The Economic Costs of Trade Sanctions: Evidence from North Korea

Jihee Kim Kyoochul Kim Sangyoon Park Chang Sun*

August 2023

Abstract

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

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: Division of Social Science, Hong Kong University of Science and Technology, sangyoon@ust.hk. Chang Sun: HKU Business School, University of Hong Kong, sunc@hku.hk. We are grateful to the editor Costas Arkolakis and three anonymous referees for suggestions that substantially improved the paper. For helpful discussions and comments, we also thank Lee Crawfurd, Taiji Furusawa, Byung-Yeon Kim, James Kung, Bingjing Li, Chunbo Liu, Hyunjoo Yang, as well as participants at various seminars. 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 A-1 shows that North Korea has been actively conducting nuclear and missile tests since 2013. It also shows that the share of (pre-sanctions) exports and imports exposed to UN sanctions increases from zero to 20 percent after the first UN sanction on trade in 2016 Q1 and gradually rises to almost 60 percent by 2017 Q4. The 2016/17 UN resolutions were the most severe sanctions in the history of the country, advocated as a policy to apply "maximum pressure" on the North Korean economy. Depicted in the same figure, the cease in nuclear testing and drop in the number of missile tests immediately after the last sanction may suggest that sanctions have worked. However, there is little quantitative evidence on the economic impact of the sanctions, which is central to understanding the pressure that these sanctions have on the country and their effectiveness in achieving their stated goals.

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

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

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

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

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

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

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

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

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

Kydland (1992).

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

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

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

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

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

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

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

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

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

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

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

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

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

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

2 Background of the Trade Sanctions

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

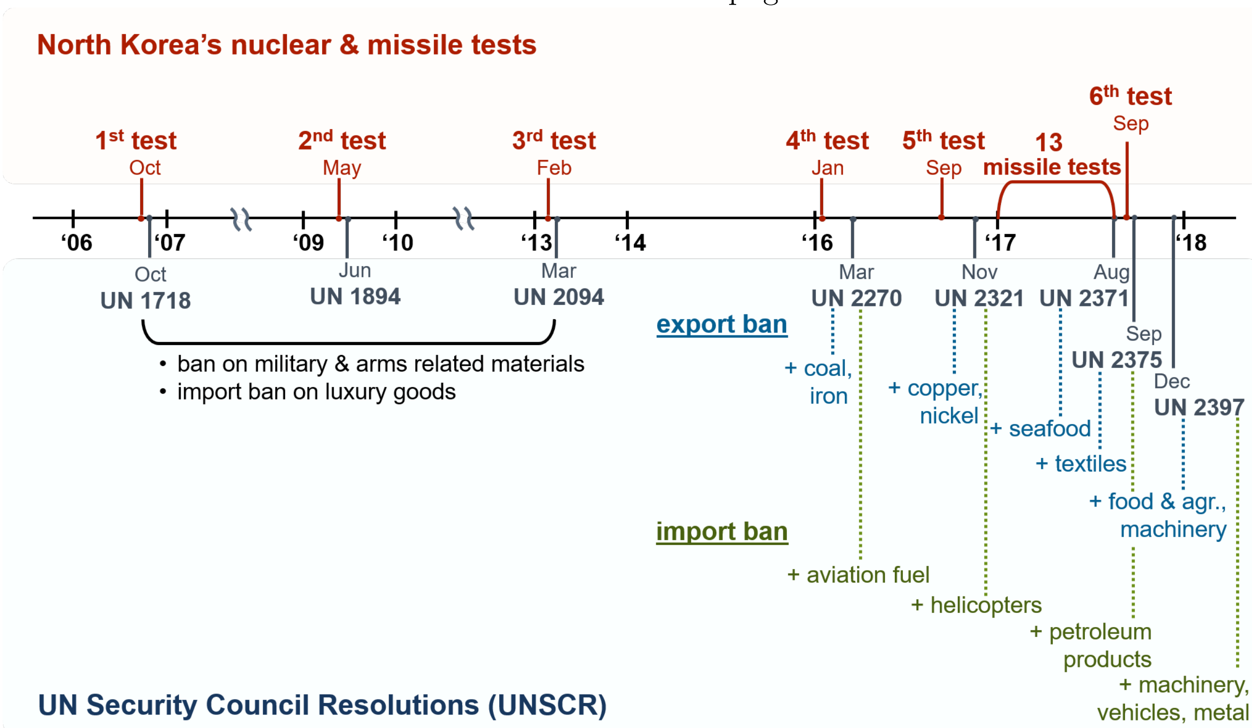
While the UN sanctions against North Korea have been strengthened over time, the UN Sanctions Committee made a notable change in its approach starting from 2016. Prior to 2016, the sanctions against North Korea mainly targeted North Korean military and nuclear operations and imposed restrictions on the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

