ×**1**(Post placebo sanction)			0.259*		0.246*	0.204
			(0.138)		(0.127)	(0.351)
R-squared	0.67	0.67	0.67	0.67	0.68	0.68
Observations	6923	6923	6749	6923	6749	6749
Panel B. Placebo sanction quarter = T-8						
Export sanctioned ×**1**(Post placebo sanction)	0.196*			0.192*	0.198*	0.183*
	(0.105)			(0.103)	(0.105)	(0.102)
Import sanctioned ×**1**(Post placebo sanction)		-0.094		-0.067		-0.260
		(0.124)		(0.104)		(0.263)
Input sanction index ×**1**(Post placebo sanction)			-0.032		-0.025	0.313
			(0.188)		(0.166)	(0.388)
R-squared	0.56	0.55	0.56	0.56	0.57	0.57
Observations	6715	6715	6559	6715	6559	6559
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of sanctions' effects 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 the 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 the product level and reported in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table A-7: City heterogeneity: Estimates of sanction impacts on market price

	Log(Normalized quarterly price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Export sanctioned $\times\mathbf{1}$(Post sanction)	-0.029			-0.040	-0.050	-0.036
	(0.070)			(0.066)	(0.068)	(0.068)
Export sanctioned $\times\mathbf{1}$(Post sanction) $\times$ Pyeongyang	-0.023			-0.005	-0.016	-0.041
	(0.042)			(0.028)	(0.035)	(0.039)
Import sanctioned $\times\mathbf{1}$(Post sanction)		0.353***		0.356***		0.389**
		(0.061)		(0.059)		(0.153)
Import sanctioned $\times\mathbf{1}$(Post sanction) $\times$ Pyeongyang		-0.204		-0.202		-0.512*
		(0.157)		(0.152)		(0.263)
Input sanction index $\times\mathbf{1}$(Post sanction)			0.370***		0.382***	-0.050
			(0.103)		(0.099)	(0.219)
Input sanction index $\times\mathbf{1}$(Post sanction) $\times$ Pyeongyang			-0.072		-0.056	0.471
			(0.197)		(0.198)	(0.305)
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	0.82	0.81	0.82	0.82
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 the first quarter of 2013 (price in Q1 2013 is set at 100). All specifications include product, period, and city fixed effects. Standard errors are clustered at the product level and reported in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table A-8: Simulated price regressions, industries in product sample

	Dep. Var.: Predicted log $\hat{P}_{n,j}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Export Sanctioned	-0.145			-0.194*	-0.153	-0.203**
	(0.173)			(0.108)	(0.146)	(0.093)
Import Sanctioned		0.571***		0.590***		0.793***
		(0.181)		(0.170)		(0.235)
Input Sanc. Index			0.573**		0.584**	-0.534
			(0.190)		(0.214)	(0.434)
N	2436	2436	2436	2436	2436	2436
# of clusters	14	14	14	14	14	14
R-squared	0.0467	0.606	0.164	0.689	0.216	0.755

Notes: The dependent variable is the change in the price index of the composite good in county n, industry j implied by the model. The sample contains 174 counties and 14 two-digit industries covered by the product price data. "Export (Import) sanctioned" is a dummy variable indicating whether the industry export (import) sanction index is above 0.9. This is to approximate the dummy variables we used in the product-level regressions in Table 9.

B Additional Data Descriptions on North Korean companies

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 B-1.

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.

B.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 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.

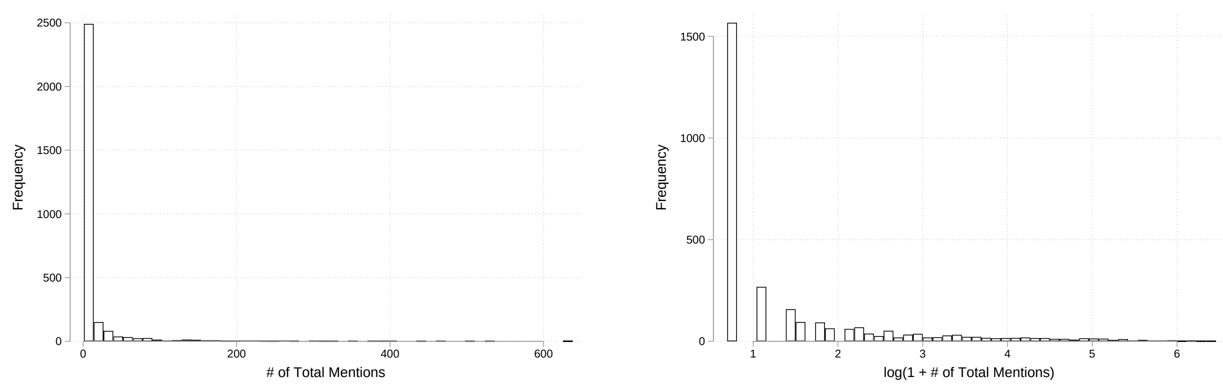
4) July 21, 2019.

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.

B.2 Distribution of Company Mentions

Figure B-1: 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 B-1: concordance between KIET industry codes (KSIC Rev. 10) and ISIC Rev. 3

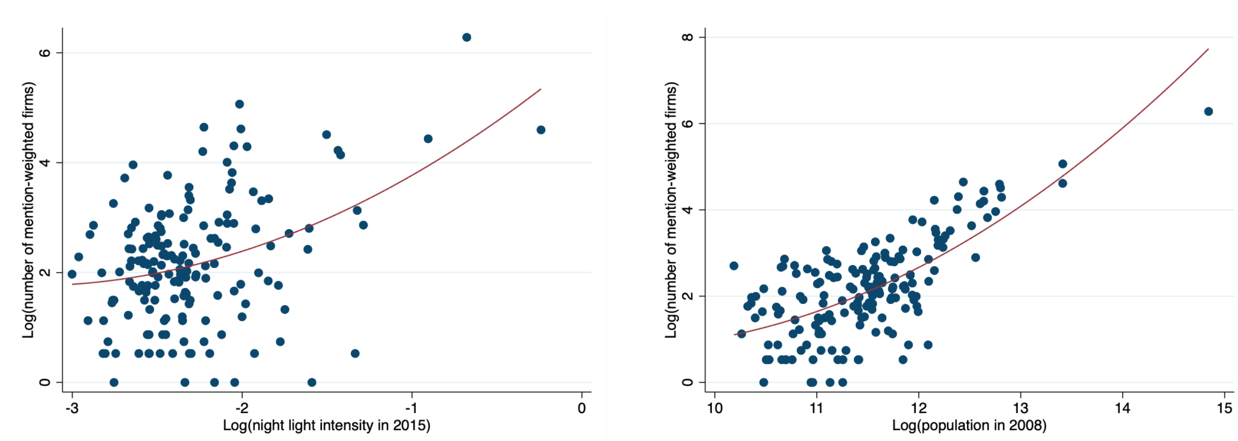
KSIC code	KSIC description	ISIC
10000	Manufacture of food products	15
10600	Manufacture of grain mill products, starches and starch products	15
10700	Manufacture of other food products	15
10800	Manufacture of prepared animal feeds and feed additives	15
11100	Manufacture of alcoholic beverages	15
11200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

B.3 Company Mentions Data Validation Exercise

We construct the regional industry share 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 lack of news report. 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 are 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 B-2 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 number of mentions between 2000 and 2015, reasonably captures the difference in economic and demographic characteristics across counties.

Figure B-2: 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 sum of firms where firms are weighted by the total number of mentions from 2000 to 2015. The horizontal axes in panel (a) is the log of night light intensity in 2015 and in panel (b) is the log of population in 2008.

B.4 Temporary Export Growth Before the Sanctions

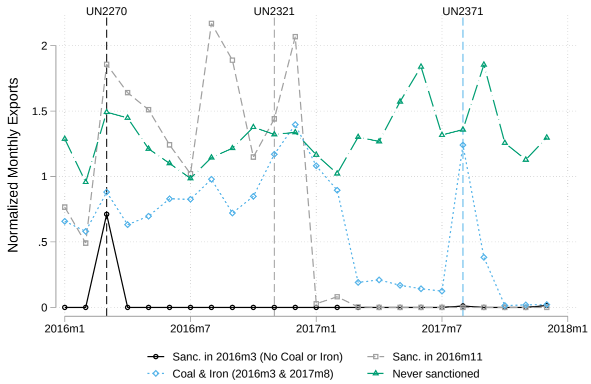
In this section, we describe the monthly trade patterns between North Korean and China and present suggestive evidence that exports of sanctioned products increase temporarily before the corresponding sanctions are imposed. We obtain the monthly trade data reported by China to the UN Comtrade database. Unfortunately, such data are reported on a voluntary basis and we only have data for 2016 and 2017.[35]

Panels (a) and (b) of Figure B-3 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 are 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 are more exposed to the export sanctions in 2016.