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

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

Figure 1: The Timeline of UN Sanctions against North Korea

sanctions timeline.png



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

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

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

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

3 Data sources and measures

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

3.1 Nighttime lights

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

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

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

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

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

3.2 North Korean Company Data

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

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

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

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

3.3 Regional Sanctions Exposure Measures

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

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

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

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

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

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

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

Table 1: List of Industries and Sanction Indices

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

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

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

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

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

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

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

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

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

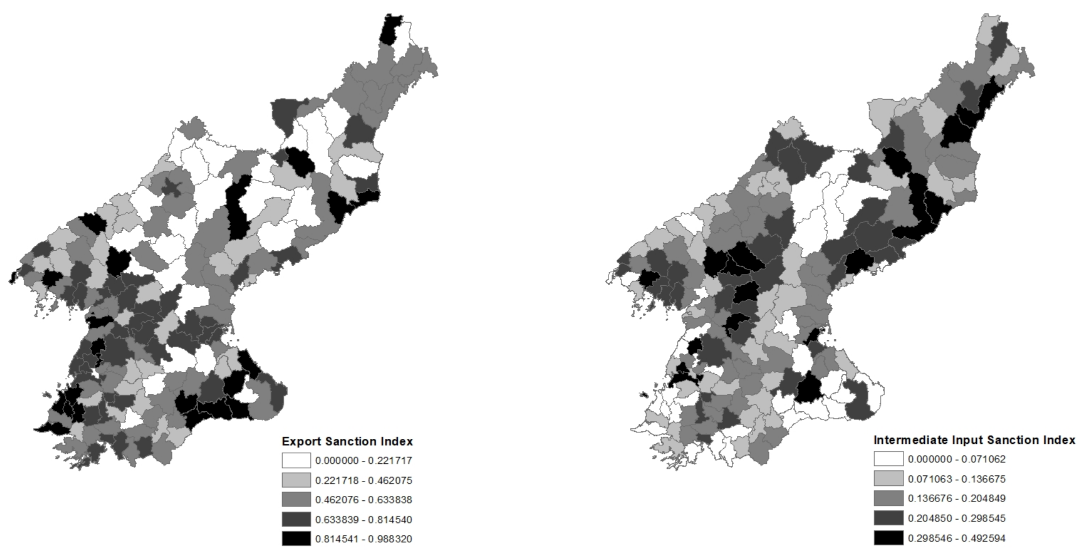
---

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

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

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

Figure 2: Spatial Distribution of Sanction Exposures



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

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

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

Table 2: County Level Summary Statistics

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

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

3.4 Market Price Data

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

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

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

4 The Impact of Trade Sanctions on Regional Economies

4.1 Empirical Strategy

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

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

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

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

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

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

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

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

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

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

4.2 Main Results

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

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

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

Table 3: Long Difference Estimates of Sanction Indices

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

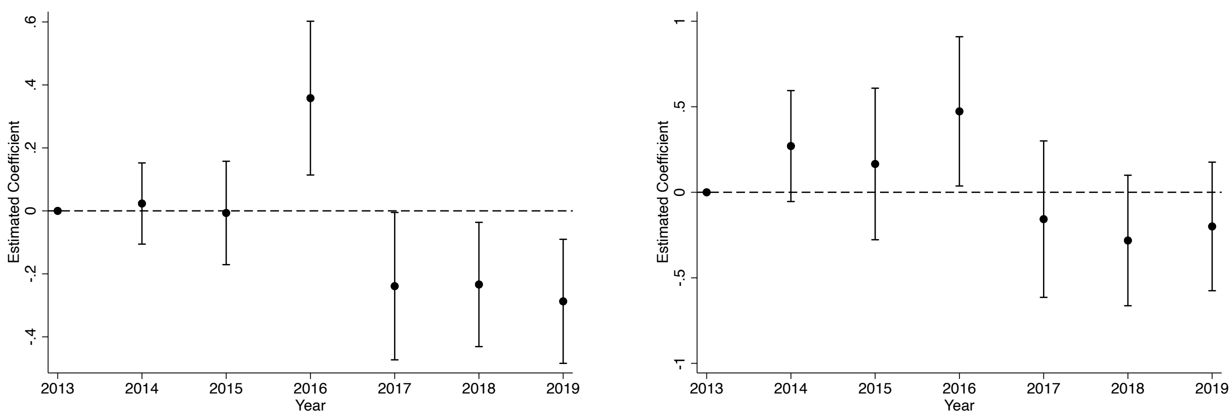
Notes: Dependent variable is the difference in log of annual mean nighttime luminosity, obtained by averaging VIIRS data at the county level. Observations are weighted by share of population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance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

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

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

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

Figure 3: Annual Coefficient Estimates of Sanction Exposures



(a) Export sanction (b) Input sanction

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

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

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

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

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

4.3 From Changes in Night Light Intensity to Changes in GDP

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

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

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

among North Korean counties.

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

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

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

4.4 Robustness Checks

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

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

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

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

	Δ Log of annual average nighttime luminosity						
	Province	Drop counties from sample				Additional controls	
	Fixed	top and bottom		Pyongyang	NK-China	Pre-trend	Nightlight
	Effects	1 perc.	3 perc.	(Captial)	border	(2013-2015)	+ regional
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Export Sanction Exposure	-0.204***	-0.295***	-0.257***	-0.220***	-0.286***	-0.286***	-0.105**
	(0.074)	(0.090)	(0.043)	(0.068)	(0.097)	(0.092)	(0.040)
Intermediate Input Sanction Exposure	-0.230	-0.254	-0.231	-0.142	-0.147	-0.225	-0.011
	(0.145)	(0.166)	(0.146)	(0.166)	(0.176)	(0.171)	(0.110)
Province FE	Yes	No	No	No	No	No	No
R-squared	0.54	0.09	0.16	0.07	0.07	0.10	0.79
Observations	174	170	162	169	158	174	174

Notes: VIIRS nighttime light data is aggregated by county and quarter from 2013 to 2019. Column (7) controls nighttime luminosity in 2015 and quartiles of country characteristics. Observations are weighted by share of population in 2008. We report hetroskedasticity-robust standard errors in parentheses. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Our key regressors, the regional sanction exposure measures, are constructed as Bartik shocks, i.e., inner products of region-industry shares and the sanction exposures at the industry level.[22] We follow Goldsmith-Pinkham et al. (2020) and make an identification assumption that the pre-sanction region-industry shares are orthogonal to other determinants of the changes in the county-level night light intensity. To provide credibility for our empirical strategy, we perform several diagnostic exercises following the suggestions in Goldsmith-Pinkham et al. (2020). We provide a detailed discussion on the Bartik instruments and diagnostic results in Online Appendix Section B.2.1. The Rotemberg decomposition exercise reveals potential heterogeneity in each industry's treatment effects. We offer more detailed discussions about the implications of the industry-specific 2SLS coefficients in Online Appendix B.3.