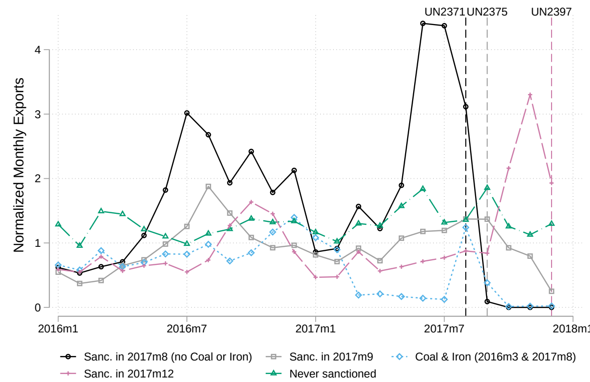
In contrast, we do not observe such temporary growth in trade on the import side. In Panel (c), we isolate three groups that are affected: vessels (sanctioned twice in Nov 2016 and Dec 2017), petroleum products (sanctioned twice in Sep 2017 and Dec 2017) and products sanctioned in Dec 2017, excluding vessels and petroleum products. We do not see large increases of imports of the sanctioned products leading up to the corresponding sanctions. We see large declines of 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.

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

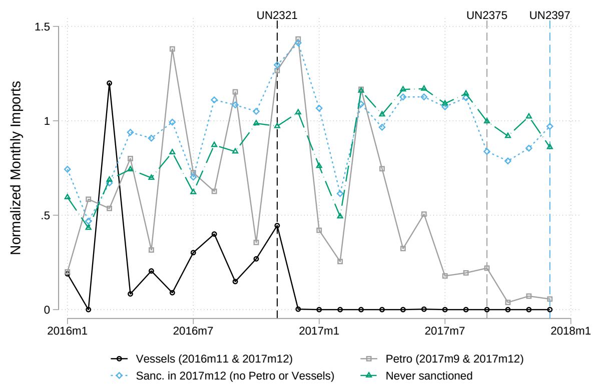
Figure B-3: North Korean monthly exports to and imports from China



(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.

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_{jt} as the log of true GDP in location j and period t, z_{jt} as the log of measured GDP, and x_{jt} as the observed nightlight intensity, we have the following statistical model:

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

where $\varepsilon_{z,jt}$ and $\varepsilon_{x,jt}$ are the measurement errors in GDP and nightlight, respectively. Under the assumption that the contemporaneous measurement errors are uncorrelated, i.e., $Corr(\varepsilon_{z,jt}, \varepsilon_{x,jt}) = 0$, and the assumption that the auto-correlation in the measurement error of nightlight intensity is zero, i.e., $Corr(\varepsilon_{x,jt}, \varepsilon_{x,j,t-1}) = 0$, the coefficient from an IV regression of z_{jt} on x_{jt} using the lagged nightlight intensity $x_{j,t-1}$ provides a consistent estimate of the GDP-nightlight elasticity $1/\beta$, while the OLS estimate contains an attenuation bias due to $\varepsilon_{x,jt}$.[36]

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 $\Delta \log(light_{jt})$) 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 (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 the range found among North Korean counties in 2014-2015. The brightest county in North Korea is Sinuiju with nightlight intensity of 0.825 $W/(cm^2 - sr)$, which is at the 84th percentile of nightlight intensity of Chinese counties in

[36]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_{jt}. For example, they assume that $\varepsilon_{z,jt} = 0$ for a set of "good data countries", estimate β directly and estimate the variance of $\varepsilon_{z,jt}$ 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: $\log(GDP_{jt})$ on $\log(light_{jt})$, instrumented by $\log(light_{j,t-1})$

IV Estimates	All Counties		Similar Nightlight	Similar Nightlight & Population Density	Northeast
	(1)	(2)	(3)	(4)	(5)
$\log(light_{jt})$	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)
$\log(light_{j,t-1})$	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 province level. Significance levels: 0.1 *, 0.05 **, 0.01 ***.

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.[37] 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).

D How the Bank of Korea estimates 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

[37]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.

Bank of Korea uses data on how much in quantity North Korea produced 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.

References

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

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