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

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

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

5 The Impact of Trade Sanctions on Market Prices

5.1 Empirical Strategy

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

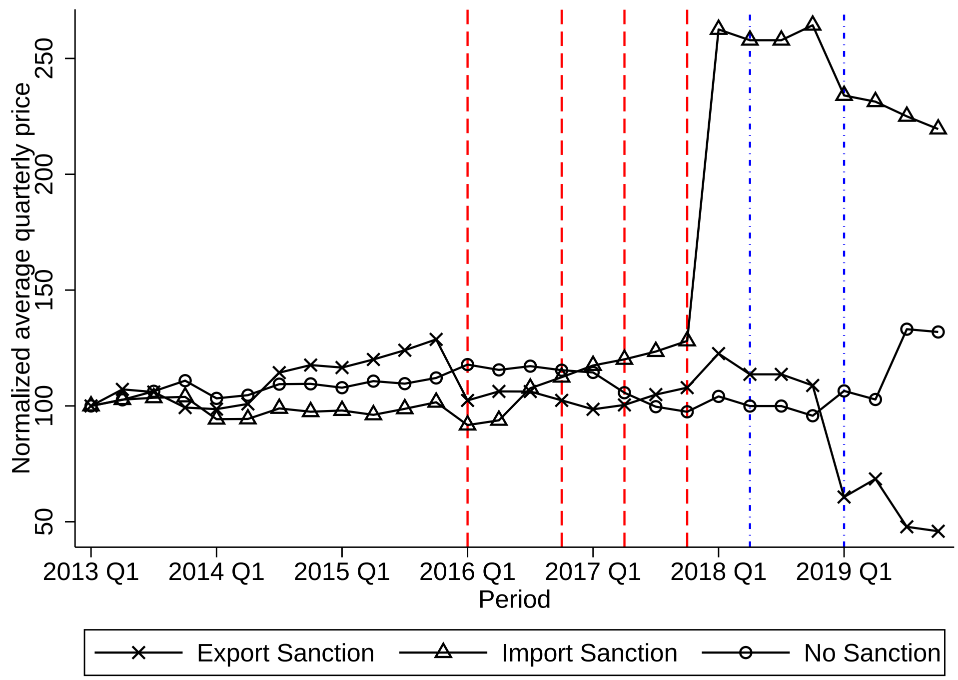
In our empirical investigation of the effect of trade sanctions on market price we compare price changes before and after the sanction shock across 72 products. Specifically, we restrict each product's sample period to eight quarters before and eight quarters after the quarter the product was sanctioned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

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

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

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

Figure 4: Price Trend by Product's Sanction Status



Notes: This figure plots normalized average quarterly price trends of products grouped by sanction type. Average quarterly price is obtained by averaging across six cities in North Korea (Pyeongyang, Shineuijoo, Kwaksan, Wonsan, Hweiryoung, Hamheung) and normalized with respect to first quarter of 2013. Red dashed horizontal lines indicate periods in which sanctions were imposed. Blue short-dashed horizontal lines mark periods at which the two NK-US summits took place: Singapore summit in June 12, 2018 and Hanoi summit in February 27, 2019.

5.2 Estimation Results

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

Table 5: Estimated Impacts of Sanctions on Market Price

	Log(Quarterly Mean Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Export Sanction $\times \mathbf{1}$(Post Sanction)	-0.032		-0.040	-0.029		-0.040
	(0.068)		(0.065)	(0.070)		(0.066)
Import Sanction $\times \mathbf{1}$(Post Sanction)		0.319***	0.322***		0.353***	0.356***
		(0.056)	(0.052)		(0.061)	(0.059)
Export Sanction $\times \mathbf{1}$(Post Sanction) $\times$ Pyongyang				-0.023		-0.005
				(0.042)		(0.028)
Import Sanction $\times \mathbf{1}$(Post Sanction) $\times$ Pyongyang					-0.204	-0.202
					(0.157)	(0.152)
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.81	0.81	0.81	0.81	0.81	0.81
Number of products	72	72	72	72	72	72
Observations	6825	6825	6825	6825	6825	6825

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

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

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

6 Quantifying the General Equilibrium Impact of the Sanctions

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

6.1 Model Setup

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

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

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

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

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

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

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

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

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

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

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

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

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 is perfect mobile in the pre-sanction equilibrium ($\alpha_m = 1$) but cannot move at all after the sanctions ($\alpha_m = 0$). We use perfect mobility $\alpha_m = 1$ for the post-sanction equilibrium as a robustness check. Due to

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

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

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

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

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

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

The corresponding price index for the domestic composite goods is

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

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

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

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

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

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

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

Therefore, the goods market clearing condition can be written as

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

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

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

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

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

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

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

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

income (and total expenditure) E_n equals

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

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

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

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

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

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

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

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

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

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

as

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

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

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

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

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

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

6.2 Parameterization and the Aggregate Impact

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

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

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

Table 6: Calibrated and Estimated Parameters

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

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

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

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

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

minimize

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

6.3 Extension with Government Taxes/Subsidies

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

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

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

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

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

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

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

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

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

6.4 Evaluating the Fit of the Model

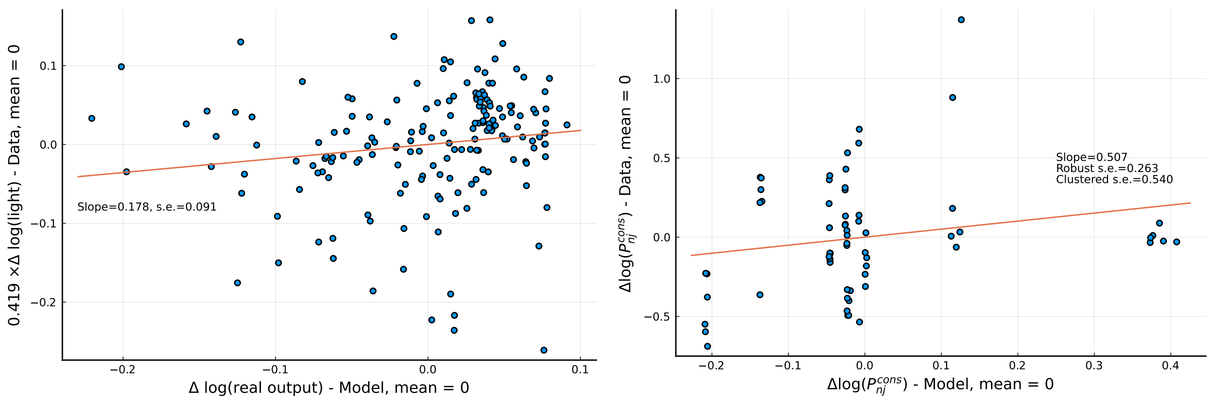
In this section, we evaluate the fit of the model using moments that we do not directly target in our calibration/estimation. In particular, we follow Adão et al. (2022): we regress the changes in output and prices in the data on the corresponding changes predicted by the model and examine whether the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

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

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

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

Figure 5: Goodness of Fit, Baseline Calibration



(a) Change in Output

(b) Change in Prices

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

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

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

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

6.5 Counterfactual Sanctions

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

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

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

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

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

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

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

7 Conclusion

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

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

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.

Acemoglu, Daron, David Autor, David Dorn, Gordon H. Hanson, and Brendan Price, "Import competition and the great US employment sag of the 2000s," *Journal of Labor Economics*, 2016, *34* (S1), S141–S198.

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

______, 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.

Allen, Treb and Costas Arkolakis, "Trade and the Topography of the Spatial Economy," *The Quarterly Journal of Economics*, August 2014, *129* (3), 1085–1140.

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 Intranational 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, "International Real Business Cycles," *Journal of Political Economy*, 1992, *100* (4), 745–775.

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.

______ and Robert C. Feenstra, "Foundation of the Small Open Economy Model with Product Differentiation," Working Paper 2022.

______, Fernando Parro, 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.

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.

Dix-Carneiro, Rafael and Brian K Kovak, "Trade liberalization and regional dynamics," *American Economic Review*, 2017, *107* (10), 2908–46.

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.

Feenstra, Robert C., Philip Luck, Maurice Obstfeld, and Katheryn N. Russ, "In Search of the Armington Elasticity," *The Review of Economics and Statistics*, August 2017, *100* (1), 135–150.

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.

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.

Ward, Peter and Kibum Han, "Assessing North Korea's 'Five-Year Economic Strategy (2016-2020)': Background, targets, and causes of its failure," *Journal of North Korea Studies*, 2021, *7* (1), 101–127.

World Bank, *Global Economic Prospects, January 2018: Broad-Based Upturn, but for How Long?*, The World Bank, 2018.

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